On Social Value of Risk Information in Risk Communication

Yan Wang
Georgia Institute of Technology
801 Ferst Drive NW, Atlanta, GA 30332-0405
yan.wang@me.gatech.edu
Tel: +1-404-894-4714

Abstract

The conventional research of risk communication centers on how scientific community can improve trust and credibility in public perception, enhance public understanding of risks, and change public behaviors to conform to technocratic values. More recently, the emphasis of risk communication has evolved from conveying scientific data and risk information to establishing effective information flows. It has been recognized that establishing two-way communication channels among experts, governments, corporate, and general public is important to build trust relationship. With conflicting interests and coordination motive among stakeholders, the societal aspects of risk communication need to be considered. In this paper, a mathematical model of social value of risk information is proposed to explicitly incorporate factors such as public and private information, personal bias, knowledge, and social behavior in risk communication. Uncertainties associated with the perceived risks due to both the lack of knowledge and individual differences in population are considered in the proposed model. The impacts of precision and accuracy of risk information as well as subjective bias on social welfare are characterized. Some of the model predictions on the effectiveness of communication are verified with the observations in other's survey studies. The proposed model could potentially be used to help devise risk communication strategies and policies. Its use in is demonstrated in a case study of Fukushima nuclear accident.

Keywords: risk perception, risk communication, social welfare, value of information, game theory, Fukushima

1. Introduction

The traditional objectives of risk communication to the public are to raise awareness of potential hazards (earthquakes, hurricanes, flooding, nuclear radiation, epidemics, etc.) and motivate preventive actions. The conventional research on risk communication centers on how scientific community can improve trust and credibility in public perception, enhance public understanding of risks, and change public behaviors to conform to technocratic values [1, 2, 3]. In the past three decades, the emphasis of risk communication has evolved from conveying scientific data and risk information to establishing effective information flows [4]. Particularly, the traditional normative one-way communication from experts to general public has been replaced by two-way communication among stakeholders [5]. The layperson stakeholders are no longer perceived as being incapable of handling uncertainty information. Communicating uncertainty has become essential to establish trust relationships among experts, public policy makers, and the general public [6, 7].

The major goal of risk communication is to reconcile the discrepancy of risk perceptions between the general public and experts [8]. Various approaches have been developed to model the differences of risk perceptions among individuals, such as mental models [9], social amplification theory [10], risk information processing model [11], psychometric paradigm [12,13], attitude-behavior model [14], and cultural risk theory [15]. Risk perception is influenced by many factors, such as cultural differences [16], political and ideological bias [17,], genders [18], risk targets [19], affect and emotion [20,21], communicator's characteristics [22], the sense of control [23], and others.

The recent social media bring more channels that enable peer-to-peer risk communication [24]. Stakeholders may have different sources of information in addition to government agencies.

Risk information may be shared publically or privately within some communities. Public information is accessible for all stakeholders, whereas private information is only accessible by certain stakeholders. The risk perceptions of stakeholders thus are formed according to both the public and their respective private information. The public information of risk is the one announced through government agencies or public entities and its access is controlled by the public entities. All stakeholders have access to it. In contrast, the private information is acquired by individual stakeholders but not all. Note that the public and private information may not be clearly categorized. For example, there are different forms of media coverage, such as television, radio, newspapers and magazines in print, news and bulletin board on the Internet, websites of academic institution, scholarly publications, social networking services, etc. Depending on the sizes of users and audience for some specific issues, the different forms of media could be regarded as public or private, depending on the context. To simplify, here private information is defined as the one where the access is controlled by private entities. Therefore, most of media are regarded as private information based on this definition. Limited research has been done on how to use different types and forms of media effectively in risk communication.

In addition, one of the general public's concerns that hinder their trust is that they are afraid of 'hidden agenda' from other stakeholders. The implication is that the communication of risk information could potentially bring benefits to certain stakeholders. In current research of risk communication, it is typically assumed that all stakeholders experience losses as the consequence of hazards. Yet, the dissemination of hazard and risk information may cause social welfare effects that are much more complicated than we used to think. Natural and man-made hazards cause damages and losses to many people. However, at the same time, some stakeholders may gain benefits out of them. For instance, insurance companies may use the opportunities to market their new products, and preventive equipment vendors may gain more market shares because of the public awareness. Therefore, hazards should not be simply treated as losses for all stakeholders. They bring potential benefits to some stakeholders.

Furthermore, a stakeholder in a society makes decisions not only based on his/her own perceived risk, but also his/her perception of other stakeholders' risk perceptions. These social behaviors are inherently embedded in human activities. For example, insurance companies calculate a policy holder's premium based on the individual's risk perception by providing different options of deductable. This behavior is characterized as the willingness of *coordination* among stakeholders. The degree of coordination affects the efficiency of the use of information [25]. A higher degree of coordination among the stakeholders implies that one's perception is more inclined to be influenced by others' opinions. The conflict of interests and social behavior aspects of risk communication should be studied comprehensively. There is virtually no research on this aspect.

Given complex factors that affect the effectiveness of risk communication, there is a need to develop quantitative approaches to help formalize and design risk communication strategies. The formal approaches should incorporate influential factors, not only traditionally studied education level, knowledge, gender, etc., but also different media and information channels, conflicting goals between stakeholders, social value and social behaviors. In this paper, a mathematical model of risk perception and social value of risk information is proposed to support risk communication with the explicit considerations the factors of public and private information, social behaviors, and perception. The uncertainties in the perceived risks that are due to the lack of perfect knowledge, ambiguity, contradiction, or indeterminacy and due to individual differences in population are considered. Uncertainty is an important component of risk information communicated to the general public [26,27,28,29]. The influence of the precision and accuracy of risk information on social welfare can be predicted in the proposed model.

In this model, the social value of risk information is quantified, similar to the model of *social value of information* developed in economics for monetary policy [30]. Although the concept of *signal value* of a hazard event was proposed in the social amplification of risk framework [10], which provides new information about the probability that similar or even more destructive mishaps might occur with this type of activity, the social value of risk information has not been studied. Different from the value of information for risk management [31], the social value of information is about how the transparency and precision of public and private information will affect the welfare of society as a whole. The proposed social value model captures the conflict of interests and coordination behavior of stakeholders.

A good risk communication strategy is to add value to society and enhance public relations [32]. The social value and social welfare are quantified as utilities in the proposed model, and the impacts of uncertainties, information precision, bias, and social behavior on the social welfare can be assessed in studying the effectiveness of communication. Risk communication policies can be devised so that they benefit the society by improving the expected welfare. The quantitative model predicts that culture diversity, personal prior beliefs, information transparency, and knowledge levels have critical influences on the effectiveness of risk communication.

In the remainder of the paper, the value of information in risk analysis is summarized in Section 2. The social value of information in economics is also introduced. In Section 3, the proposed mathematical model of social value of risk information is described. The predictions from the model are discussed in Section 4. In Section 5, a case study of Fukushima nuclear accident is used to illustrate how the proposed model can be applied in risk communication.

2. Background

In this section, the background of value of information in risk analysis is first given. Then the social value of information in the context of economics is introduced.

2.1. Value of Information in Risk Analysis

The value of information is a well established concept in decision analysis [33,34,35], which is to decide the right kind of experiments to collect the right amount of extra information. It has been applied in health risk management [31]. Recently it was demonstrated in cost analysis for decease surveillance [36] and control [37].

