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Towards Understanding Socially Influenced Vaccination Decision Making: An Integrated Model of Multiple Criteria Belief Modelling and Social Network Analysis

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Abstract

Understanding the socially influenced decision-making process that determines voluntary vaccination is essential for developing strategies and interventions of vaccine-preventable diseases. Both theoretical and experimental studies have suggested that a variety of factors, such as safety of vaccines, severity of diseases, information and advice from healthcare professionals, influence an individual's intention to vaccinate. However, limited research has been conducted on analysing systematically how individuals' vaccine acceptance decisions are made from their beliefs and judgements on the influential factors. In particular, there is lack of quantitative analysis on how individuals' beliefs and judgements may evolve from the spreading of vaccination-related information in a social network, which further affects their decision making. In this paper, an integrated model is first proposed to characterise the socially influenced vaccination decision-making process, in which each individual's beliefs and subjective judgements on the decision criteria are formulated as belief distributions in the framework of multiple criteria decision analysis (MCDA). The spreading of social influence in the network environment is further incorporated into the information aggregation process for supporting informed vaccination decision analysis. A series of simulation-based analyses on a real-world social network is conducted to demonstrate that the overall vaccination coverage is determined primarily by individuals' beliefs and judgements on the decision criteria, and is also affected sensitively by the characteristics of influence spreading (including the content and amount of vaccination-related information) in the social network.

Keywords: OR in health services, vaccination decision making, influence spreading, social network, evidential reasoning

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1. Introduction

Vaccination is widely recognised by health organisations as one of the most effective ways to protect people from infectious diseases, such as diphtheria, tetanus, pertussis, polio, measles, and influenza. It can increase the probability of herd immunity and reduce the medical burden of vaccine-preventable diseases (Plans-Rubió, 2012; WHO, 2019). Since the first smallpox vaccine, developed in 1796 by Edward Jenner, widespread vaccination programmes have made significant contributions to global health by eradicating or greatly reducing some infectious diseases, such as smallpox and polio, which used to cause common infections with severe consequences (Greenwood, 2014; WHO, 2019). However, regional outbreaks of some highly contagious vaccine-preventable diseases and evidence from vaccination records demonstrated that not all vaccination campaigns achieved the desired immunisation coverage. For example, the total number of people infected with measles in Europe in 2018 was more than tripled to nearly 83,000 from 23,927 cases in 2017 due to the uneven vaccination coverage between and within countries (Thornton, 2019). The influenza vaccine uptake for older people (aged 65+) in England during the 2019-20 winter season was only 72.4%, which did not attain the vaccination coverage of ≥75% recommended by the European Council for all people at high risk (Public Health England, 2020). Undoubtedly, it is even more challenging to deliver the annual influenza vaccination programme comprehensively for the 2020-21 winter season in light of the impact of the novel coronavirus disease (COVID-19) pandemic on public health and social care services.

A series of studies have been conducted to understand the determinants of vaccine hesitancy and their potential to impact on vaccination coverage (Larson et al., 2014; MacDonald et al., 2015; Fournet et al., 2018). Godlee et al. (2011) discussed that the misinformation linking measles-mumps-rubella (MMR) vaccine with autism in Wakefield's fraudulent article (Wakefield et al., 1998) caused a profound damage to parents' trust in the MMR vaccination, which led to insufficient vaccination coverage in the UK for a long period. Smith et al. (2011) evaluated the association between parents' beliefs about vaccines and their vaccination decisions, and they highlighted that vaccine safety concerns and fewer perceived benefits are key reasons for parents to delay or refuse vaccine doses for their children. Kang et al. (2017) and Fournet et al. (2018) reviewed respectively that a variety of factors, including vaccine efficacy, disease susceptibility and severity, vaccine benefits, concerns regarding vaccine safety, vaccine-related adverse effects and even religious reasons, can all potentially affect the acceptance or refusal of vaccination by parents or under-vaccinated groups. The SAGE working group on vaccine hesitancy established by World Health Organization in 2012 categorised the determinants of vaccine hesitancy to three categories, namely complacency, convenience and confidence, and they also highlighted that vaccine hesitancy occurs on the continuum between full acceptance and outright refusal of vaccines with unsureness (MacDonald et al., 2015).

In addition to the aforementioned factors in literature, social influence has also attracted considerable attention in analysing vaccination decisions (Brunson, 2013; De Bekker-Grob, 2020; Larson et al., 2011; MacDonald et al., 2015; Xia & Liu, 2014). For example, it has been widely accepted that the contextual information from health workers, their family and communities plays a critical role in influencing individuals' beliefs, attitudes or motivation for vaccination (Akıs et al., 2011; Flood et al., 2010; Hwang et al., 2017). With the use of game-theoretical models, a number of population-based studies have been performed to analyse the effects of social influence on vaccination decisions (Bauch & Earn, 2004; Chapman et al., 2012; Molina & Earn, 2015). However, it is often assumed in the game-theoretical analysis of vaccination decision that every individual is provided with and uses the same information in an entirely rational way, which is not realistic in practice. Besides, several studies have pointed out that altruism in a social network also plays an essential role in vaccination decision making (Balfour et al., 2010; Shim et al., 2012), which is to some extent contradictory to the basic assumption of game theory that individuals act rationally according to their self-interest only and make decisions that maximise their own payoffs.

The primary objective of this research is to analyse the socially influenced vaccination decision-making process from the perspectives of individuals so as to better understand its intrinsic link with the population-level decision behaviours and vaccination coverage. First of all, the vaccination decision-making problem influenced by a spectrum of factors is formulated in the framework of multiple criteria decision analysis (MCDA). As its name suggests, MCDA is mainly concerned with structuring and solving complex decision problems associated with multiple and even conflicting criteria (Belton & Stewart, 2002). In this paper, multiple decision criteria associated with vaccination are structured into a hierarchical model, and an individual's belief or subjective judgement on each decision criterion is represented as a belief distribution (Yang & Singh, 1994; Yang & Xu, 2002). Secondly, social influence that affects individuals' vaccine hesitancy in a social network is further incorporated into the MCDA model, and it is formulated as supporting evidence for individuals to update their beliefs on the corresponding decision criteria. For example, a piece of information related to an increasing number of infected cases can potentially raise people's awareness and beliefs on their susceptibility to the disease, while any vaccine scandal can deepen their concerns on vaccine safety. Furthermore, the evidential reasoning (ER) approach (Yang & Xu, 2002; Xu et al., 2006) is employed to aggregate the belief distributions of characterising an individual’s beliefs and judgements on all the relevant decision criteria systematically. The ER approach was originally developed from the classic Dempster–Shafer (D–S) theory (Shafer, 1976) to solve MCDA problems under uncertainties (Yang & Singh, 1994), and its primary strength in this particular vaccination decision-making problem lies at the capability of formulating and aggregating individuals’ beliefs and subjective judgements coherently with the generalised probabilistic framework of belief distributions (Chen et al., 2013; Yang & Xu, 2013).

The main contributions of this research are twofold: (1) Theoretically, a novel model integrating multiple criteria belief modelling with social network analysis is proposed to characterise the socially influenced vaccination decision making. To the best of our knowledge, there is no previous research that formally incorporates social influence into the information aggregation process of MCDA. (2) Practically, the research provides an alternative perspective of understanding population-level vaccination coverage from individuals’ vaccination decision making in a social network.

