Stopping Healthcare Misinformation:
The Effect of Financial Incentives and Legislation

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Abstract

Fake news and misinformation have become a major social issue. And yet, many researchers concern primarily about political misinformation, leaving healthcare misinformation less emphasized. Nevertheless, healthcare misinformation may create consequences such as delayed diagnosis or treatment of patients or even public health crisis. We conducted an online experiment to test the role of financial incentives and legislation on disseminating online healthcare misinformation. Our findings revealed that financial incentives have a positive but diminishing impact on the likelihood of sharing online healthcare information regardless of validity. However, financial incentives have a stronger impact on attracting readers to share healthcare misinformation that they perceived to be fake. Surprisingly, legislation may deter the sharing of healthcare information that users perceive to be true but cannot deter them from sharing the healthcare misinformation they perceive to be fake. We also provided some practical implications for formulating measures of battling against healthcare misinformation for policymakers.

Keywords: Fake news, Healthcare misinformation, Social media, Online experiment

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1. Introduction

Online misinformation is now gaining more attention, given its serious consequences, such as creating an influence on outcomes of major political events. From an academic perspective, online misinformation may be understood as any wrong information on the Internet [1, 2], which may create dangerous effects such as causing people to stop believing in facts [3]. Given the growing popularity of different social media platforms and their potential to propagate misinformation, the ability to judge the credibility of information has become vital [4]. Because of the increasing adoption of social media as news sources, online information may be intermingled with news from many Internet users' perspectives, regardless of authenticity [5].

In recent years, healthcare misinformation has also proliferated in social media and has become a major public concern [6], although it emerged before the proliferation of social media. For example, Yongxin Yang, a physician in China, advocated using electroconvulsive therapy without anesthesia or muscle relaxants to cure Internet addiction. Yang had gained wide attention from some Chinese state-owned media and was described as a hero against Internet addiction. However, the so-called "therapy" was later found to lead to various psychological issues, while the media's framing and description became healthcare misinformation [7]. Therefore, online healthcare misinformation is gaining increasing attention from researchers in healthcare, information systems, and communications. Li et al. [8] identified the four most investigated themes around healthcare misinformation on social media in the literature as (1) feature, (2) spread, (3) impact, and (4) coping strategy.

Most studies related to misinformation cover the aspects of political fake news and misinformation, putting less emphasis on healthcare misinformation. However, healthcare

misinformation can mislead patients and lead to severe consequences such as delayed diagnosis or treatment [9]. According to the World Health Organization, recent online anti-vaccination advocates have caused a global healthcare threat in 2019. This online advocation indirectly helped vaccine-preventable diseases to become more predominant and consume more public healthcare resources [6]. During the COVID-19 pandemic, pro-Beijing Hong Kong lawmakers Ann Chiang openly recommended steaming face masks to re-use them, ridiculed by many public health experts. Pak-Leung Ho, an infectious disease expert from the University of Hong Kong, warned that the repeated use of face masks was a major reason for some medical workers being infected [10].

Given the information that Internet users can see on social media comes largely from what their friends share [5], understanding the incentives for sharing healthcare information online is vital for formulating practices to decrease the circulation of healthcare misinformation and to increase those of correct healthcare information. Therefore, we conducted an online experiment related to online healthcare misinformation sharing. Including six pieces of healthcare information (three true, three false) in the experiment, we asked the respondents to judge the authenticity of the information (i.e., perceived believability) and to reveal the likelihood they would share it. We also tested the role of financial incentives and legislation on sharing healthcare information. Hence, our research question is as follows: ***In what way do financial incentives and legislation impede or catalyze the dissemination of healthcare misinformation?***

2. Materials and methods

2.1 Background of research

As indicated in Appendix A, healthcare misinformation is usually more easily read and accepted by the audience [9]. Still, such information may often include exaggerated language, unclear evidence, unfair opinions, denial of common knowledge, and standard treatment options