2.2. Social Value of Public Information

The social value of public information has been studied in economics, where individual decision makers' choices are made in isolation from each other given their available public and private information. The motivation of the model was to study the effect of media on speculation based upon market events. The social welfare model is summarized as follows. A population of agents have access to public and private information and aim to take actions appropriate to the underlying true but unknown state. At the same time, they also engage in a so-called "beauty contest" zero-sum race to second guess the actions of other individuals. The prize to a player is proportional to the difference between his or her own action and the average actions of all others. That is, an individual agent's utility is defined as

$$u_i(\boldsymbol{a}, \theta) = -(1-r)(a_i - \theta)^2 - r(D_i - \overline{D}) \tag{1}$$

where θ is the underlying socially optimum solution, yet the i^{th} agent takes action a_i. The vector $\boldsymbol{a}$ denotes the collection of all actions. The first component thus is a quadratic loss weighted by $1-r$. The second component is the "beauty contest" term, where $D_i = \int (a_j - a_i)^2 dj$ is the accumulative deviation of the i^{th} agent because his or her action deviates away from other individuals, assuming the number of agents is large so that the integral notation instead of summation is used as a simplification, and $\overline{D} = \int D_j dj$ indicates the average action for the population. The i^{th} agent's loss increases (with the reduced utility) if the distance between his or her action and the average of the population increases. There is an externality in which an individual tries to second-guess the decisions of the others. The individual gains by predicting the average opinion better than others. The parameter r gives the weight on this second-guessing motive. The larger the value of r has, the more significant is the external effect on the individual utility arising from the coordination motive of agents. Note that the second-guess term is very similar to the high-order beliefs in game theory with incomplete information, where decisions are made according to payoffs and hierarchies of beliefs [38,39].

The second term in the right-hand side of Eq.(1) also indicates the conflict between individual decision makers. This conflict disappears at the social level. The social welfare is defined as the average of individual utilities as

$$W(\boldsymbol{a}, \theta) = \int u_i(\boldsymbol{a}, \theta) di \,/ (1 - r) = -\int (a_i - \theta)^2 di \tag{2}$$

In this zero-sum game, coordination affects individual payoffs, but not social welfare. Each agent receives a private signal $x_i = \theta + \epsilon_i$ where $\epsilon_i \sim N(0, 1/\beta)$ is the uncertainty associated with the signal modeled as a white noise with the variance $1/\beta$. He or she also receives a public signal $y = \theta + \eta$ where $\eta \sim N(0, 1/\alpha)$.

Morris and Shin [30] showed that the expected value of social welfare as in Eq.(2) always increases as the precision of the private signals increases. However, if agents have access to very precise private information and the precision of public information is much smaller, the increased amount of public information actually reduces welfare. In this case, more transparency of monetary policy causes volatility of market and leads to inflationary bias. Cornand and Heinemann [40] extended Morris-Shin model by including a probability that public information is received by the agents, as the degree of publicity, instead of one in the original model. It was shown that the optimal degree of publicity is smaller than one if and only if $\alpha/\beta<3r-1$. The conclusion was that it is better to disclose public information with a low precision only to a limited audience if the motive of coordination is sufficiently strong. The intuition is that a partial disclosure of information can avoid over reaction to a signal, which is potentially far from the true optimum state when the public signal is imprecise.

The model of social value of information and its extension were proposed in the context of monetary policy in economics. Evidences such as in credit registry [41] and in private sector forecast [42] have been studied to check the validity of this model. Yet, in these models, uncertainty associated with scientific knowledge and the bias in the information are not considered.

Social policies should seek to maximize the welfare of a society as a whole. In the context of risk communication, the amount of risk information needs to be determined so that the maximum social welfare is obtained. The goal of this paper is to develop a mathematical formalism to describe the societal phenomena of risk communication and to serve as the theoretical foundation to devise effective risk communication policies.

3. Social Value of Risk Information

The purpose of the proposed social value model is to describe the mathematical relationship between risk perceptions and the influential factors so that the effects can be predicted qualitatively. Suppose that the i^{th} stakeholder's perceived risk is R_i. The underlying true state of risk is θ. Although risk is usually regarded as the combination of probabilities of events and the corresponding consequences, there is no unique and universally accepted definition [43]. Here, the perception of risk is abstractly treated as a probabilistic measure represented as a stochastic variable. Similar to Eq.(1), the individual stakeholder's utility with respect to risk perception is defined as

$$u_i = (R_1, \dots, R_n; \theta) = -(1-r)(R_i - \theta)^2 - r(D_i - \overline{D}) \tag{3}$$

where $D_i = \sum_{j=1}^{n} \left(R_j - R_i\right)^2 /n = \left(R_i - \overline{R}\right)^2 + (\sum_{j=1}^{n} R_j^2 /n - \overline{R}^2)$, $\overline{R} = \sum_{j=1}^{n} R_j /n$, $\overline{D} = \sum_{j=1}^{n} D_j /n$, and the *cohesion coefficient* r captures the coordination motive. In other words, different stakeholders have varied perceptions of a risk which could be very different from the underlying true one. The utility that a stakeholder has for decision making is related to not only the deviation of the perceived risk from the true one, but also his/her perception of other stakeholders' views on the risk. In other words, personal and group risk perceptions have correlations [44,45]. Therefore the "second-order" perception is considered, as the term $r(D_i - \overline{D})$ in Eq.(3). This model captures the conflict of interests and social behaviors of stakeholders associated with the formation of their risk perceptions.

3.1. Expected Welfare

Suppose that the observable state variable z corresponding to the underlying true risk θ according to the scientific knowledge is

$$z = \theta + \nu \tag{4}$$

where the observation error ν follows a normal distribution as $\nu \sim N(\mu, \tau_\nu^{-1})$ with mean μ and variance τ_ν^{-1}. ν captures the uncertainty that is due to the lack of complete scientific knowledge.

The public information that the i^{th} stakeholder receives regarding the risk is

$$y = z + \eta \tag{5}$$

in which $\eta \sim N(0, \tau_\eta^{-1})$ follows a zero-mean normal distribution with variance τ_η^{-1}. It represents the variability about the interpretation of the risk. The precision of public information is $\tau_y = \left(\tau_v^{-1} + \tau_\eta^{-1}\right)^{-1}$.

The private information that the i^{th} stakeholder receives is

$$x_i = z + \epsilon_i \tag{6}$$

where $\epsilon_i \sim N(0, \tau_\epsilon^{-1})$ represents the variability about the interpretation of the risk in the private information channel. The precision of private information is $\tau_x = (\tau_v^{-1} + \tau_\epsilon^{-1})^{-1}$.

Here it is assumed that v, η_i, and ε_i's are independent. Among the parameters, μ is the bias due to the lack of perfect knowledge, whereas τ_v, τ_y, and τ_x capture the precision of the information.

The i^{th} stakeholder's prior belief or bias of the risk before receiving external signals is represented as

$$s_i = \theta + \lambda_i \tag{7}$$

where $\lambda_i \sim N(0, \tau_\lambda^{-1})$ represents the variability of personal beliefs.

Based on the public information only, the i^{th} stakeholder's perceived risk is

$$R_i(\theta|y) = (\tau_\lambda s_i + \tau_y y)/(\tau_\lambda + \tau_y) \tag{8}$$

based on Bayesian belief update. If the i^{th} stakeholder has both public and private information, the perceived risk is

$$R_i(\theta|y, x_i) = (\tau_\lambda s_i + \tau_y y + \tau_x x_i)/(\tau_\lambda + \tau_y + \tau_x) \tag{9}$$

The i^{th} stakeholder's estimate of the j^{th} stakeholder's risk perception is

$$E_i(R_j(\theta|y)) = (\tau_\lambda s_i + \tau_y y)/(\tau_\lambda + \tau_y) \tag{10}$$

because the i^{th} stakeholder assumes that others only have access to public information. The i^{th} stakeholder's reasonable response to the risk is

$$a_i = \kappa x_i + (1 - \kappa)(\tau_\lambda s_i + \tau_y y)/(\tau_\lambda + \tau_y) \tag{11}$$

with weight κ ($0 \leq \kappa \leq 1$) as personal confidence index.