The rest of this paper is organised as follows. A comprehensive literature review on vaccination decision making is conducted in Section 2. The decision model integrating multiple criteria belief modelling with social network analysis is developed systematically for analysing the socially influenced vaccination decision-making process in Section 3. In Section 4, a series of simulation-based analyses on a real-world social network is conducted to illustrate the effects of individuals’ vaccination decision making on the population vaccination coverage. The main conclusions and further research are summarised in the final section.

2. Literature Review

2.1 Vaccination decision making

Vaccination is one of the most effective ways of preventing infectious diseases, including smallpox, polio, measles and influenza (Greenwood, 2014; Plans-Rubió, 2012; WHO, 2019). It protects people from infections with vaccine-preventable diseases as well as dramatically reduces disease, disability, death and inequity worldwide (Andre et al., 2008). In addition to reducing the incidence of diseases among those vaccinated effectively, herd immunity can also be achieved from a sufficiently high vaccination coverage, which indirectly prevents the non-vaccinated susceptible populations from being infected (Brisson & Edmunds, 2003). However, herd immunity is particularly vulnerable to the impact of “anti-vaxxers” and “free riders”, who potentially benefit from other individuals' vaccination without bearing the cost of getting vaccination for themselves. This long-standing social dilemma of vaccination makes it challenging to analyse individuals' behavioural choices. Game theory has been widely used as a mathematical tool in combination with various epidemiological models to evaluate the evolving process between individuals’ vaccination decisions and population-level vaccination behaviours (Bauch & Earn, 2004; Reluga et al., 2006; Chapman et al., 2012; Molina & Earn, 2015). For example, Reluga et al. (2006) coupled game-theoretical models with an extended Susceptible–Infected–Recovered (SIR) epidemic model and demonstrated that the pursuit of self-interest could result in stable dynamics as well as oscillations in vaccine uptake over time. Chapman et al. (2012) conducted a game-theory experiment to examine the contribution of social incentives for young people being vaccinated to protect the elderly under the risk of influenza. Although the game-theoretical analysis could well explain certain population-level vaccination behaviours, its assumptions, e.g., fully rational self-interest maximisation, have been challenged by recent studies. Shim et al. (2012) demonstrated from a psychological survey study that altruism would significantly motivate individuals to undergo vaccination in the context of influenza vaccination decisions. Mbah et al. (2012) casted doubt on individuals’ full rationality in vaccination and investigated the effects of imitation on vaccination decision-making, among which imitating highly connected neighbours can lead to clustering of susceptible individuals.

Research has also been conducted from the perspective of psychology to understand people’s vaccination decision behaviours. Two classic theories of health behaviour, namely health belief model (HBM) and theory of planned behaviour (TPB) have been widely applied to predict individuals’ vaccination decision making with psychological factors, e.g., attitudes, beliefs and intentions (Myers & Goodwin, 2011; Smith et al., 2011). These health behaviour models have underpinned numerous studies, but the results of the behavioural analysis are primarily limited by the scale of survey or questionnaire-based data, and the impact of social influence is not taken into consideration explicitly in modelling individuals’ vaccination decisions.

2.2 Factors affecting individuals' vaccination decision making

It was well discussed by the SAGE working group on vaccine hesitancy of WHO that the acceptance of vaccination involves a complex decision-making process that can be potentially influenced by a wide range of factors (MacDonald et al., 2015). A spectrum of empirical or survey-based studies have also been carried out to investigate which factors might have hindered or promoted individuals' vaccination decision making. For example, Grant et al. (2003) surveyed that the primary concerns against influenza vaccination for parents in Canada included '*their children were not at risk*', '*immunisation resulted in a flu-like illness*', '*side effects were worse than the illness itself*', and '*vaccine could weaken the immune system*'. Flood et al. (2010) concluded that the main drivers for influenza vaccination were prevention of influenza, reduction of influenza symptoms, and a physician's recommendation, while the main barriers were perceived low risk of influenza, the misperception that the vaccine caused influenza, and the side effects caused by the vaccine. Weston et al. (2017) analysed the flu watch data in England during the 2009 H1N1 pandemic and emphasised that vaccine efficacy/safety and perceived risk of pandemic influenza were significant predictors for both self- and parental vaccination decisions. Larson et al. (2014) conducted a systematic review of thousands of peer-reviewed studies published between 2007 and 2012, and they identified a comprehensive list of barriers or promoters for childhood vaccination and mapped them onto the model of determinants of vaccine hesitancy developed by the WHO SAGE working group on vaccine hesitancy.

In line with the focused literature review, we summarised a collection of 'positive' and 'negative' factors that influence individuals' vaccination decisions in Table 1. Broadly speaking, individuals' primary concerns on vaccination decision making are associated with either the disease or the vaccine.

Table 1. A brief summary of main influential factors associated with individuals' vaccination decision making.

Main Drivers (Positive)	Main Barriers (Negative)
• Immunisation (Grant *et al*., 2003; Flood *et al*., 2010; Akıs *et al*., 2011; Bhat-Schelbert *et al*., 2012; Larson *et al*., 2014; MacDonald *et al*., 2015; Kang *et al*., 2017; Bukhsh *et al*., 2018)	• Side effects (Flood *et al*., 2010; Bults *et al*., 2011; Larson *et al*., 2014; Malosh *et al*., 2014; MacDonald *et al*., 2015; Hwang *et al*., 2017; Kang *et al*., 2017; Weston *et al*., 2017; Bukhsh *et al*., 2018)
• Susceptibility to disease	• Perceived low risk of disease

(Bults *et al*., 2011; Akıs *et al*., 2011; Larson *et al*., 2014; MacDonald *et al*., 2015; Weston *et al*., 2017; Kang *et al*., 2017) • Recommendations from health workers, family and friends, etc. (Grant *et al*., 2003; Bults *et al*., 2011; Akıs *et al*., 2011; Bhat-Schelbert *et al*., 2012; Larson *et al*., 2014; MacDonald *et al*., 2015; Hwang *et al*., 2017)	(Flood *et al*., 2010; Akıs *et al*., 2011; Larson *et al*., 2014; Malosh *et al*., 2014; MacDonald *et al*., 2015; Bukhsh *et al*., 2018) • Vaccine being unnecessary (Bhat-Schelbert *et al*., 2012; Larson *et al*., 2014; Bukhsh *et al*., 2018) • Difficulty or inconvenience in accessing vaccination services (Bhat-Schelbert *et al*., 2012; MacDonald *et al*., 2015)

It is worth noting that individuals can have very different beliefs, attitudes, perceptions or judgements on the same factors, which explains the acceptance or refusal of vaccination in reality. For example, individuals who perceive higher severity of the same disease and its complications seem to be more motivated to vaccinate themselves, and vice versa.

Given the fact that vaccination decision is often determined by multi-dimensional factors, it can be formulated as a typical multiple criteria decision-making problem, which hence can be facilitated by MCDA methodologies. In the past decades, MCDA and more broadly Operational Research (OR) techniques have received increasing attention in the field of healthcare (Rais and Viana, 2011; Adunlin et al., 2015; Enayati & Özaltın, 2020; Silal et al., 2020). For example, Goetghebeur et al. (2012) constructed a decision-making framework for the transparent and systematic appraisal of healthcare interventions through incorporating MCDA into health technology assessment (HTA). Ivlev et al. (2015) combined MCDA, specifically the analytic hierarchy process (AHP) method with HTA to support hospitals on the selection of medical devices under uncertain conditions. The International Society for Pharmacoeconomics and Outcomes Research (ISPOR) established an MCDA emerging good practices task force in 2014 to facilitate the innovative applications of MCDA in healthcare decisions (Thokala et al., 2016). Barocchi et al. (2016) emphasised the necessity of performing MCDA to support the prioritisation of vaccine development and deployment. Silal et al. (2020) reviewed recently the opportunities for applying OR methods, including MCDA to support and improve the management of infectious diseases.