[11]. It may even involve some self-proclaimed experts who in fact, lack the relevant knowledge [12]. The speed of disseminating healthcare misinformation is higher than that of verified stories [13] and may be catalyzed by financial incentives [14]. Furthermore, when Internet users search for healthcare information they are interested in, they may give more weight to the unverified anecdotal information they found than the professional reports they cannot understand [15]. Ordinary readers may find it difficult to assess the accuracy and credibility of online healthcare information, hesitate to take advantage of early-stage screening and treatment options, and misbelieve healthcare misinformation [12, 15]. These impacts, however, may not be effectively addressed simply by correcting misinformation or presenting the right information [16]. Medical institutions and professionals should adopt different measures, such as early education and collaboration with social media providers [17, 18] transparently with a significant consideration on public fears and concerns [13, 18]. More specifically about education, the promotion of media literacy and misinformation awareness was highlighted in previous studies related to political misinformation, but there are fundamental differences between political and healthcare misinformation. For example, fact-checking political information may include checking multiple sources, but fact-checking medical information is highly dependent on professional knowledge [19]. Without adequate background knowledge on healthcare, even well-established information consumption habits and identification capabilities may not help identify the validity of online healthcare information. Moreover, there are always new types of viruses or diseases that have not been previously identified. It will usually be the health experts, but not the general public, studying how to battle.

With the emergence of social media, media literacy and misinformation awareness may keep readers from being misled by misinformation, even though what social media users read is

highly dependent on what friends share on social media [5]. Although posting misinformation in social media can be easy, misinformation is only impactful when many people disseminate it [1]. Therefore, when Internet users are more capable of correctly judging the authenticity and accuracy of healthcare information, they may be less likely to share healthcare misinformation because sharing misinformation may harm their prestige [20].

2.2 Development of the theoretical model

Given that the general public may not be capable of identifying the validity of health information, the dissemination of healthcare misinformation cannot be stopped by individual Internet users. Healthcare institutions should foster the dissemination of accurate healthcare information and impede the dissemination of healthcare misinformation, and they need to know how to do this [17]. If the dissemination of healthcare misinformation among ordinary Internet users is reduced, these users are less likely to read and believe inaccurate information, which lowers the impact of healthcare misinformation. Considering the previous literature about the role of financial incentives [2, 14] and legislation [21] on disseminating misinformation, we proposed a theoretical model that tests the role of perceived believability of information, financial incentives, and legislation on the likelihood of sharing online healthcare information.

Previous scholars have indicated that much online misinformation is tailored, for example, by using exaggerated words to highlight the importance and believability of the subject issues [2, 22]. Therefore, we proposed,

H1: The perceived believability of information is positively related to the likelihood that online healthcare information is shared.

Content providers may create misinformation to attract more clicks that are convertible to advertising revenue as a result of any relevant reactions on social media [2]. Some Internet users

may be paid to manipulate opinions about misinformation [23], promote specific products [24], and comment on or follow various social media accounts to facilitate misinformation distribution [25]. Besides, the role of misinformation in fostering fake political news is also commonly discussed [23, 25]. Taking into account prior literature on prospect theory [26] regarding the positive but diminishing impact of financial incentives on utility, we proposed,

H2: Financial incentives have a positive but diminishing impact on the likelihood that online healthcare information will be shared.

In response to the proliferation of online fake news and political misinformation, some countries, such as Germany and Italy, have introduced some forms of anti-misinformation legislation [27]. To evaluate the effect of such legislation on health misinformation, we proposed,

H3: The existence of legislation is negatively related to the likelihood to share of online healthcare information.

In light of the potential impact of perceived believability in online information sharing, we also considered the perceived authenticity from the respondents' perspective to evaluate both H2 and H3. Respondents were then asked to re-think their sharing decisions if there were financial incentives or legislation that punished Internet users who shared healthcare misinformation. See Appendix B for the questions in this experiment, including the mean, standard deviation (SD), loading, and Cronbach's α.

2.3 Research method

Our study was conducted primarily by an online experiment. Participants were paid HKD 38 (about USD 4.87) for their participation, close to the minimum hourly wage in Hong Kong. Online banking was used to transfer the payments to filter repeated and fake participants. The measures for perceived believability of information were adapted from Lee et al. [28] to measure

information quality, whereas the measures for information-sharing behavior were adapted from Thompson et al. [29].