The public perception of risk from the viewpoint of the i^{th} stakeholder is the weighted average between his/her own perception and others' perception (based on his/her assumption that other stakeholders have only public information) as

$$E_i(\overline{\theta}) = \kappa R_i(\theta|y, x_i) + (1-\kappa)E_i(R_j(\theta|y)) \tag{12}$$

The i^{th} stakeholder's reasonable response to the risk is a fusion of personal risk perception and the perceived public perception as

$$a_i = (1-r)R_i(\theta|y, x_i) + rE_i(\overline{\theta}) \tag{13}$$

where the cohesion coefficient r measures the degree of complementarity or substitutability of stakeholders' responses. In general, $0 \leq r \leq 1$, which means that responses are complementary and the optimum response increases as other stakeholders increase the expectations of their responses. The value of r indicates how sensitive a stakeholder can be influenced by the popular opinions. The larger the value is, the closer the individual is to the average perception of the society. It is assumed that $r < 0.5$ in a diverse or individualistic society whereas $r > 0.5$ in a more uniform, conforming, or collectivistic society.

At an equilibrium state, Eqs.(11) and (13) are equal, which leads to

$$\kappa = (1-\mathrm{r})\tau_x/(\tau_\lambda + \tau_y + (1-r)\tau_x) \tag{14}$$

By substituting Eq.(14) back to Eq.(13), we obtain the optimum response

$$a_i = \theta + \nu + (\tau_\lambda\lambda_i + \tau_y\eta + (1-r)\tau_x\epsilon_i)/(\tau_\lambda + \tau_y + (1-r)\tau_x) \tag{15}$$

From Eq.(2), the expected welfare for the equilibrium state is given by

$$\mathbb{E}[W(\boldsymbol{a}, \theta)] = -\mathbb{E}[\nu^2] - \frac{\tau_\lambda^2\mathbb{E}[\lambda_i^2] + \tau_y^2\mathbb{E}[\eta^2] + (1-r)\tau_x^2\mathbb{E}[\epsilon_i^2]}{\left(\tau_\lambda + \tau_y + (1-r)\tau_x\right)^2}$$

$$= -\mu^2 - \tau_v^{-1} - \frac{\tau_\lambda + \tau_y^2(\tau_y^{-1} - \tau_v^{-1}) + (1-r)^2\tau_x^2(\tau_x^{-1} - \tau_v^{-1})}{\left(\tau_\lambda + \tau_y + (1-r)\tau_x\right)^2}$$

(16)

3.2. Sensitivity Analysis

The sensitivity analysis of the expected social welfare in Eq.(16) gives the major results of this paper, which is how the uncertainty associated with risk information affects welfare. This analysis is intended to provide the qualitative relationships among the public and private information in risk communication and the risk perception of individual stakeholders. The qualitative model can provide some insights of how to devise risk communication policies in promoting social welfare. If the expected social welfare increases as the uncertainty reduces, we call it *positive social effect*.

3.2.1. Effect of knowledge

The sensitivity of expected welfare with respect to the systematic bias in scientific knowledge is

$$\frac{\partial}{\partial \mu}\mathbb{E}[W] = -2\mu \tag{17}$$

Eq.(17) shows that systematic bias affects the expected social welfare monotonically. When the risk has been overestimated with a positive μ, any further overestimation will decrease the welfare. On the other hand, when the risk has been underestimated, any positive bias will help adjust the risk perception and increase social value.

The sensitivity of expected welfare with respect to the precision of scientific knowledge is

$$\frac{\partial}{\partial \tau_v}\mathbb{E}[W] = \frac{\tau_\lambda^2 + 2\tau_\lambda\tau_y + 2(1-r)\tau_x\tau_y + 2(1-r)\tau_x\tau_\lambda}{\left(\tau_\lambda + \tau_y + (1-r)\tau_x\right)^2\tau_v^2}$$

(18)

which is always positive. This implies that increasing the precision of scientific knowledge about risks always has positive social effects and brings benefits to the society. The sensitivity is quadratically reduced as τ_v increases. For instance, the scientific uncertainty associated with climate change is one major reason that the public is reluctant to take adaptive action. The public prefers unanimous scientific descriptions of problems [46]. Therefore increasing the precision of scientific knowledge will always benefit stakeholders as a whole. Yet, it has to be kept in mind that uncertainty associated with risk includes two components, bias μ and precision τ_v. A well accepted bias is equally harmful to the society.

3.2.2. Effect of public information

The sensitivity of expected welfare with respect to the variability of public information is

$$\frac{\partial}{\partial \tau_y}\mathbb{E}[W] = \frac{\tau_\lambda + \tau_y + (1-r)(1-2r)\tau_x + 2\tau_v^{-1}\left(\tau_\lambda\tau_y + (1-r)\tau_x\tau_y - (1-r)^2\tau_x^2\right)}{\left(\tau_\lambda + \tau_y + (1-r)\tau_x\right)^3}$$

(19)

The sensitivity of public information is related to the precision of scientific knowledge τ_v. For a new risk domain with $\tau_v^{-1} \gg 1$ in which scientists have limited knowledge, it is important to keep

$$\tau_\lambda\tau_y + (1-r)\tau_x\tau_y - (1-r)^2\tau_x^2 > 0 \qquad (20)$$

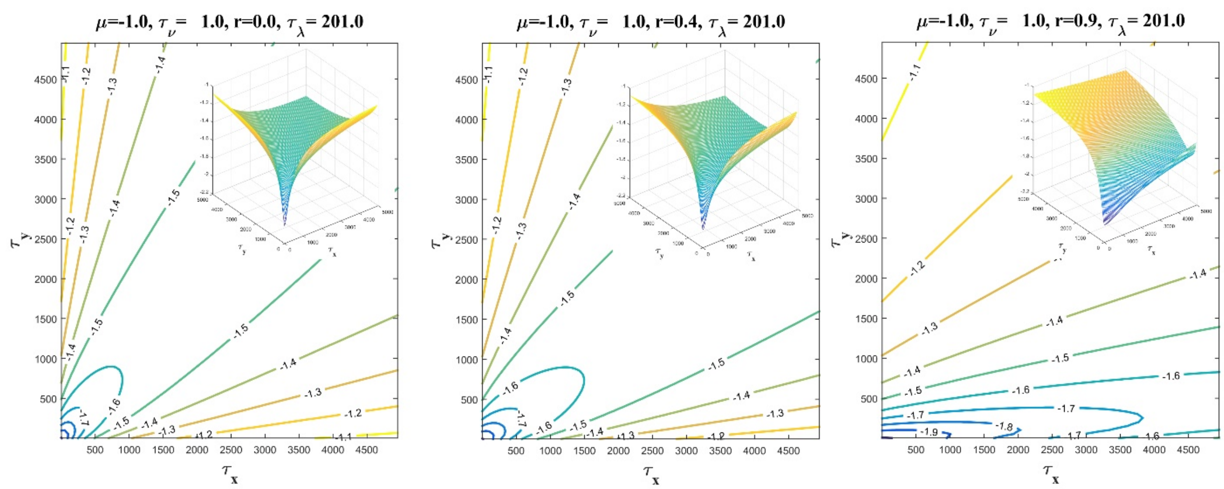
such that Eq.(19) is positive. Particularly, when

$$\tau_y > (1-r)\tau_x \qquad (21)$$

Eq.(20) will hold, and increasing the precision of public information brings the positive social effect. In other words, the precision of public information should be greater than a threshold ratio of the precision of private information. The ratio is society dependent. The condition in Eq.(21) is easier to satisfy in a collectivistic and conforming society with a large *r* than in an individualistic and diverse society with a smaller r. Therefore it is easier to communicate risk information in a conforming society when there is a lack of knowledge about the risk. Public information needs to be more precise when external influence is less for the individual stakeholders in a diverse society. A safe strategy to devise risk communication policy is to ensure that $\tau_y > \tau_x$, i.e. the precision of public information is always greater than that of private information, regardless the value of r. As the domain of the risk becomes well-known with reduced variance τ_v^{-1}, the influence of the condition in Eq.(20) is reduced. Nevertheless, Eq.(21) is still a sufficient condition for the positive value of Eq.(19).