In addition to the factors associated with the disease or the vaccine, social influence as a contextual and external force also plays a significant role in the vaccination decision-making process (Larson et al., 2011; 2014; Brunson, 2013; MacDonald et al., 2015). Rao et al. (2007) indicated that social exposure to medical information not only raises people's perceptions of the benefits of immunisation but also influences their vaccination decisions positively. Brunson

(2013) found that individuals barely make independent decisions on vaccine uptake, and instead they tend to seek advice from healthcare professionals or experienced friends. Besides, advice from trusted family members and peers also has a significant impact on individuals' vaccination decisions (Bults et al., 2011). MacDonald et al. (2015) reviewed that contextual influences from influential leaders and mass media, and individual or group influences, e.g., the knowledge and experiences of vaccination shared by healthcare professionals, family and community members can affect people's acceptance and hesitancy around vaccines. These influences can often be attributed to the information propagation through peer-to-peer interactions in a social community or network (Moussaïd, 2013). Brunson (2013) examined how parents are influenced by their people networks and information source networks through the application of social network analysis to analyse vaccination decisions. Moussaïd (2013) presented a model of opinion formation and dynamics specifically to address risk judgments, such as attitudes towards climate change, terrorist threats, or children vaccination. Stahl et al. (2016) demonstrated that spreading vaccination-related information commonly happens in social networks, which further shapes individuals' vaccination decision-making behaviours. However, the previous research of social network analysis and opinion dynamics on vaccination is mainly concerned with the formation of the overall opinions and decision behaviours, without fully analysing the aforementioned decision factors from the individuals' perspective.

3. An Integrated Model for Analysing Socially Influenced Vaccination Decision Making

From the above literature review, it can be concluded firmly that: (1) Individuals' vaccination decision making is determined by multiple factors or so-called decision criteria, which can further be broken down into more detailed sub-criteria in the context of MCDA (Larson et al., 2014; MacDonald et al., 2015). (2) Social influence plays an important role in shaping individuals' decisions on vaccine uptake in social networks (Brunson, 2013; MacDonald et al., 2015). Thus, in this paper we develop an integrated decision model of multiple criteria belief modelling and social network analysis in order to analyse the socially influenced vaccination decision-making process systematically.

3.1 Multiple criteria vaccination decision modelling

3.1.1 Formulating the criterion hierarchy for vaccination decision making

In vaccination decision modelling, it is important to consider the main drivers and barriers affecting vaccine uptake as summarised in Table 1 in a systematic way. A decision criterion hierarchy can then be built with an overall decision criterion C at the top level and I main criteria C_i $(i = 1, \ldots, I)$ at the lower level. It was discussed previously that people's beliefs, attitudes, perceptions or judgements on vaccination decision making mainly focus on the disease itself or the vaccine-related issues, thus two main criteria of '*Perceived risk of disease*' C_1 and '*Vaccine-specific issues*' C_2 are defined at the lower level, which contribute jointly to an individual's vaccination intention (i.e., the overall decision criterion C). Each main criterion C_i can be further decomposed into J_i sub-criteria $C_{i,j}$ $(i = 1, \ldots, I; j = 1, \ldots, J_i)$ as illustrated in Figure 1. Some further explanations are included for each of the sub-criteria $C_{i,j}$ below.

- Susceptibility (to the disease) $C_{1,1}$: how an individual perceives their susceptibility to the disease.
- Severity (of the disease) $C_{1,2}$: how an individual perceives the severity of the disease if infected.
- Safety (of the vaccine) $C_{2,1}$: potential risks and side effects.
- Effectiveness (of the vaccine) $C_{2,2}$: immunisation or reduction of disease symptoms.
- Convenience (of vaccination) $C_{2,3}$: how accessible to get vaccination in terms of physical availability, affordability, etc.

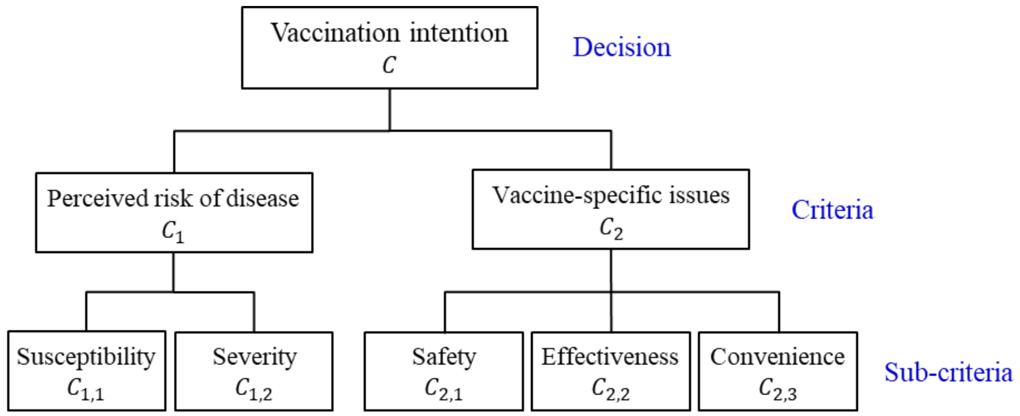


Figure 1. A criterion hierarchy for vaccination decision making

In reality, the evaluation of these sub-criteria can be facilitated by even more granular and context-specific factors.

3.1.2 Representing subjective judgements on vaccination with belief distributions

In most decision-making problems, it is often challenging for decision makers to obtain complete knowledge or make precise judgements on all the decision criteria. Particularly in vaccination decision making, the WHO/UNICEF joint reporting on immunisation emphasised that lack of knowledge, awareness and sureness of vaccination and its importance has been one of the key reasons for the delay in acceptance or refusal of vaccination despite the availability of vaccination services (Lane et al., 2018). Thus, in this paper, the generalised probabilistic scheme of belief distributions is applied to characterise the uncertain decision information resulting from incomplete knowledge or subjective judgements on vaccination. The concept of belief distribution was originally developed from the Dempster–Shafer (D–S) theory (Shafer, 1976) to support multiple criteria decision making under uncertainty (Yang & Singh, 1994; Yang & Xu, 2002; Chen et al., 2013), and it formulates the degrees of belief, to which the decision maker can actually judge a decision criterion to the corresponding evaluation grades in a consistent manner.