The experiment was designed based on the recommendation of a group of practitioners and researchers in information systems and health policy using the Delphi Method [30]. This group consisted of six members, including two social media and information systems researchers, one health economic and public policy researcher, two senior management of digital media, and one practitioner from the media industry. In the experiment, participants were shown these six healthcare-related articles recommended by the Delphi group. The selection was based on the content of the information and misinformation presented in these news articles. The decision to use six pieces of news for data collection is to balance the time spent on the experiment (as the participants needed to respond four times per news and this arrangement can avoid them getting fatigued) and obtained sufficient representative data for the data analysis. See Appendix C for the title list of articles included and more details of the article selection criteria.

For each of the articles, they were asked about the perceived believability of the article (predictor), their familiarity with the article (predictor), and the likelihood they would share the article (outcome). They were also asked a yes-no question about whether the article was true or false. The questions about the likelihood of sharing were repeated, assuming the presence of incentives (predictor) or legislation (predictor) that punishes Internet users for disseminating online misinformation regardless of intention. The two monetary levels were chosen as 10 HKD (approximately US$1.28, i.e., the price of a local magazine) and 50 HKD (approximately US$6.41, i.e., the price of a set meal in a local restaurant), respectively as a hypothetical incentive for encouraging the participants to share the news for testing the diminishing returns. Educational level, gender, and age were also included as control variables.

3. Results

In this study, we use binary logistic regression to analyze our data. According to Peduzzi et al. [31], as our model would have 8 covariates (see Table 2) and the proportion of positive cases was 50% (as we would use median split), the minimum number of samples needed should be 160 (= $10 \times 3 \div 0.5$). We recruited 393 participants, and 363 responses were included after incomplete and contradicting responses were filtered out (see Table 1 for the descriptive statistics), which exceeds the minimum sample size required.

Table 1. Demographic information of participants

Demographics	Female (n = 137)	Male (n = 210)	Not responded (n = 16)	Overall (n = 363)
Age	32.7	32.3	30.1	32.4
Education Level (Note 1)				
➢ Elementary School or below	0	0	0	0
➢ Middle School	1	3	0	4
➢ High School	15	28	0	43
➢ Associate degree	22	29	1	52
➢ Bachelor degree	69	110	5	184
➢ Master degree or equivalent	30	35	0	65
➢ Doctoral degree and above	0	2	0	2
➢ Not answer	0	3	10	13
Correctness (Cases/Percentage) (Note 2):				
➢ Able to identify true information	209 (25.4%)	309 (24.5%)	25 (26.0%)	543 (24.9%)
➢ Unable to identify true information	202 (24.6%)	321 (25.5%)	23 (24.0%)	546 (25.1%)
➢ Able to identify fake information	258 (31.4%)	409 (32.5%)	28 (29.2%)	695 (31.9%)
➢ Unable to identify fake information	153 (18.6%)	221 (17.5%)	20 (20.8%)	394 (18.1%)
➢ Correctness:	**56.8%**	**57.0%**	**55.2%**	**56.8%**
Notes: 1. Pearson χ^2 (df = 5) = 21.422 (p = 0.001). 2. Given that each respondent has answered six sets of healthcare information questions, the total case number is six times the number of participants of a particular gender type.				

In this experiment, we showed the participants six pieces of healthcare information (three real and three fake) and asked how likely they would be to share it. We repeated this question assuming the existence of a low-value incentive (HKD 10), a high-value incentive (HKD 50), and legislation. We also asked our respondents to report whether they were familiar with the information we showed to them (as a control variable). Appendix D shows the definitions of our variables in this study.

We analyzed our data collected using binary logistic regression, with the likelihood to share as the outcome (see Table 2). As we measured the likelihood to share using a 9-point Likert Scale using three measurement items (see Appendix B), we perform a median split (median = 14) with the total score ≤ 14 coded as 0 (i.e., low willingness to share) and total score > 14 coded as 1 (i.e., high willingness to share). Our result shows that H1 is supported. For H2, financial incentives demonstrated an effect of encouraging respondents to share as both have odds ratios larger than 1. We also observed per-dollar effect of the incentive decreased as the odds ratios decreased from 0.3003 per dollar (= 3.003 / 10 HKD) to 0.07648 units per dollar (= 3.824 /50 HKD) when the incentive was increased from HKD 10 to HKD 50. Therefore, H2 is also supported. However, our result indicates that legislation that punishes misinformation spread would not reduce our participants' intention to share healthcare information they received or found online, as we found a positive odd ratio. In other words, H3 is not supported.