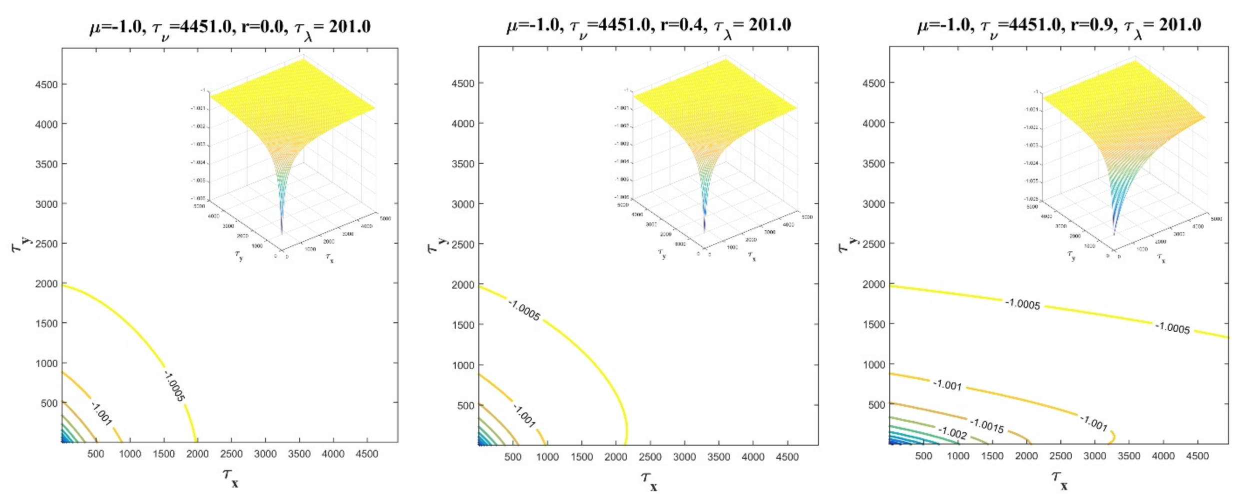
The above analysis can be confirmed and visualized in Figure 1 and Figure 2, where the expected social welfare in Eq.(16) with respect to the precisions of public and private information are shown. Both the response surfaces and contours are plotted. It is seen in Figure 1 that as the r value increases, the positive social effect of increasing the precision of public information becomes more evident, and the sufficient condition in Eq.(21) is easier to satisfy. The condition in Eq.(21) requires that the precisions of public and private information should fall into the upper left half of the τ_x-τ_y domain in the contour plots of Figure 1. As r increases, the region with positive social effect by increasing the precision of public information also increases. For the case when there is a lack of scientific knowledge about some recently emerging hazards and risks, as shown in Figure 1 (τ_v=1.0), the gain of social welfare by increasing the precision of public information is substantial, compared to the case where the hazards and risks are well known, as shown in Figure 2 (τ_v=4451.0). Nevertheless, for the case of well-known risks, the social welfare almost surely increases, in spite of its small amount, as the precisions of public and private information increase.

The effect of public information is also influenced by the personal bias and illustrated in Figure 3. The levels of personal bias and belief range from very strong (τ_λ=1.0) to weak (τ_λ=4451.0) in the figure. When personal bias is strong and diverse, increasing the precision of public information does not necessary brings positive social effect, as shown in Figure 3(a) and (b), and the gain of benefits is small. When personal bias is weak, increasing the transparency of public information communicated to the public will most likely bring substantial social benefits, as shown in Figure 3(c).



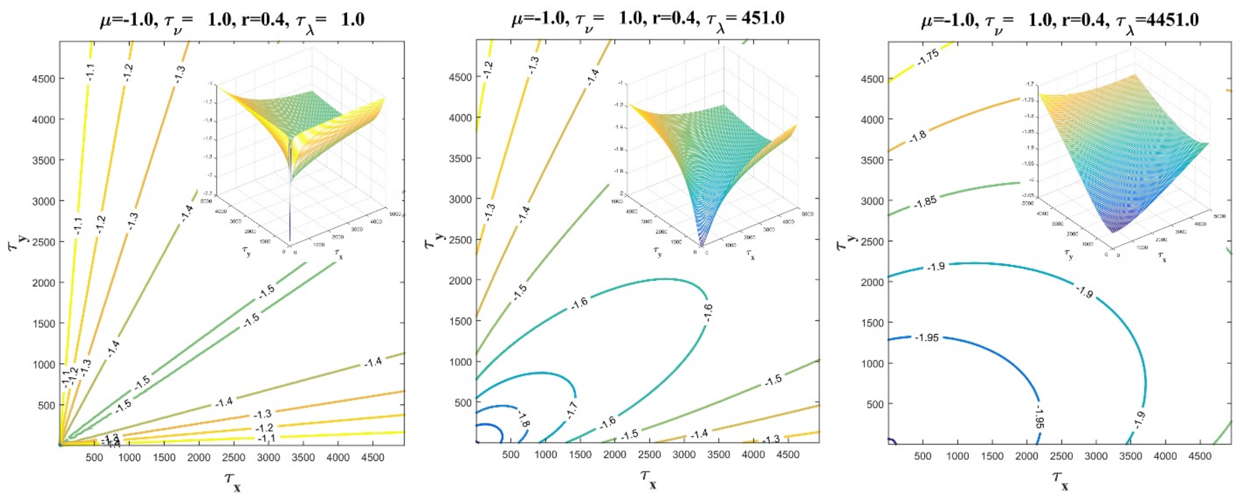
(a) (b) (c)

Figure 1. The effects of τ_x and τ_y on the expected welfare with limited scientific knowledge: (a) μ=−1.0, τ_v=1.0, r=0, τ_λ=201; (b) μ=−1.0, τ_v=1.0, r=0.4, τ_λ=201; (c) μ=−1.0, τ_v=1.0, r=0.9, τ_λ=201.



(a) (b) (c)

Figure 2. The effects of τ_x and τ_y on the expected welfare with sufficient knowledge: (a) μ=−1.0, τ_v=4451.0, r=0, τ_λ=201; (b) μ=−1.0, τ_v=4451.0, r=0.4, τ_λ=201; (c) μ=−1.0, τ_v=4451.0, r=0.9, τ_λ=201.



(a) (b) (c)

Figure 3. The effects of personal bias on τ_x and τ_y: (a) μ=−1.0, τ_v=1.0, r=0, τ_λ=1.0; (b) μ=−1.0, τ_v=1.0, r=0.4, τ_λ=451.0; (c) μ=−1.0, τ_v=1.0, r=0.4, τ_λ=4451.0.