Suppose that an individual decision maker's judgement on the sub-criterion $C_{i,j}$ $(i = 1, \ldots, I; j = 1, \ldots, J_i)$ in the criterion hierarchy in Figure 1 can be formulated by a set of N evaluation grades H_n $(n = 1, \ldots, N)$, and the belief distribution can be profiled as follows,

$$S(C_{i,j}) = \{(H_n, \beta_{n,i,j}), n = 1, \ldots, N;\ i = 1, \ldots, I; j = 1, \ldots, J_i\} \tag{1}$$

where $\beta_{n,i,j}$ represents the degree of belief that the sub-criterion $C_{i,j}$ is evaluated to be the evaluation grade H_n. It satisfies the conditions: $0 \leq \beta_{n,i,j} \leq 1$ and $\sum_{n=1}^{N} \beta_{n,i,j} \leq 1$. The distributed judgement $S(C_{i,j})$ is complete if $\sum_{n=1}^{N} \beta_{n,i,j} = 1$; otherwise it is incomplete. The framework of belief distributions can well characterise the subjectiveness and/or incompleteness of the decision information, which may result from the lack of knowledge or the inability of the individual to provide precise judgments in vaccination decision making. It is worth noting that a different set of evaluation grades could be defined for each of the decision criteria. For example, in the questionnaire designed by Bults et al. (2011), parents were asked '*Do you think your child was susceptible to Mexican flu?*'. The evaluation grades for parents to choose from consisted of '*not susceptible*', '*susceptible*', and '*very susceptible*'. Then for the sub-criterion $C_{1,1}$ '*Susceptibility'*, the set of evaluation grades can be represented as,

$$H = \{H_1, H_2, H_3\} = \{not\ susceptible, susceptible, very\ susceptible\} \quad (2)$$

If an individual perceives the disease susceptibility to have an equal likelihood of '*susceptible*' and '*very susceptible*' (i.e., 50% degree of belief each), the judgemental information can then be described by the following belief distribution,

$$S(C_{1,1}) = \{(not\ susceptible, 0), (susceptible, 0.5), (very\ susceptible, 0.5)\} \quad (3)$$

In addition, the importance of each criterion in terms of vaccination decision could also differ for each of the individual decision makers. For example, Bults et al. (2011) also indicated that immigrant parents would consider the severity a few times more worrying than the actual susceptibility to a disease. In this case, suppose w_i is the normalised weight of the main criterion C_i $(i = 1, \ldots, I)$ which reflects its relative importance on an individual's vaccination decision making. The normalised weights of all the main criteria satisfy:

$$0 \leq w_i \leq 1 \ \ for\ i = 1, \ldots, I\ and\ \sum_{i=1}^{I} w_i = 1 \quad (4)$$

The same weighting procedure applies to each set of sub-criteria associated with a main criterion. In the context of MCDA, the weights of criteria are also of great importance in determining the decision outcome, and they can often be specified by experts using their domain knowledge or be elicited from individual decision makers using subjective or objective weighting methods (Belton and Stewart, 2002; Danielson et al., 2014; Zavadskas & Podvezko, 2016; Marttunen et al., 2017).

An illustrative example is developed in Table 2, where an individual's judgements on the vaccination decision criteria are represented as belief distributions. Suppose that the same number of evaluation grades H_n $(n = 1,2,3)$ is used for assessing each decision criterion, but they can be associated with different linguistic terms. For example, the evaluation grades for $C_{1,2}$ '*Severity*' can be described as '*not severe*', '*severe*', and '*very severe*', while for $C_{1,1}$ '*Susceptibility*' as '*not susceptible*', '*susceptible*', and '*very susceptible*'.

Table 2. An illustrative example of an individual's belief distributions on vaccination decision criteria

Main criterion (C_i)	**Weight** (w_i)	**Sub-criterion** ($C_{i,j}$)	**Weight** ($w_{i,j}$)	**Belief distributions**
Perceived risk of disease (C_1)	0.5 (w_1)	Susceptibility ($C_{1,1}$)	0.4 ($w_{1,1}$)	$\{(H_1, 0), (H_2, 0.5), (H_3, 0.5)\}$
		Severity ($C_{1,2}$)	0.6 ($w_{1,2}$)	$\{(H_1, 0), (H_2, 0.8), (H_3, 0.2)\}$
Vaccine	0.5 (w_2)	Safety ($C_{2,1}$)	0.7 ($w_{2,1}$)	$\{(H_1, 0.7), (H_2, 0.3), (H_3, 0)\}$
		Effectiveness ($C_{2,2}$)	0.2 ($w_{2,2}$)	$\{(H_1, 0.4), (H_2, 0.6), (H_3, 0)\}$

-specific issues (C_2)		Convenience ($C_{2,3}$)	0.1 ($w_{2,3}$)	{(H_1, 0), (H_2, 0.1), (H_3, 0.9)}

Without loss of generality, assume that H_{n+1} is preferred to H_n in supporting vaccination. The belief distributions in Table 2 can be interpreted as, for instances, an individual's judgements in terms of their susceptibility to the disease are 50% '*susceptible*' and 50% '*very susceptible*', while their judgements on the severity are 80% '*severe*' and 20% '*very severe*'. In addition, suppose that the two main criteria (i.e., '*Perceived risk of disease*' and '*Vaccine-specific issues*') are equally important in determining voluntary vaccination decision, and their weights are set to be 0.5 respectively for the purpose of illustration. In reality, the information gathering of beliefs, attitudes, perceptions or judgements on the factors affecting vaccination decision making can often be done through launching surveys to a representative sample of the whole population, like in WHO-led Vaccine Confidence Project (De Figueiredo, et al., 2020). It is worth mentioning that individual decision makers may not provide information in the format of belief distributions directly, and their judgements on the sub-criteria in Table 2 can simply point to one specific evaluation grade. However, the inherent uncertainties on the main criteria and the overall vaccination intention with taking into account all the relevant sub-criteria can still be modelled by the belief distributions in a more comprehensive way.

3.2 Analysing individuals' vaccination decisions with belief aggregation

3.2.1 Aggregating belief distributions using the ER approach

On the basis of the above multiple criteria belief modelling, the ER approach is then employed to aggregate the judgemental information and generate the combined belief distribution on the overall criterion of vaccination intention. According to Eq. (1), the distributed assessments based on a common set of N evaluation grades H_n $(n = 1, \dots, N)$ for a set of sub-criteria (e.g., $C_{1,1}$ and $C_{1,2}$) can be profiled as,

$$\begin{cases} S(C_{1,1}) = \{(H_n, \beta_{n,1,1}),\ n = 1, \dots, N\} \\ S(C_{1,2}) = \{(H_n, \beta_{n,1,2}),\ n = 1, \dots, N\} \end{cases} \tag{5}$$

Let $m_{n,i,j}$ be the basic probability mass (Shafer, 1976; Yang & Xu, 2002) representing the belief assigned to the evaluation grade H_n on the higher-level criterion C_i in terms of the sub-criterion $C_{i,j}$. Then $m_{n,i,j}$ can be obtained as follows,

$$\begin{cases} m_{n,i,j} = w_{i,j}\beta_{n,i,j} \\ m_{H,i,j} = 1 - \sum_{n=1}^{N} m_{n,i,j} = 1 - w_{i,j}\sum_{n=1}^{N}\beta_{n,i,j} \end{cases} \tag{6}$$

with $n = 1, \ldots, N$; $i = 1, \ldots, I$, and $j = 1, \ldots, J_i$. $m_{H,i,j}$ is the remaining probability mass which is not committed and cannot be assigned by the sub-criterion $C_{i,j}$ alone to any of the evaluation grades. It can be further split into two parts $\bar{m}_{H,i,j}$ and $\tilde{m}_{H,i,j}$: the former $\bar{m}_{H,i,j} = 1 - w_{i,j}$, which is bounded by the relative importance of the sub-criterion $C_{i,j}$, while the latter $\tilde{m}_{H,i,j} = w_{i,j}(1 - \sum_{n=1}^{N} \beta_{n,i,j})$, which is due to the incompleteness of the judgemental information on the sub-criterion.