For our control variables, we noted that gender (coded as female = 0, male = 1), age, and education level all had significant effects, i.e., female respondents were more likely to share online health information, and participants who were older or having a higher education level were less likely to share online health information. These findings somehow echoed results reported in prior literature. First, females were more likely to use social media for the news [32] and more to search

for online health information [33]. Therefore, we conjecture that they are more readily sharing online health information online. Also, young people were more frequently sharing online news [32], and therefore, they would be more likely to share online health information than older generations. However, we noted that more educated people were less likely to share online health information. This result might echo the findings of Bonfadelli [34], which suggests that educated people searched for online information due to their information needs and less educated people searched for information for entertainment purposes. As a result, the less educated people would have an incentive to share the information found with others based on an entertainment/hedonic reason. In contrast, more educated people would use the information to solve their problems.

Table 2. Result of logistic regression (Outcome variable = Likelihood to share)

Variables	β	S.E.	Wald Statistics	Df	*p*-value	Odds Ratio
Predictors						
Believability	0.101	0.004	534.5	1	< 0.001	1.106
HKD 10	1.100	0.068	261.6	1	< 0.001	3.003
HKD 50	1.341	0.069	381.8	1	< 0.001	3.824
Legislation	0.550	0.068	65.91	1	< 0.001	1.734
Control Variables						
Age	–0.013	0.002	28.80	1	< 0.001	0.987
Gender	–0.103	0.043	5.651	1	0.017	0.902
Education Level	–0.100	0.022	21.03	1	< 0.001	0.905
Familiarity	0.097	0.012	63.20	1	< 0.001	1.101
Intercept	–1.452	0.148	96.81	1	< 0.001	0.234
Pseudo R^2	Cox & Snell R^2		0.167	Nagelkerke R^2		0.223
Classification Table						
			Predicted		Percentage Correct	
			0	1		
Observed		0	3,323	1,348	70.5	
		1	1,612	2,529	61.1	
Overall Percentage					66.0	

Reputation may motivate people to share information in the hope of increasing their prestige in the online community, whereas sharing low-quality information can be damaging to an individual's status, and they try to avoid it [29]. Hence, this study also explored the difference in users' actions in response to information with different perceived authenticity. A set of ANOVAs was conducted to investigate whether our participants would be less likely to share perceived misinformation (see Table 3). The number of cases in which our respondents thought that the information was true (i.e., they correctly identified a piece of true information or incorrectly identified a piece of misinformation as true) or fake (i.e., they incorrectly identified a piece of true information or correctly identified a piece of misinformation as fake) were 937 and 1,241, respectively. The data also showed that our participants were more likely to share a piece of information perceived as true than a piece of perceived misinformation for all four scenarios. The impact of the provision of financial incentives and legislation was further investigated through a series of paired sample *t*-tests (see Table 4).

Table 3. ANOVA result (Outcome = Likelihood to share)

Analysis	Perceived Authenticity	Mean	St. Dev.	95% CI	F-value
Share information without incentive	True	4.673	2.010	[4.544, 4.802]	475.11 ***
	Fake	2.959	1.658	[2.866, 3.051]	
	Overall	3.696	2.006	[3.612, 3.781]	
Share information with HKD10 incentive	True	5.080	2.658	[4.910, 5.250]	133.24 ***
	Fake	3.867	2.239	[3.742, 3.992]	
	Overall	4.389	2.501	[4.284, 4.494]	
Share information with HKD50 incentives	True	5.486	2.768	[5.309, 5.664]	144.76 ***
	Fake	4.174	2.316	[4.045, 4.303]	
	Overall	4.739	2.602	[4.629, 4.848]	
Share information with legislation	True	3.952	2.372	[3.800, 4.104]	19.63 ***
	Fake	3.524	2.122	[3.405, 3.642]	
	Overall	3.708	2.242	[3.614, 3.802]	

*Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. The total cases included in the analysis is 2,178, of which our respondents perceived that 937 were true and 1,241 were fake. We used the average score of the likelihood to share in the ANOVA for simplicity of presentation.*

Table 4. Paired Sample *t*-test

Analysis	Perceived Authenticity	Mean Difference	St. Dev.	95% CI	*t*-value
Share information with HKD10 incentive vs. Share information without incentive	True	0.407	2.875	[0.223, 0.591]	4.33 ***
	Fake	0.908	2.157	[0.796, 1.021]	15.84 ***
	Overall	0.693	2.437	[0.590, 0.795]	13.26 ***
Share information with HKD50 incentives vs. Share information without incentive	True	0.813	2.930	[0.625, 1.001]	8.50 ***
	Fake	1.215	2.157	[1.095, 1.336]	19.85 ***
	Overall	1.042	2.526	[0.936, 1.149]	19.26 ***
Share information with legislation vs. Share information without incentive	True	–0.722	2.636	[–0.890, –0.553]	–8.38 ***
	Fake	0.565	1.873	[0.461, 0.669]	10.62 ***
	Overall	0.012	2.322	[–0.086, 0.109]	0.82

*Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. The total cases included in the analysis is 2,178, of which our respondents perceived that 937 were true and 1,241 were fake. We used the average score of the likelihood to share in the paired t-tests for simplicity of presentation*

The results of the paired *t*-tests are counter-intuitive. First, our findings indicated that the provision of financial incentives might foster the distribution of both perceived true and fake healthcare information. However, it is more effective in fostering the spreading of perceived healthcare misinformation. Further, with legislation that punishes misinformation dissemination, respondents surprisingly reported a lower likelihood of sharing the healthcare information they perceive as true but a higher likelihood of sharing the healthcare information they perceive as false.

4. Discussion

4.1 Theoretical implications

Our first theoretical implication is related to the role of financial incentives on the dissemination of healthcare misinformation. More specifically, we have found that perceived believability and financial incentives may increase the likelihood of sharing healthcare information. We have also compared the roles of financial incentives and legislation in terms of authenticity

consideration. Although respondents, in general, will be more motivated to share online healthcare information when given financial incentives, the impact created by the financial incentives is stronger when the respondents consider the information to be fake. This echoes with previous arguments related to the role of financial incentives on misinformation dissemination [23], except we have extended the boundary conditions of the argument beyond the political context. Furthermore, the power of financial incentives may demonstrate a marginal diminishing effect. While a small financial incentive may help foster the dissemination of healthcare information, increasing the size of financial incentives may not foster the same level of additional dissemination effect. This echoes the prior literature on prospect theory [26] regarding the positive but diminishing impact of financial incentives on utility.

Our second theoretical implication is related to the role of legislation in stopping the dissemination of health misinformation. More specifically, we have found that legislation may deter the sharing of healthcare information that users perceive to be true but encourage them to share the healthcare misinformation that they perceive to be fake. These results may sound counter-intuitive, especially to many government officials. However, according to Penney [35], governmental online surveillance measures may drive some users to become more careful when sharing or posting messages, but other users may take a rebellious approach because they disagree with such measures. In our context, a possible explanation is related to the attitude of Internet users toward proposed legislation regarding online misinformation. They may choose to share the misinformation that they perceive to be fake so that an average person will not be harmed, but they can still show their discontent toward the government.

4.2 Practical implications

Our first practical implication is related to the actions that government and health-related institutions can perform. Because financial incentives may encourage social media users to share healthcare information, government and health-related institutions could pay different social media users to share authentic healthcare information. This could be achieved by establishing an online platform to engage these social media users, possibly with gamification measures [36], while the remuneration could depend on their number of followers. While Internet celebrities and public figures may also be the targets for engagement, platform hosts should also invest efforts in engaging ordinary individual social media users, given friends on social media, as a message source, may have a positive impact on the users' trust in the messages [37]. The dissemination of correct online health information among peers and friends may therefore be more effective than information dissemination by celebrities alone. However, the platform hosts should be aware of the marginal diminishing effect of the financial incentives, and should not overpay the social media users. The operation and maintenance of these platforms could also be done together with some online news platforms or media companies that are more experienced in managing social media. Besides, these platforms should not only correct health misinformation, but also actively offer correct health information because displacing misinformation alone may not correct the misbelief [16, 38]. This aligns with the argument of Gesser-Edelsburg et al. [18], except our recommendation is better tailored to the sharing and co-creating characteristics of social media [39] and the role of financial incentives as identified in our findings. Prior research has also mentioned how news of an adverse event (i.e., not even misinformation but negative news) can lead to the public's perception of a public health policy [40], care should be taken in handling this strategy.