In summary, the proposed model predicts that the coordination effect in a society is related to the benefit of public risk information. In order to gain social benefits, the risk information communicated to the public needs to be more precise in a diverse society than in a conforming one. It is always a good practice to keep the public information more precise than available private information. When the scientific knowledge is sufficiently high and the public is well educated, increasing the precision of the public information communicated to people will always bring positive effects. However, the extra value of social welfare tends to be reduced as the level of knowledge increases. In addition, the personal bias also affects the effectiveness of risk communication with public information. Reducing the extent of personal bias increases the chance of a larger gain for the society. When comparing two risks, one with more precise scientific knowledge does not necessarily cause positive social effects if the associated personal bias is extreme. For instance, it has been observed that communicating risk of climate change by providing scientific knowledge and information does not necessarily increases the awareness and public perception. Political and personal bias affects the effectiveness of communication [47,48].

People who have the strong political and ideological attitude do not easily alter their perception based on public information [49,50]. The personal knowledge also plays a role in the effect of public information. As the knowledge level increases, the effect of public information given by managing authorities tends to be reduced [51], which is consistent with the model prediction in Eq.(19) about the effects of τ_λ and τ_v^{-1}. Intuitively more disclosure of public information does not necessarily improve the social value. For instance, the over exposure might be damaging to certain stakeholder because it eliminates insurance possibilities. The public may also over react on the information and incur irrational behaviors.

3.2.3. Effect of private information

As a special case when *r*=1, Eq.(16) becomes independent of τ_x. That is, the social welfare in an extremely conforming society is irrelevant to the precision of private information, since the opinions of other people on risks dominantly influence a stakeholder's perception.

The sensitivity of expected welfare with respect to the variability of private information is

$$\frac{\partial}{\partial \tau_x}\mathbb{E}[W] = (1-r)\frac{(1+r)(\tau_\lambda+\tau_y)+(1-r)^2\tau_x+2\tau_v^{-1}\big((1-r)(\tau_\lambda\tau_x+\tau_x\tau_y)-2\tau_y^2\big)}{\big(\tau_\lambda+\tau_y+(1-r)\tau_x\big)^3} \tag{22}$$

Similar to the effect of public information, it is seen in Eq.(22) that when the precision of scientific knowledge τ_v is sufficiently high, increasing the precision of private information almost always benefits the society. This is also confirmed in Figure 1 and Figure 2. Again, when the scientific nature of a risk is well understood and the public is well educated, it is easier to devise risk communication policy.

A sufficient condition that Eq.(22) remains positive is

$$\tau_x > 2\tau_y^2/\big[(1-r)\big(\tau_\lambda+\tau_y\big)\big] \tag{23}$$

which indicates that the precision of private information is related to the ones of public information and personal bias. The condition in Eq.(23) is easier to satisfy for small r values. In other words, the precision of private information for effective communication in a conforming society should be higher than the one in a diverse society. The precision requirement is also more restrictive if diverse personal biases exist. Risk communication through private channels could be not very effective unless there is little personal bias. In a diverse society where stakeholders are less sensitive to the coordinated behavior and less likely to be influenced by the risk perceptions of others, the requirement of little personal bias is not as restrictive as in a conforming society.

When the level of variation for personal bias is comparable to the precision of public information, i.e. $\tau_\lambda \approx \tau_y$, Eq.(23) is further reduced to

$$\tau_x > (1-r)^{-1}\tau_y \tag{24}$$

which connects to the sufficient condition for public information in Eq.(21). It can be confirmed from Figure 1 that the condition in Eq.(24) is satisfied in the lower right portion of the τ_x-τ_y domain in the contour plots, whereas the condition in Eq.(21) is satisfied in the upper left portion of the domain.

It is seen that Eq.(24) for private information and Eq.(21) for public information have conflicting goals. Therefore the social welfare can be increased by improving the quality of both public and private information iteratively. From the public policy perspective, given existing private information channels, the goal of public announcement is to provide more precise information than those available private ones. On the other hand, from the private information providers' perspective, given the available public announcement, the further improvement of the quality of risk information in private channels is also regarded as value-adding activity.

Nevertheless, strong personal bias may be a damping factor if opinionated prior beliefs exist among people.

3.2.4. *Effect of personal bias*

The sensitivity of expected welfare with respect to the personal bias is

$$\frac{\partial}{\partial \tau_\lambda}\mathbb{E}[W] = \frac{\tau_\lambda + \tau_y + (1-r)(1-2r)\tau_x - 2\left(\tau_y^2 + (1-r)^2\tau_x^2\right)\tau_v^{-1}}{\left(\tau_\lambda + \tau_y + (1-r)\tau_x\right)^3} \tag{25}$$

Eq.(25) shows that increasing τ_λ does not necessarily increase the social welfare. The coupled relationships among τ_λ, τ_x, τ_y, and τ_v decide the trend. The coefficient $(1-r)(1-2r)$ of τ_x in the numerator of Eq.(25) becomes negative when $0.5 < r < 1$. Therefore, reducing the personal bias is more effective for positive social effects in a diverse society than in a conforming society. The minimum value of -0.125 for $(1-r)(1-2r)$ is reached at r=0.75. When the level of scientific knowledge is low, the negative effect of $2\left(\tau_y^2 + (1-r)^2\tau_x^2\right)\tau_v^{-1}$ in the numerator of Eq.(25) dominates. That is, reducing personal bias does not bring benefits when there is a lack of knowledge. When the level of knowledge is high, the negative effect of $2\left(\tau_y^2 + (1-r)^2\tau_x^2\right)\tau_v^{-1}$ becomes negligible. Therefore, a sufficient condition to ensure positive effect of reducing personal bias is

$$\tau_\lambda + \tau_y > 0.125\tau_x \text{ and } \tau_v \gg 0 \tag{26}$$

That is, the combination of public information and personal bias should be much more precise than private information. At the same time, there should be sufficient scientific knowledge about the risk. For stakeholders with a wide range of opinions, public announcements should be more unequivocal, as also indicated in Eq.(26).

The above analysis is confirmed in Figure 4. When the scientific knowledge is limited as shown in Figure 4(a), reducing personal bias to a larger value of τ_λ introduces negative effects to social welfare. The negativity becomes evident when the precision of private information increases. As more knowledge is available, reducing bias can bring positive social effect. As shown in Figure 4(b), the social welfare increases by increasing the value of τ_λ for low-precision private information. When the precision of private information increases, the negative effect resumes. When the scientific knowledge is abundant as shown in Figure 4(c), increasing the precision of private information and reducing personal bias will surely result in positive social effects.