Next, the recursive ER algorithm (Yang & Xu, 2002) is used to aggregate the basic probability assignments on a set of sub-criteria $C_{i,j}(j = 1, \ldots, J_i)$ to the higher-level criterion $C_i(i = 1, \ldots, I)$. Let $m_{n,i,J(1)} = m_{n,i,1}(n = 1, \ldots, N; i = 1, \ldots, I)$, $\bar{m}_{H,i,J(1)} = \bar{m}_{H,i,1}$ and $\tilde{m}_{H,i,J(1)} = \tilde{m}_{H,i,1}$. The combined probability assignments $m_{n,i,J(J_i)}(n = 1, \ldots, N; i = 1, \ldots, I)$, $\bar{m}_{H,i,J(J_i)}$ and $\tilde{m}_{H,i,J(J_i)}$ can be generated by aggregating all the basic probability assignments on the set of sub-criteria $C_{i,j}(j = 1, \ldots, J_i)$ recursively.

$$\begin{cases} m_{n,i,J(j+1)} = K_{i,J(j+1)}\left(m_{n,i,J(j)}m_{n,i,j+1} + m_{H,i,J(j)}m_{n,i,j+1} + m_{n,i,J(j)}m_{H,i,j+1}\right) \\ \bar{m}_{H,i,J(j+1)} = K_{i,J(j+1)}\left(\bar{m}_{H,i,J(j)}\bar{m}_{H,i,j+1}\right) \\ \tilde{m}_{H,i,J(j+1)} = K_{i,J(j+1)}(\tilde{m}_{H,i,J(j)}\tilde{m}_{H,i,j+1} + \bar{m}_{H,i,J(j)}\tilde{m}_{H,i,j+1} + \tilde{m}_{H,i,J(j)}\bar{m}_{H,i,j+1}) \\ m_{H,i,J(j)} = \bar{m}_{H,i,J(j)} + \tilde{m}_{H,i,J(j)} \end{cases} \tag{7}$$

where $K_{i,J(j+1)} = \left[1 - \sum_{n=1}^{N} \sum_{t=1, t \neq n}^{N} m_{n,i,J(j)} m_{t,i,j+1}\right]^{-1}$, $i = 1, \ldots, I$ and $j = 1, \ldots, J_i - 1$. As soon as all the J_i sub-criteria $C_{i,j}(j = 1, \ldots, J_i)$ associated with the higher-level criterion C_i are aggregated together, the combined degrees of belief, which are represented as $\beta_{n,i}(n = 1, \ldots, N; i = 1, \ldots, I)$ can then be calculated by,

$$\begin{cases} \beta_{n,i} = \frac{m_{n,i,J(J_i)}}{1 - \bar{m}_{H,i,J(J_i)}}, \quad n = 1, \ldots, N \\ \beta_{H,i} = \frac{\tilde{m}_{H,i,J(J_i)}}{1 - \bar{m}_{H,i,J(J_i)}} = 1 - \sum_{n=1}^{N} \beta_{n,i} \end{cases} \tag{8}$$

where $\beta_{H,i}$ represents the remaining belief degree unassigned to any evaluation grade $H_n(n = 1, \ldots, N)$ on the criterion $C_i(i = 1, \ldots, N)$. Similarly, the ER approach defined in Eqs. (5)-(8) can be applied to aggregate the basic probability assignments on the main criteria $C_i(i = 1, \ldots, I)$, and the overall belief distribution on the top-level decision criterion C can then be profiled as follows,

$$S(C) = \{(H_n, \beta_n), \; n = 1, \ldots, N\} \tag{9}$$

Specifically, Table 3 shows the overall belief distribution aggregated from the illustrative example in Table 2. The combined belief distribution can be interpreted that the individual has an overall intention level of 28.38% on the evaluation grade of '*low*', 57.47% on '*medium*' and 14.15% on '*high*', through taking into consideration the individual's beliefs and subjective judgements on all the vaccination decision criteria in Table 2.

Table 3. The aggregated belief distribution on vaccination from the above illustrative example

Level of intention	(H_1, β_1)	(H_2, β_2)	(H_3, β_3)	(H, β_H)
Belief distribution $S(C)$	0.2838	0.5747	0.1415	0

It is worth mentioning that $\beta_n (n = 1, \ldots, N)$ may not necessarily add up to unity, which is strictly required in the Bayesian probabilistic inference (Yang & Xu, 2013). If an individual does not have much prior knowledge on some of the decision criteria, especially about a newly-invented vaccine, the remaining belief degree $\beta_H = 1 - \sum_{n=1}^{N} \beta_n$, which cannot be assigned to any intention level, is then greater than 0.

3.2.2 Transforming the aggregated belief distribution to decision making

The aggregated belief distribution provides a panoramic view about an individual's vaccination intention, and it can then be used to interpret the individual's vaccination decision making. Here, it is assumed that an individual decides to 'accept' or 'reject' vaccination voluntarily based on their aggregated belief distribution on vaccination, and thus the decision outcome, e.g., either acceptance or refusal of the influenza vaccine in the annual flu vaccination programme, can be considered to be binary. However, if an individual does not have enough confidence or prior knowledge to decide for or against vaccination, it can be further assumed that they will not make any firm decision for the time being but '*wait and see*' further information (Bhattacharyya & Bauch, 2011; Xia & Liu, 2014; MacDonald et al., 2015). The intermediate state of '*wait and see*' or so-called '*yet to decide*' is not regarded as a third decision outcome in this research, as essentially the calculation of vaccination coverage only takes into account whether or not the vaccine is accepted by an individual. However, the belief distribution can formulate the undecided state explicitly as a generalised probabilistic framework. The frame of discernment is defined as $\Theta = \{accept, reject\}$, which includes the two mutually exclusive and collectively exhaustive decision outcomes, i.e., '*accept*' and '*reject*' vaccination, and the power set of Θ is,

$$2^{\Theta} = \{\emptyset, \{accept\}, \{reject\}, \Theta\} \tag{10}$$

where $\emptyset$ is an empty set. Θ can be used to represent the intermediate '*wait and set*' state, but it is expected that the individual's belief will evolve over time with social influence, and this intermediate state will eventually converge to one of the two decision outcomes defined in the frame of discernment. As a result, the basic probability mass, which measures the degree of belief for the individual to make a decision based on the prior knowledge and currently available information, can be represented as,

$$\begin{cases} m: 2^{\Theta} \to [0,1] \\ m(\emptyset) = 0 \\ m(\Theta) = 1 - m(accept) - m(reject) \end{cases} \tag{11}$$

where $m(accept)$ and $m(reject)$ represent respectively the degrees of belief on the individual's acceptance or refusal of getting vaccinated, while $m(\Theta)$ indicates the uncertain degree of belief with which the individual currently holds about whether or not to get vaccination. The undecided state is labelled as '*wait'* hereinafter. Further, a linear utility-based information transformation method as illustrated in Figure 2 is used to calculate the probability masses from the aggregated belief distribution on vaccination intention in Eq. (9).

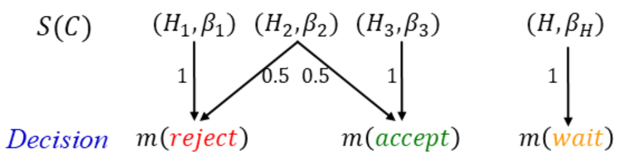


Figure 2. Utility-based information transformation of the aggregated belief distribution

Mathematically, the information transformation method can be written as,

$$\begin{cases} m(reject) = \sum_{n=1}^{N} \beta_n \frac{N-n}{N-1} \\ m(accept) = \sum_{n=1}^{N} \beta_n \frac{n-1}{N-1} \\ m(wait) = \beta_H \end{cases} \tag{12}$$

Note that this linear information transformation method can also be customised in accordance with the decision maker's preference or utility function (Belton and Stewart, 2002; Yang & Xu, 2002). For the aggregated belief distribution in Table 3, the individual's probability masses on vaccination decision can be obtained as $m(reject) = 0.57$, $m(accept) = 0.43$ and $m(wait) = 0$. Obviously, the individual is more likely to reject vaccination based on the given belief distributions on all the decision criteria in Table 2.