Our second practical implication is that the adoption of hard approaches to suppress the dissemination of online healthcare misinformation should be discouraged, which is an important implication for government officials and lawmakers worldwide. As shown in our results, the existence of punitive legislation could suppress the proliferation of true healthcare information. It could eliminate the potential social media to promote desirable healthcare habits and information. In contrast, it could aggravate the controversy surrounding freedom-of-speech suppression without correcting the wrong beliefs created by the healthcare misinformation due to belief perseverance [38]. In recent years, there is an increasing number of increasing anti-fake news legislation in different countries. For example, the Singaporean Government has introduced a bill known as the Protection from Online Falsehoods and Manipulation Bill (POFMA), which has triggered some controversies and critics from opposition parties related to freedom of speech [21]. Given the experience of Singapore, our findings that suggested the ineffectiveness and side effect of legislation, as well as the issue of belief perseverance, we argued that legislation might not be the answer to battling online healthcare misinformation.

5. Conclusion

Our research is not without limitations. First, our sample frame (Internet users in Hong Kong) could limit the generalizability of the findings. Despite the high Internet penetration rate in Hong Kong [41], the findings of this study would be more representative if our sample included more diverse respondents with different characteristics (e.g., personal medical history and personality and those of family members), which may be addressed in future research. The other concern is that the news articles used would not be diversified enough. However, as the six articles used in this study covered different healthcare topics (e.g., GM foods, cancer, and eating habits), we believe such diversified selection of healthcare-related articles will ensure the generalizability

of our findings. For future research, we first recommend that researchers test for tailoring in the (mis)information message and see if tailoring would influence readers' perception of the news. Further, researchers can also explore the diminishing effect of monetary incentives by including more levels of monetary incentives in the model. Future research can also explore the effectiveness of other information consumption habits in identifying the authenticity of online healthcare misinformation.

Our paper mostly focused on the influence of financial incentives and legislation on healthcare misinformation dissemination on social media. Besides, we provided healthcare institutions and universities with guidance on steering Internet users more effectively toward sharing authentic online healthcare information. The directions for healthcare institutions and governments to address the impact of online healthcare misinformation may be similar to doctors' common advice in response to different types of disease: "*prevention is better than cure*." In particular, during this COVID-19 pandemic time, we witness the intermingling of politics, misinformation, and health policymakers' effort to find ways to save humankind [42]. The prevention of the impact of online healthcare misinformation may be a better solution than addressing the problem after the impact has become significant and misbelief has been created. In the end, it is hoped that our findings and implications will save more people from suffering the consequences of online healthcare misinformation.

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Online Appendices

Appendix A. Themes around Healthcare Misinformation on Social Media in the Literature