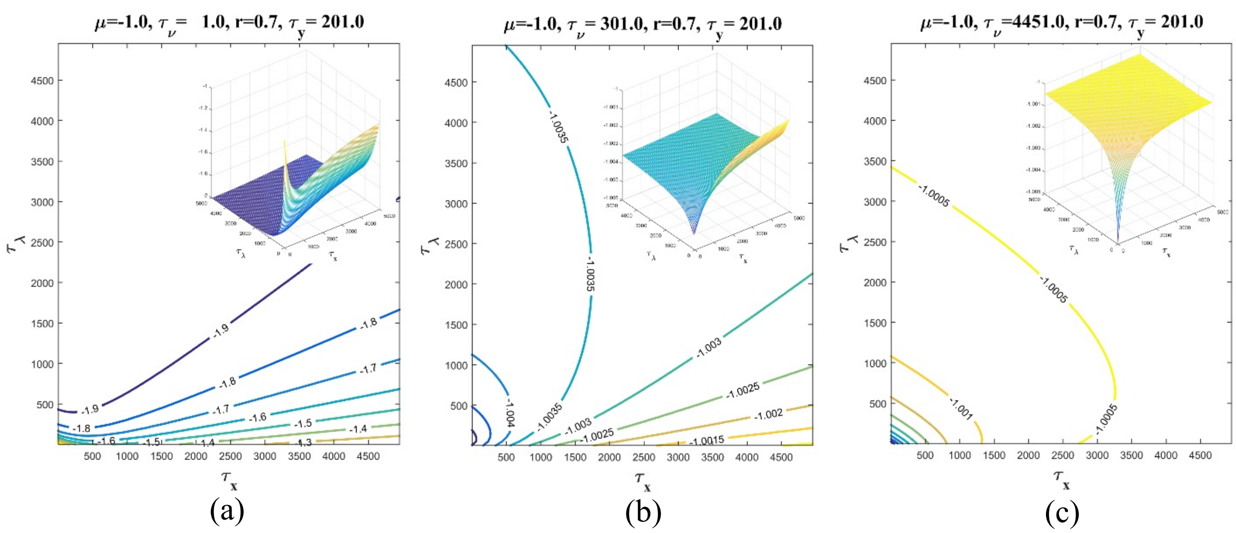


Figure 4. The effects of scientific knowledge and personal bias: (a) μ=−1.0, τ_v=1.0, r=0.7, τ_y=201.0; (b) μ=−1.0, τ_v=301.0, r=0.7, τ_y=201.0; (c) μ=−1.0, τ_v=4451.0, r=0.7, τ_y=201.0.

4. Discussions

The mathematical model proposed in this paper is intended to provide a formal approach to assess the impact of risk information to social welfare. The behaviors of stakeholders can be qualitatively assessed and predicted by the mathematical model. Particularly, the risk perception of the general public is influenced by the lack of confidence on scientific knowledge given the uncertainties, including bias and imprecision. The effectiveness of risk communication is determined by factors such as the personal characteristics and attitudes toward others' opinions, which are modeled by the cohesion coefficient r. A larger r indicates that individuals tend to 'go with the flow'. The clarity and precision of risk information communicated through public and private channels have different effects on the benefit of the society. As a rule of thumb, in a more diverse society with a smaller r, the public announcement of risks needs to be clearer and less ambiguous. For a more cohesive and collectivistic society with a larger r, the public announcement can be less precise. In either case, the influence of public information to a society is reduced as the knowledge level of the public increases.

When communicating risk information to the public via public announcements, the information should be clearer and more precise than the available private information stakeholders may have. Otherwise, the public information may not bring positive impacts to the society. On the other hand, with various forms of media and customized consulting/advisory services are available for people to receive risk information, the individual one-to-one communication should have higher precision than available public information in order to gain stakeholders' attentions and bring social benefits.

Education to the public still plays an important role according to the model. Increasing the knowledge levels of stakeholders and reducing their personal biases are conflated. When there is a lack of knowledge in the science community for a new type of risk, personal biases of stakeholders have strong influence on risk perception. It could be futile to try to convince the public via both government announcement and private media. The lack of trust from the public makes risk communication challenging. Unless the nature of the problem is better understood, providing more information to the public with the intention of reducing personal biases will not be effective. The ultra precise information provided by the private media may have a damping effect, since the strong opinions of media could alienate stakeholders who have different opinions. Only after the scientific knowledge of a risk has been accumulated to a certain level, risk perception can be effectively guided by providing more information.

The proposed model provides some potential guideline to devise risk communication policies. The form of risk communication in a society with a culture of diversity should not be the same as the one in a society with high uniformity. In other words, a risk communication policy works well for one country or community does not necessarily works well for others with different cultures. The diversity of personal opinions, educational background, etc. of the target population needs to be taken into account. Gaining more scientific knowledge about risks is always beneficial. It is seemingly easier to deliver risk messages to a community with relatively uniform culture and homogeneous background than the one with high diversity.

The proposed model is the first quantitative model of its kind to quantify the relationships among risk information, risk perception, uncertainty, and social welfare. Some of the predications from the model are consistent with the phenomena observed by other researchers. For instance, it has been shown that providing more risk information does not necessarily enhance the public's understanding of risks [52]. The risk perception in the proposed model is affected by knowledge levels and personal biases, in addition to the public and private information. It has been realized that the consideration of the general public's scientific knowledge and personal belief about risks is important in risk communication [53]. The model explicitly incorporates the precision of information, uncertainty associated with scientific knowledge, and variability of biases. In addition, it has been observed that personal bias plays a dominating role in forming the perception of a new risk when there is still a lack of scientific understanding [50]. The proposed model shows that the effect of personal biases diminishes as scientific knowledge becomes sufficient and the level of epistemic uncertainty is reduced to certain levels.

The mathematical model also makes some quantitative predictions. For instance, when public channels are used in risk communication, the precision of public information needs to be higher than the ones that are available in private channels in order to improve the effectiveness of communication. On the other hand, if private channels are employed, the precision of the information needs to be higher than the available one in the public channel for its effectiveness. Public information needs to be more precise when group influence is less for the individual stakeholders in a diverse society for effective communication. Similarly the precision of private information in a conforming society should be higher than the one in a diverse society. The validity of these predictions are unknown. Experimental studies are needed to validate them. Some other predictions that need to be verified include when scientific knowledge about a risk is sufficient, the influence of other factors for risk communication diminishes. Reducing personal bias may not bring positive social effects unless the level of scientific knowledge is sufficiently high. For stakeholders with a wide range of opinions, public announcements should be more unequivocal.

5. Case Study

On March 11th, 2011, Great East Japan earthquake and the triggered tsunami caused one of the worst nuclear accidents in human history, when Tokyo Electric Power Company's Fukushima Daiichi nuclear plant was flooded, followed by explosions because of loss of cooling. Radioactive materials were released into natural environment and ecosystem through water and air. The impacts were observed across the borders between nations in Asia, Pacific-ocean, and Americas. This event provided researchers the opportunity to study risk communication.

How risk information about nuclear energy is communicated to public is crucial to the effectiveness of communication. It was found the precision of public information by government as a singular message is paramount to maintaining trust [54]. The levels of knowledge that stakeholders have also affect the effectiveness. Well-educated citizens typically require more and adequate information, whereas under-educated ones need less but precise and consistent information [55]. As our model predicts in Figure 1 and Figure 2, increasing the precision of public information is more effective in communicating with stakeholders who have less scientific knowledge than with those who are well-educated. The benefit from improving public information precision becomes marginal when people have accumulated sufficient knowledge. The model predictions match well with the observations from the survey studies. In addition, the model predicts that communication through public channels tends to be more effective than through private channels in a culturally conforming society, as shown in Figure 1, and public information needs to be more precise than private ones. Current government practice however does not necessarily follow these predictions. For example, Japanese people have been frustrated by the lack of available public data about radiation levels in their living environment after the accident. As an alternative, volunteers are using a crowd-sourced network called 'Safecast' to monitor environment with open-source devices and share the radiation map of the whole country [56]. Yet Japanese authority still urged people to rely only on government readings. From our model prediction, the government should have encouraged information sharing and openly published data and information that are consistent and more precise than the crowd-sourced ones in order to gain the public trust.