In order to estimate the proportion of individuals getting vaccinated in a social community or network, this research further adopts the widely accepted mechanism of integration-to-boundary (Zhang, 2012; Glickman & Usher, 2019) in psychology which refers to the presence of a decision boundary governing the establishment of decisions. In other words, a decision will not be made until the accumulated evidence or belief reaches a boundary level. The boundary mechanism provides a psychological function to constrain the knowledge and evidence needed for rendering a decision as well as a mechanism to determine the termination of the decision-making process.

Suppose an individual x has an independent belief boundary $\varphi^x (0 \le \varphi^x \le 1)$, which is a threshold value representing the individual's lower bound of belief to make a decision. The individual will be assumed to accept the vaccine if the probability mass satisfies

$$m^x(accept) \ge \varphi^x \tag{13}$$

Similarly, the individual will reject the vaccine if $m^x(reject) \ge \varphi^x$. It is noted that the belief boundary φ^x can be different for each individual decision maker. Implicitly, the higher the belief boundary an individual has, the harder it is to convince the individual to make a decision (e.g., take the action of getting vaccinated). In the above illustrative example, if the belief boundary is set to be 0.8, which is obviously higher than both $m(accept)$ and $m(reject)$, the individual will delay in either acceptance or refusal of vaccination.

3.3 Characterising the spread of social influence in social networks

For those who fail to make a decision based on their prior knowledge or subjective judgements, any information and evidence on the disease and vaccine from social neighbours can potentially facilitate their decision-making process. In view of the fact that the dynamic decision-making process evolves over time from evidence accumulation to belief updating (Usher et al., 2013; Schöbel et al., 2016), the spread of social influence is incorporated into the framework of MCDA by mapping the effects of influence spreading into the updates of belief distributions on the corresponding decision criteria. As a result, the evolving decision-making process under social influence could be characterised effectively for voluntary vaccination decision. In the context of socially influenced vaccination decision making, a social community can be formulated as a directed network $G =< V, E >$, which consists of a set of vertices connected with edges. Each individual among a population of M people is described as a vertex $V = \{v^1, \dots, v^M\}$ and each edge $E = \{e^{x,y} | 1 \le x, y \le M;\ x \ne y\}$ indicates the social interaction between two individuals. The weight $\tau^{x,y}$ of edge $e^{x,y}$ for any pair of vertices (x, y) is a measurement of the strength of the link between the two individuals, and it can be interpreted as an individual's willingness or openness to accept the influence from his/her social neighbours. Obviously, the mutual influence between two individuals is not necessarily equivalent in reality, and usually $\tau^{x,y} \neq \tau^{y,x}$.

It is illustrated in Figure 3 how information or evidence as the medium of social influence can potentially spread between individuals in a social network. $I_{i,j}^{x}$ $(x = 1, \ldots, M)$ denotes a piece of information received by the individual v^x at certain time, which is related to the sub-criterion $C_{i,j}$ affecting vaccination decision making.

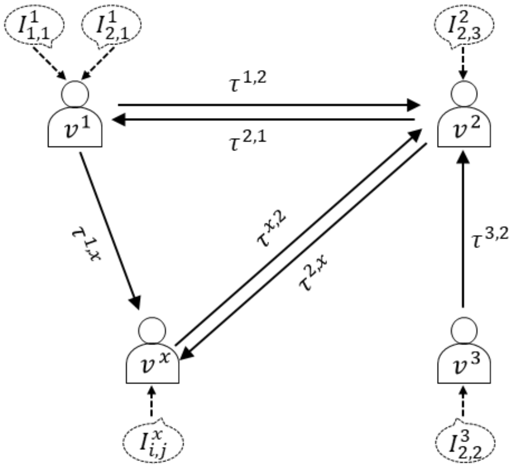


Figure 3. An illustrative example of social influence spreading in a social network

It has previously been studied how social influence can facilitate or hinder vaccination from different perspectives and on a variety of factors (De Bekker-Grob, 2020; Ling et al., 2019; Wheelock, 2013; Xia & Liu, 2014). For example, when being told by a social neighbour about the severe side effects after getting vaccinated, an individual will be highly likely to update his/her judgements on the safety of vaccine accordingly. However, the judgements on other decision factors such as the severity of disease may remain unaffected. In this case, the effects of social influence are reflected on the updates of the individual's degrees of belief on the specific criterion in accordance with the information which the individual obtained from his/her social neighbours. Here, multiple pieces of information can possibly influence an individual's vaccination decision-making process simultaneously or consecutively.

Figure 4 illustrates how an individual's judgements on vaccination are affected due to the receipt of new information from social neighbours. Let $I_{1,1}^{1}$ be a piece of information received by the individual v^1 relating to the sub-criterion $C_{1,1}$ '*Susceptibility*', e.g., about the increasing number of infected cases. While v^1 aggregates the new piece of information with his/her prior belief distribution on the sub-criterion, he/she may also spread the information to his/her social neighbours, such as v^2 in Figure 4. As a result, v^2 will update his/her beliefs and judgements on the sub-criterion correspondingly. However, the influence of the information passed from v^1 to v^2will be weighted by $\tau^{1,2}$ which indicates how willing or open v^2 is to be influenced by v^1.

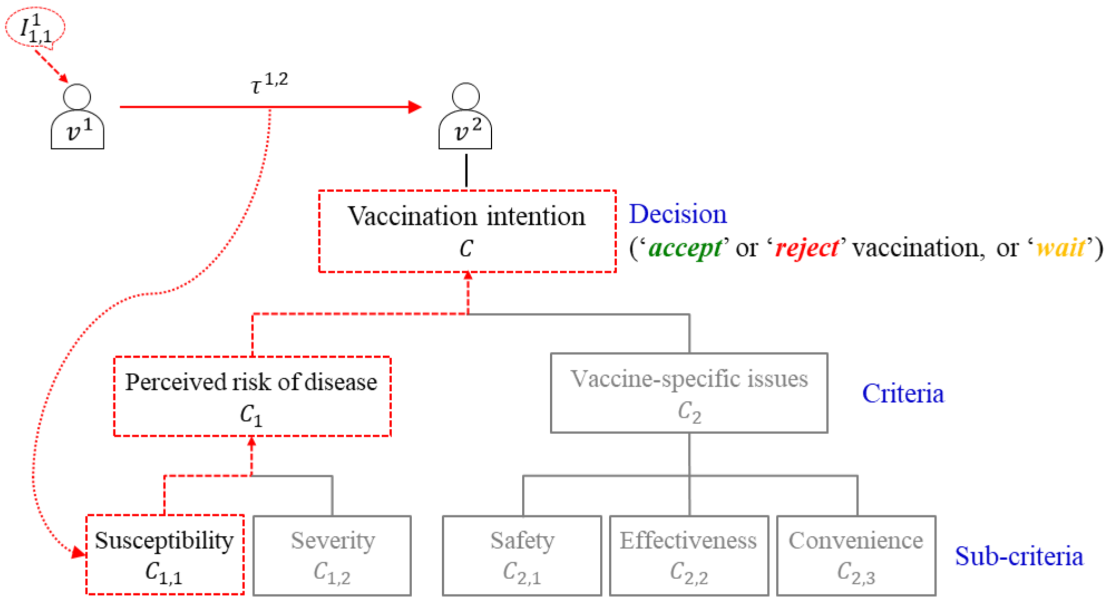


Figure 4. Illustration of information spreading and belief updating in the framework of MCDA