Source	Argument
Feature	
Okuhara et al. [9]	Healthcare misinformation often exaggerates the side effects of traditional treatment and is usually easier to read and to be accepted by the target audience. Some self-claimed experts may be mentioned in the healthcare information, but they are in fact, self-proclaimed specialists who nevertheless lack specialized knowledge or licenses.
Li et al. [11]	Online healthcare misinformation commonly uses an exaggerated and absolute tone regarding the subject health issues. In addition, misinformation is often mixed with unfair opinions or lacks proper sources to support it.
Okuhara et al. [12]	Online healthcare misinformation often involves the destruction of common knowledge, denial of standard medical treatment control, education about alternative treatment and hidden truths, and a sense of authors' superiority of "only I know the truth."
Chen et al. [17]	Much online healthcare information is provided by patients and caregivers based on their personal experience, which may include fake statements. Falsehoods in such misinformation may be related to background knowledge (e.g., risk factors), prevention measures (e.g., lifestyle), and treatment (e.g., the side effect of treatment).
Spread	
Okuhara et al. [9]	Healthcare misinformation can be uncritically shared online among many individuals owing to the advances in social distribution brought about by the Web 2.0. Users can interact with like-minded individuals and easily formulate the illusion that many others share their beliefs, when, in reality, those others may only be a small and dedicated group.
Sommariva et al. [13]	A study on the distribution of information about the Zika Virus indicated that rumors were more likely to be disseminated than verified stories and appeared more frequently when the topic was popular.
Trembath et al. [14]	Some healthcare and lifestyle bloggers may publish healthcare misinformation, possibly mixed with pseudoscientific information to promote themselves or recommend some products for payment.
Madathil and Greenstein [15]	Many Internet users use search engines to find healthcare information that they are interested. Yet, they may give more weight to anecdotal healthcare information found online because the public reports are usually harder to comprehend.
Impact	
Okuhara et al. [12]	Because individuals have difficulty assessing the accuracy and credibility of healthcare information on the Internet, online healthcare misinformation may incite the doubt and fear of the general public. Thus, such misinformation will bar the promotion of early health checks and create public distrust in modern medicine.

Chen et al. [17]	Healthcare misinformation circulated on social media can affect individuals' attitudinal and behavioral responses to cancer. In addition, misinformation may be disseminated significantly more broadly and deeply than true information on social media.
Trembath et al. [14]	Unwarranted belief in healthcare misinformation on the Internet and various "infotainment" media channels can lead to numerous catastrophic healthcare and welfare outcomes for individuals, their families, and the professionals involved. For example, patients who misbelieve in such misinformation may rely on ineffective treatments.
Madathil and Greenstein [15]	In the healthcare context, an initial perception established based on online anecdotal information is not easily changed even after the presentation of more reliable public reports, given these reports may be hard to be understood and only partly relevant to the conditions of individuals.
Coping Strategy	
Chen et al. [17]	The correction and reduction of healthcare misinformation requires the efforts of both social media service providers and medical professionals. For example, they could create a digital library for health-related misinformation for self-cleaning by the public.
Sommariva et al. [13]	The fight against healthcare misinformation should involve the promotion of media literacy so that the public can evaluate healthcare messages. Practitioners could adopt social media in improving the reach of accurate information, especially in a crisis context.
Gesser-Edelsburg et al. [18]	In the context of the battle against misinformation, it is essential for professional bodies to correct misinformation transparently and to respond to the public's fears and concerns more comprehensively.
Chua and Banerjee [16]	The presence of counter-rumors lowers the intention to trust, but not the intention to share. Therefore, counter-rumors may not always be efficient in curtailing rumors.

Appendix B. Detailed Procedures for Online Experiment

This survey was conducted as part of a research study. Six pieces of news (see Appendix C) were selected by the Delphi Group (see Appendix D for details). Each piece of news was shown on a separate webpage, and the related survey questions were shown on the same page. When the first time a piece of news was shown, we asked the items related to "likelihood to share" (outcome) and its "perceived believability" (predictor), and a true-or-false question regarding the given information (for recorded down the perceived authenticity). After going through one round of all the news, we started the second round by including a statement telling them that HKD 10 would be paid if they agreed to share the news and asked them to respond again to the items related to "likelihood to share." The third and fourth rounds were using a similar setting by providing a statement telling them that HKD 50 would be paid if they agreed to share the news, and legislation was enacted to punish people for spreading misinformation, respectively. The descriptive statistics of the perceived believability and likelihood to share are reported below.

Item	Mean	SD	Loading	Cronbach's α
Perceived Believability of Information (BELN) - Lee, et al. [28]				
BELN1. This news story or information is believable.	4.05	2.29	0.956	0.96
BELN2. This news story or information is trustworthy.	4.07	2.30	0.964	
BELN3. This news story or information is credible.	4.08	2.27	0.959	
Likelihood of Sharing (SHARE) - Thompson, et al. [29]				
SHARE1. I will share this story on social media.	3.51	2.19	0.884	0.88
SHARE2. I think my friends should also know about this story.	3.75	2.20	0.934	
SHARE3. It would be useful for others to know about this story.	3.83	2.29	0.884	
Note: Both of the above measures used a 9-point Likert scale.				
Overall, do you think the information is true or false? (Binary)				

Appendix C. Title List of the Information Included in the Study

The selection of these 6 pieces of news was performed by the Delphi Group mentioned in the paper. The selection was based on the relevance of the content of the information and misinformation presented in these news articles.