Recent survey studies in Switzerland before and after Fukushima [57,58] show that people's attitude change toward nuclear energy is influenced by personal bias (risk benefit arguments, political orientations). For the groups who had either strong negative or strong positive attitude prior to the accident, their attitudes do not change much after the accident in spite of the abundant information they collected during the period of accident, in comparison with other groups. That is, the stronger personal bias makes communication less effective, which is also predicted by the model in Figure 3, regardless public or private information channels. A similar survey study of Fukushima effect in U.S. [59] also shows that polarized political environment with strong bias in personal belief and media makes communication ineffective.

Additional survey studies [60,61,62] have shown that different levels of attitude changes before and after Fukushima nuclear accident exist among different countries. Comparative studies of Three Mile Island and Chernobyl nuclear accidents also found the varied responses from country to country [55]. The common explanation offered by the researchers is that it might be due to different levels of nuclear energy programs in these countries. Geographical proximity to the accident location yet is not crucial. For instance, U.S. public attitude of nuclear energy remained stable after Three Mile Island accident in U.S., and residents of Washington state in U.S. where radioactive plume was detected after Chernobyl accident reacted similarly [63], whereas people in Italy, Greece, and Spain who live far away from the sites became much more skeptical and negative after the accidents. In the proposed model, the factors that could potentially explain this phenomenon include personal prior bias, social or group influence, and levels of knowledge. As discussed in Sections 3.2.2 and 3.2.4, the information communicated with stakeholders who have a wide spectrum of personal bias will be less effective. Strong opinions in a polarized society make risk communication challenging. Additionally, the culture of society that how much individualism is tolerable also decides the effectiveness. Opinions of reference groups and viewpoints of majorities play important roles in attitude formation and change in nuclear accidents [55]. The prior beliefs and knowledge levels are related to the attitude change [64]. Compared to western cultures, Japanese society promotes collectivism. For instance, some parents who wanted to opt their children out of the obligatory lunch program fearing of food contamination were characterized by others as egoists against national sense of bonds and solidarity [65]. Social factors such as altruism and benevolence (caring and morality) [66] in a society have been shown to be related to the risk perception of nuclear energy, which provides further indication that there is a need to consider them, just as parameter r in the proposed model. Note that the referred difference between societal influence or peer pressure in the proposed model is not just nations and can also be related to community, working environment, gender, or other local groups.

6. Concluding Remarks

The mathematical model proposed in this paper is an attempt to quantify the relationships among the influential factors that affect the public's risk perception. From the societal perspective, risk communication policies should be devised based on the criterion of maximizing the expected social welfare so that they benefit the majority of stakeholders in a society. The precision and transparency of the information communicated to the public via either public or private channels need to be carefully designed. The proposed model elucidates the connections among the influential factors. The model predictions show that it is important to incorporate the dynamics of the community culture, personal beliefs, and uncertainty of knowledge in risk communication policies. Policies need to be customized at the fine-grained level based on the actual needs of the target community. The types of risks, diversities of opinions, and associated knowledge levels determine how much information should be provided to the community and which form of communication should be taken. While some of the predictions from the proposed model have been verified, others require further experimental studies.

References

[1] Kasperson, R. E., & Stallen, P. J. M. (Eds.). (1991). *Communicating Risks to the Public: Technology, Risk, and Society*. Kluwer Academic (Dordrecht, The Netherlands).

[2] Fischhoff, B. (1995). Risk perception and communication unplugged: Twenty years of process1. *Risk Analysis*, *15*(2), 137-145.

[3] Bier, V. M. (2001). On the state of the art: risk communication to the public. *Reliability engineering & system safety*, *71*(2), 139-150

[4] Leiss, W. (1996). Three phases in the evolution of risk communication practice. *The Annals of the American Academy of Political and Social Science*, 85-94.

[5] Wardman, J. K. (2008). The constitution of risk communication in advanced liberal societies. *Risk Analysis*, *28*(6), 1619-1637.

[6] Frewer, L. (2004). The public and effective risk communication. *Toxicology Letters*, *149*(1), 391-397

[7] Löfstedt, R. E. (2006). How can we make food risk communication better: where are we and where are we going?. *Journal of Risk Research*, *9*(8), 869-890.

[8] Fischhoff, B., Bostrom, A., & Quadrel, M. J. (1993). Risk perception and communication. *Annual Review of Public Health*, *14*(1), 183-203.

[9] Morgan, M. G., Fischhoff, B., Bostrom, A., & Atman, C. J. (2002). *Risk Communication: A Mental Models Approach*. Cambridge University Press (Cambridge, UK).

[10] Pidgeon, N., Kasperson, R. E., & Slovic, P. (Eds.). (2003). *The Social Amplification of Risk*. Cambridge University Press (Cambridge, UK)

[11] Griffin, R. J., Dunwoody, S., & Neuwirth, K. (1999). Proposed model of the relationship of risk information seeking and processing to the development of preventive behaviors. *Environmental Research*, *80*(2), S230-S245.

[12] Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sciences*, *9*(2), 127-152.

[13] Siegrist, M., Keller, C., & Kiers, H. A. (2005). A new look at the psychometric paradigm of perception of hazards. *Risk Analysis*, *25*(1), 211-222.

[14] Weber, E. U., Blais, A. R., & Betz, N. E. (2002). A domain‐specific risk‐attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making*, *15*(4), 263-290.

[15] Dake, K., & Wildavsky, A. (1991) Individual differences in risk perception and risk-taking preferences. In B.J. Garrick, & W.C. Gekler (Eds.) *The Analysis, Communication, and Perception of Risk*, Springer, New York. pp.15-24

[16] Renn, O., & Rohrmann, B. (Eds.). (2000). *Cross-Cultural Risk Perception: A Survey of Empirical Studies*. Kluwer Academic (Dordrecht, The Netherlands)

[17] Wildavsky, A., & Dake, K. (1990). Theories of risk perception: Who fears what and why?. *Daedalus*, 41-60.

[18] Gustafsod, P. E. (1998). Gender Differences in risk perception: Theoretical and methodological perspectives. *Risk Analysis*, *18*(6), 805-811.

[19] Sjöberg, L. (2000). Factors in risk perception. *Risk Analysis*, *20*(1), 1-12.

[20] Sjöberg, L. (2007). Emotions and risk perception. *Risk Management*, *9*(4), 223-237.

[21] Visschers, V. H., & Siegrist, M. (2008). Exploring the triangular relationship between trust, affect, and risk perception: A review of the literature. *Risk Management*, *10*(3), 156-167.