Assume that the information $I_{1,1}^1$ is also profiled as a belief distribution $S(I_{1,1}^1) = \{(H_n, \alpha_{n,1,1}^1), n = 1, \dots, N\}$. The probability masses which v^2 will use to aggregate with his/her prior belief distribution on the decision sub-criterion $C_{1,1}$ can be calculated by,

$$\begin{cases} m_{n,1,1}^{1,2} = \tau^{1,2}\alpha_{n,1,1}^1, n = 1, \dots, N \\ \bar{m}_{n,1,1}^{1,2} = 1 - \tau^{1,2} \\ \tilde{m}_{n,1,1}^{1,2} = \tau^{1,2}(1 - \sum_{n=1}^{N} \alpha_{n,1,1}^1) \end{cases} \tag{14}$$

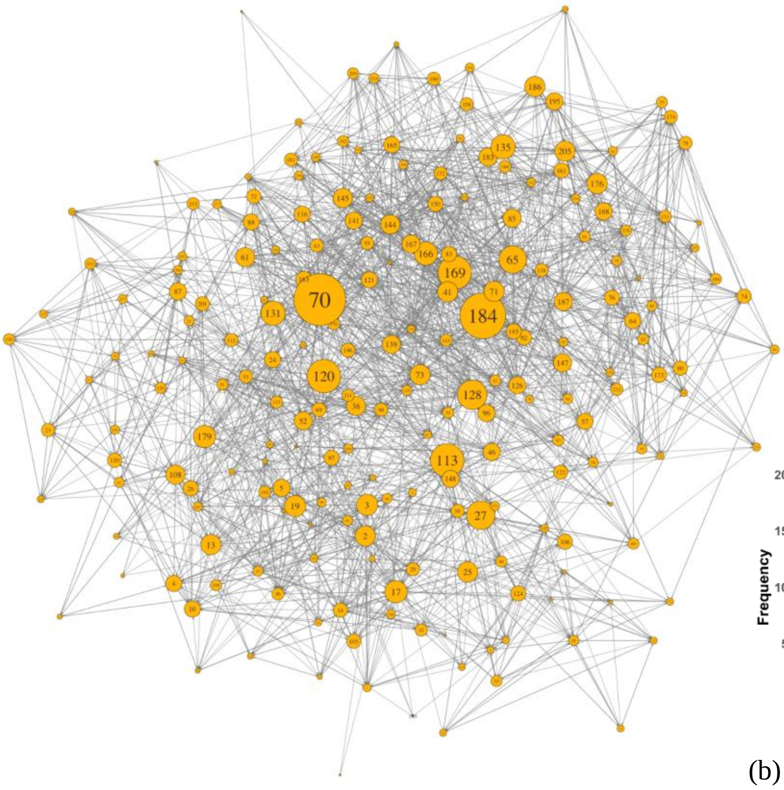
The aggregation of the newly-arrived evidence represented by the probability mass function in Eq. (14) is realised by further applying the ER algorithm in Eqs. (7) - (8) to update the individual's belief distribution. Furthermore, the overall belief distribution on the top-level decision criterion C in Eq. (9) should be updated again from the lower-level decision criteria recursively, before it is transformed to support the decision making defined in Eqs. (12) and (13). In the meantime, v^2 can also spread the information to his/her social neighbours, like v^x in Figure 3, v^x will then update his/her beliefs and judgements on the decision criteria in a similar way as discussed above. As a result, the effects of social influence spreading on vaccination decision making can be considered in the framework of MCDA in an explicit way.

4. Simulation-based Analysis

To demonstrate the effectiveness and practicality of the integrated decision model, a series of simulation-based analyses is carried out on a real-world social network, where a group of individuals are supposed to interact with each other and need to decide whether to get vaccinated. Without loss of generality, it is assumed that all individuals have some prior knowledge or are able to express their subjective judgements with the defined evaluation grades on vaccine uptake explicitly in terms of the decision criteria hierarchy in Figure 1.

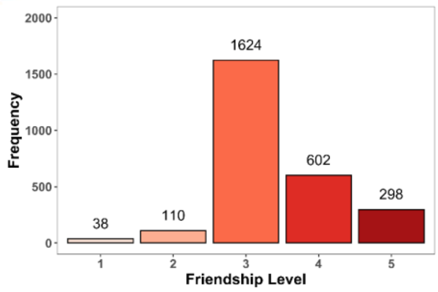
4.1 Description of the network structure

The social network data, which records the friendships among 217 residents living at a residence hall located at the Australian National University campus, was firstly collected by Freeman et al. (1998) to represent the interpersonal interactions in a real-world environment. One of the key characterises of the social network data is that the strength of social interactions among individuals were surveyed in the social community. The social network is visualised in Figure 5 with the nodes denoting individuals and the edges representing social relationships.



Density	0.057
Diameter	4
Average Path Length	2.765
Maximum Out-degree	51 (node 70)

(a) Statistics of the social network



(b) Distribution of the friendship levels

Figure 5. Structure and statistics of the social network

In the social network, the direction of each edge represents where the information is going, while the edge weight indicates the strength of the social relationship (i.e., the five friendship levels of from 1 to 5). To better reflect the characteristics of the social network, the size of the node is calculated proportionally by the number of outgoing links. It looks from Figure 5 that a small number of individuals have many more social connections than the others. The complementary Figure 5(a) provides summary statistics of the social network, and Figure 5(b) shows the frequency of the levels of friendship strength. It can be seen that the strength mainly concentrates on the level of '*3 - friend*', '*4 - close friend*', and '*5 - best friend*'. The social network structure is not highly dense in terms of its relatively small density value, and so it is very helpful to analyse the dynamics of the socially influenced vaccination decision-making process in the social network.

4.2 Illustration of socially influenced vaccination decision making

First of all, we simulate how individuals can possibly update their beliefs on vaccination in the context of social influence spreading. The parameters in the integrated decision model, including belief distributions and criterion weights for individuals, are initialised randomly by the Dirichlet distribution which is commonly used as a multivariate generalisation of the beta distribution in probabilistic inference. However, the proportion of the initial belief distributions supporting the acceptance of vaccination for simulation can be guided by a specified level of historical vaccination coverage. Here we take the overall influenza vaccine uptake of 44.9% for people aged 6 months to under 65 years with one or more underlying clinical risk factors during the 2019-20 winter season in England (Public Health England, 2020) as a benchmark to set the initial vaccination acceptance rate in the following simulation. The individuals' belief boundary is assumed to follow a uniform distribution within an interval [0.5, 1].

Here, an illustrative simulation is first carried out, and the characteristics of the information (i.e., what the content is about, and when it begins to spread from a source node) are given in Table 4.