The articles with true information were sourced from different legitimate news outlets (e.g., Radio Television Hong Kong) or healthcare websites (e.g., healthnews.com.tw), whereas misinformation was sourced from content farms or websites that published articles with unknown sources and authors and were proved to be incorrect. To determine the authenticity of such information before including it in the experiment, we cross-checked the arguments with at least two sources. For example, on finding an article that quoted the anti-cancer-screening advocation of Japanese doctor Makoto Kondo [e.g., 12], we found some other peer-reviewed academic sources to reject his claims. Accordingly, we included it as one piece of healthcare misinformation in our experiment. We also included healthcare information on different topics, including cancer, food safety, and dietary habits, to avoid the respondents' judgments from being too contextually specific to a single type of healthcare issue.

The decision of using 6 pieces of news for data collection is to balance the time spent on the survey (as the participants need to respond 4 times per news, and this arrangement can avoid them getting fatigued) and obtaining sufficient representative data for the data analysis.

Category	True/False	Chinese Title	English Title
Healthcare	True	**睡眠不足愛吃垃圾食物**	When you do not sleep enough, you will love eating junk food
Healthcare	True	喝茶減肥、防三高好處多多！只有這 8 種茶一定別喝	Drinking tea can keep you fit and prevent the "Three Highs"! However, there are eight types of tea that you should not drink.

Healthcare	True	這時喝茶喝咖啡反而更疲累！吃出疲勞的4大壞習慣	You will be more tired if you drink tea now! The four bad eating habits that make you tired.
Healthcare	False	醫界良心近藤誠教授：可怕的不是癌症，而是「癌症的治療」	The conscience of the medical sector Prof. Makoto Kondo: It is not cancer that is scary, but the treatment of cancer
Healthcare	False	美國正式宣布了：基因改造食物含有嚴重的毒素，終於爆開了	USA announcement: genetically modified food contains dangerous toxins that can burst out
Healthcare	False	**年輕人眼癌增三成！晚上熄燈後千萬不要看手機！**	30% of teenagers have eye cancer! After turning off the light at night, do not look at your phone!
Notes: In the Cantonese language context, "Three Highs" refers to high blood pressure, high blood glucose, and high blood lipids.			

Appendix D. Definition of the variables

Variable Name	Definition
Outcome	
Likelihood	Variable that measures the likelihood that a piece of information will be shared. It consists of three items (9-point Likert scale, Cronbach's α: 0.88). As we use binary logistic regression to analyze our data, we use the median split (0 = low likelihood to share with a total score lower than or equal to 14; and 1 = high likelihood to share with a total score higher than or equal to 15) as our outcome.
Predictors	
Perceived Believability	Variable that measures the level at which our participant perceives that he/she believes in a piece of information. It consists of three items (9-point Likert scale, Cronbach's α: 0.96). We use the total scores of the three items as the independent variable of our regression.
HKD 10	Coding variable for the data collected with the low-value financial incentive of HKD 10.
HKD 50	Coding variable for the data collected with the high-value financial incentive of HKD 50.
Legislation	Coding variable for the data collected with the legislation of punishment for spreading misinformation.
Control Variables	
Gender	Coding variable for the gender type (0: female; 1: male). Data for which the gender type was not reported were removed from the data analysis.
Education	Coding variable for educational background (1 = Elementary; 2 = Middle School; 3 = High School; 4 = Associate degree; 5 = Bachelor degree; 6 = Master degree or equivalent; 7 = Doctoral degree and above). Data for which the educational background was not reported were removed from the data analysis.
Familiarity	Variable measuring the level of familiarity with the information of our participant (9-point Likert scale).
Note: The measures of likelihood to share and perceived believability are reported in Appendix B.	