[22] Söderberg, I.-L. (2013). Relationships between advisor characteristics and consumer perceptions. *International Journal of Bank Marketing*, *31*(3), 147-166.
[23] Miles, S., & Frewer, L. J. (2003). Public perception of scientific uncertainty in relation to food hazards. *Journal of Risk Research*, *6*(3), 267-283.
[24] Mythen, G. (2010). Reframing risk? Citizen journalism and the transformation of news. *Journal of Risk Research*, *13*(1), 45-58.
[25] Angeletos, G. M., & Pavan, A. (2007). Efficient use of information and social value of information. *Econometrica*, *75*(4), 1103-1142.
[26] Johnson, B. B., & Slovic, P. (1995). Presenting uncertainty in health risk assessment: initial studies of its effects on risk perception and trust. *Risk Analysis*, *15*(4), 485-494.
[27] Thompson, K. M. (2002). Variability and uncertainty meet risk management and risk communication. *Risk Analysis*, *22*(3), 647-654.
[28] Van Dijk, H., Houghton, J., Van Kleef, E., Van Der Lans, I., Rowe, G., & Frewer, L. (2008). Consumer responses to communication about food risk management. *Appetite*, *50*(2), 340-352.
[29] Markon, M. P. L., & Lemyre, L. (2013). Public Reactions to Risk Messages Communicating Different Sources of Uncertainty: An Experimental Test. *Human and Ecological Risk Assessment: An International Journal*, *19*(4), 1102-1126.
[30] Morris, S., & Shin, H. S. (2002). Social value of public information. *The American Economic Review*, *92*(5), 1521-1534.
[31] Yokota, F., & Thompson, K. M. (2004). Value of information analysis in environmental health risk management decisions: past, present, and future. *Risk analysis*, *24*(3), 635-650.
[32] Palenchar, M. J., & Heath, R. L. (2007). Strategic risk communication: Adding value to society. *Public Relations Review*, *33*(2), 120-129.
[33] Lindley, D. V. (1956). On a measure of the information provided by an experiment. *The Annals of Mathematical Statistics*, 986-1005
[34] Howard, R. A. (1966). Information value theory. *IEEE Transactions on Systems Science and Cybernetics*, *2*(1), 22-26.
[35] Bernardo, J. M. (1979). Expected information as expected utility. *The Annals of Statistics*, *7*(3), 686-690
[36] Cox, L. A., Popken, D. A., VanSickle, J. J., & Sahu, R. (2005). Optimal Tracking and Testing of US and Canadian Herds for BSE: A Value ‐ of ‐ Information (VOI) Approach. *Risk Analysis*, *25*(4), 827-840.
[37] De Gourville, E., Duintjer Tebbens, R. J., Sangrujee, N., Pallansch, M. A., & Thompson, K. M. (2006). Global surveillance and the value of information: the case of the global polio laboratory network. *Risk Analysis*, *26*(6), 1557-1569.
[38] Harsanyi, J. C. (1967). Games with incomplete information played by "Bayesian" players I-III, Part I. The basic model. *Management science*, *14*(3), 159-182.
[39] Mertens, J. F., & Zamir, S. (1985). Formulation of Bayesian analysis for games with incomplete information. *International Journal of Game Theory*, *14*(1), 1-29.
[40] Cornand, C., & Heinemann, F. (2008). Optimal Degree of Public Information Dissemination. *The Economic Journal*, *118*(528), 718-742.
[41] Hertzberg, A., Liberti, J., & Paravisini, D. (2011). Public information and coordination: evidence from a credit registry expansion. *The Journal of Finance*, *66*(2), 379-412.
[42] Crowe, C. (2010). Testing the transparency benefits of inflation targeting: Evidence from private sector forecasts. *Journal of Monetary Economics*, *57*(2), 226-232.

[43] Aven, T. (2012). The risk concept – historical and recent development trends. *Reliability Engineering & System Safety*, *99*, 33-44.
[44] Kasperson, R. E., Renn, O., Slovic, P., Brown, H. S., Emel, J., Goble, R., Kasperson, J. X., & Ratick, S. (1988). The social amplification of risk: A conceptual framework. *Risk Analysis*, *8*(2), 177-187.
[45] Wahlberg, A. A., & Sjoberg, L. (2000). Risk perception and the media. *Journal of Risk Research*, *3*(1), 31-50.
[46] Vulturius, G., & Swartling, Å. G. (2013) Transformative learning and engagement with climate change adaptation: Experiences with Sweden's forestry sector. *Stockholm Environment Institute, Report # SEI-2013-12*
[47] Leiserowitz, A. A. (2005). American risk perceptions: Is climate change dangerous? *Risk Analysis*, *25*(6), 1433-1442.
[48] Vulturius, G., & Swartling, Å. G. (2013). Transformative Learning and Engagement with Climate Change Adaptation: Experiences with Sweden's Forestry Sector. Stockholm Environment Institute, Working Paper No.2013-12
[49] Kellstedt, P. M., Zahran, S., & Vedlitz, A. (2008). Personal efficacy, the information environment, and attitudes toward global warming and climate change in the United States. *Risk Analysis*, *28*(1), 113-126.
[50] Malka, A., Krosnick, J. A., & Langer, G. (2009). The association of knowledge with concern about global warming: Trusted information sources shape public thinking. *Risk Analysis*, *29*(5), 633-647.
[51] Siegrist, M., & Cvetkovich, G. (2000). Perception of hazards: The role of social trust and knowledge. *Risk Analysis*, *20*(5), 713-720.
[52] Hampel, J. (2006). Different concepts of risk–A challenge for risk communication. *International Journal of Medical Microbiology*, *296*, 5-10.
[53] Rabinovich, A., & Morton, T. A. (2012). Unquestioned answers or unanswered questions: beliefs about science guide responses to uncertainty in climate change risk communication. *Risk Analysis*, *32*(6), 992-1002.
[54] Spencer, M. L. (2013). Lessons from Japan: resilience after Tokyo and Fukushima. *Journal of Strategic Security*, *6*(2), 70-79.
[55] Renn, O. (1990). Public responses to the Chernobyl accident. *Journal of Environmental Psychology*, *10*(2), 151-167.
[56] Brown, A., Franken, P., Bonner, S., Dolezal, N., & Moross, J. (2016). Safecast: successful citizen-science for radiation measurement and communication after Fukushima. *Journal of radiological protection: official journal of the Society for Radiological Protection*, *36*(2), S82-S101
[57] Siegrist, M., & Visschers, V. H. (2013). Acceptance of nuclear power: The Fukushima effect. *Energy Policy*, *59*, 112-119
[58] Crettaz von Roten, F., Clémence, A., & Thevenet, A. (2016). Understanding Attitudes Toward Nuclear Energy After the Fukushima Accident: Differences Between Asserted and Ambivalent Positions. *Social Science Quarterly*.
[59] Yeo, S. K., Cacciatore, M. A., Brossard, D., Scheufele, D. A., Runge, K., Su, L. Y., Kim, J., Xenos, M., & Corley, E. A. (2014). Partisan amplification of risk: American perceptions of nuclear energy risk in the wake of the Fukushima Daiichi disaster. *Energy Policy*, *67*, 727-736.

[60] Prati, G., & Zani, B. (2012). The effect of the Fukushima nuclear accident on risk perception, antinuclear behavioral intentions, attitude, trust, environmental beliefs, and values. *Environment and behavior*, 0013916512444286
[61] Poortinga, W., Aoyagi, M., & Pidgeon, N. F. (2013). Public perceptions of climate change and energy futures before and after the Fukushima accident: A comparison between Britain and Japan. *Energy Policy*, *62*, 1204-1211
[62] Kim, Y., Kim, W., & Kim, M. (2014). An international comparative analysis of public acceptance of nuclear energy. *Energy Policy*, *66*, 475-483.
[63] Lindell, M. K., & Perry, R. W. (1990). Effects of the Chernobyl accident on public perceptions of nuclear plant accident risks. *Risk Analysis*, *10*(3), 393-399.
[64] Visschers, V. H., & Wallquist, L. (2013). Nuclear power before and after Fukushima: The relations between acceptance, ambivalence and knowledge. *Journal of Environmental Psychology*, *36*, 77-86.
[65] Belyakov, A. (2015). From Chernobyl to Fukushima: an interdisciplinary framework for managing and communicating food security risks after nuclear plant accidents. *Journal of Environmental Studies and Sciences*, *5*(3), 404-417.
[66] Park, J., Bain, P., & Kusumi, T. (2015). Nuclear Power and Japan's Collective Future: Understanding Beliefs About How Nuclear Policies Will Affect Society. *Journal of Pacific Rim Psychology*, *9*(02), 78-85.