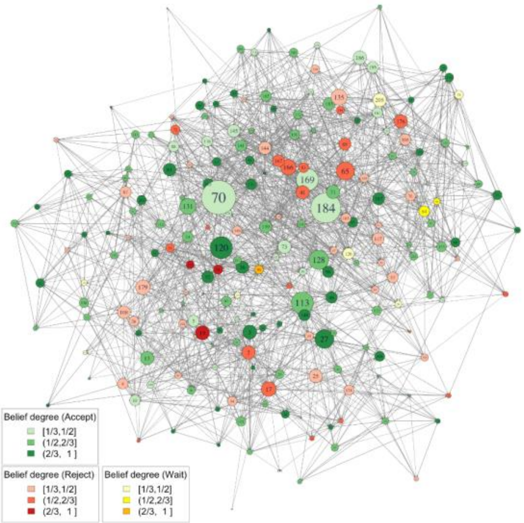
Table 4. Characteristics of the information spreading in the social network

Time (step)	*Information about which criterion*	*Positive/Negative*	*Source node*
t_1	Susceptibility ($C_{1,1}$)	Positive ($I_{1,1}^{70}$)	v^{70}
t_2	Severity ($C_{1,2}$)	Negative ($I_{1,2}^{184}$)	v^{184}

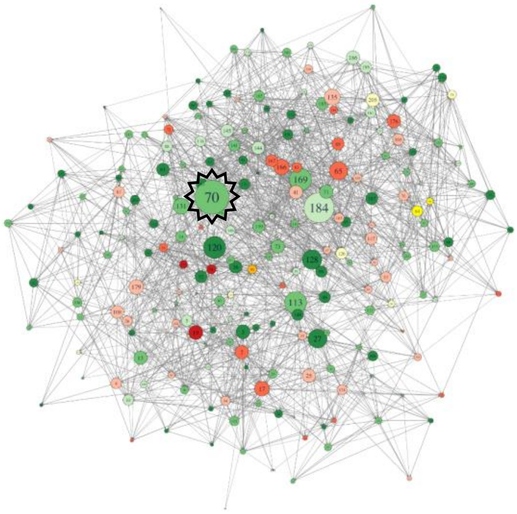
t_3	Safety ($C_{2,1}$)	Positive ($I_{2,1}^{169}$)	v^{169}
t_4	Effectiveness ($C_{2,2}$)	Positive ($I_{2,2}^{120}$)	v^{120}
t_5	Convenience ($C_{2,3}$)	Negative ($I_{2,3}^{113}$)	v^{113}

Specifically, the individual v^{70} receives a new piece of positive information or supportive evidence for vaccination on the sub-criterion $C_{1,1}$ (i.e., '*Susceptibility'* to the disease) at time t_1. While updating his/her own belief distribution on the sub-criterion, he/she will also spread this piece of information through his/her social connections. It is assumed that further information related to other decision criteria, which can be positive or negative, are to be received and spread by other individuals at time t_2 to t_5. Here, it is intuitively clear that a piece of positive information or supportive evidence, e.g., successful immunisation after vaccination, will facilitate individuals' vaccination acceptance, and its belief distribution is simply profiled as $\{(H_1, 0), (H_2, 0), (H_3, 1)\}$. In contrast, a piece of negative information or unsupportive evidence will hinder vaccination acceptance, and its belief distribution is represented as $\{(H_1, 1), (H_2, 0), (H_3, 0)\}$.

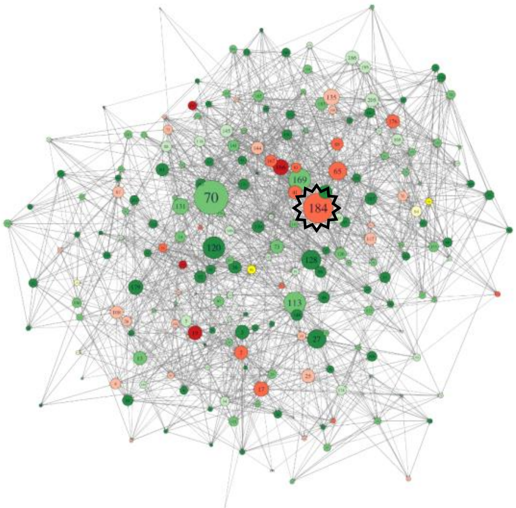
The dynamic processes of updating individuals' beliefs on vaccination under social influence spreading in the social network are visualised in Figure 6. In the networks, the three traffic light colours of nodes (i.e., green, amber, or red) indicate if an individual has a higher degree of belief on '*accept*', '*wait*', or '*reject*', respectively. For example, if the degree of belief on accepting vaccination for an individual dominates the degrees of belief on '*reject*' and '*wait*', node will be coloured as green. The colour scale is determined by the exact value of the dominating belief degree. It is obvious from Figure 6(a) that a good proportion of individuals opt to accept vaccination at the beginning time t_0, as it was discussed above that the influenza vaccination coverage data in England was used to guide the initial parameter settings.



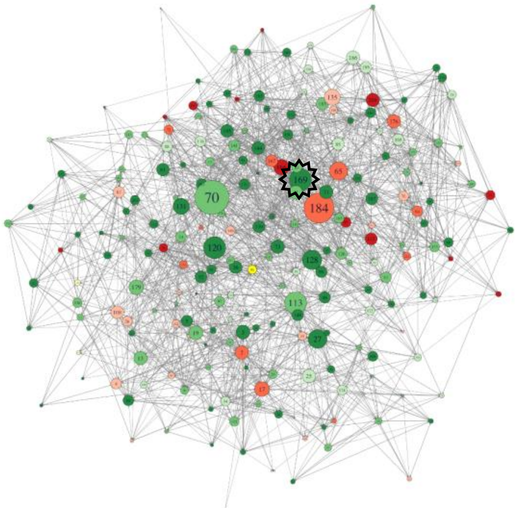
(a) Time (t_0)



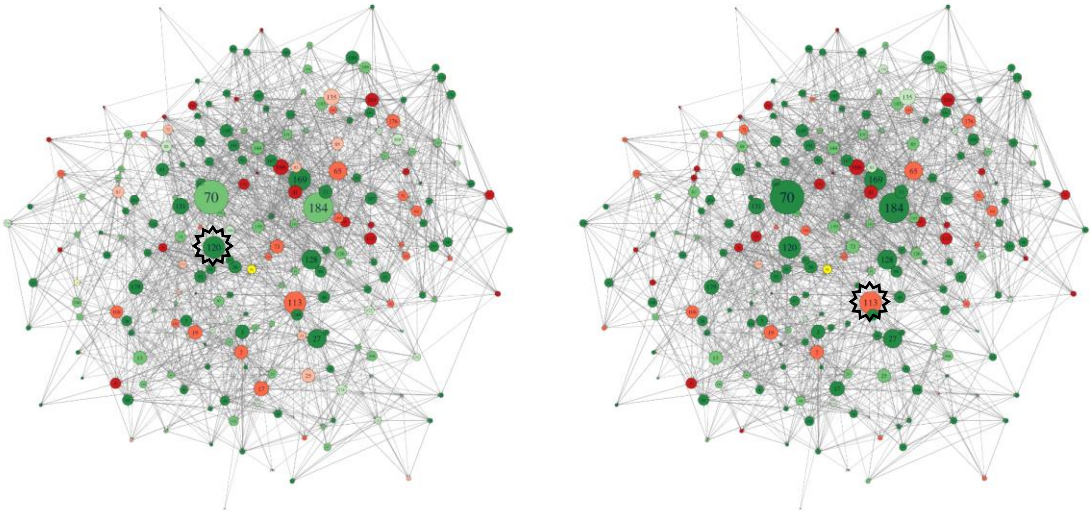
(b) Time (t_1)



(c) Time (t_2)



(d) Time (t_3)

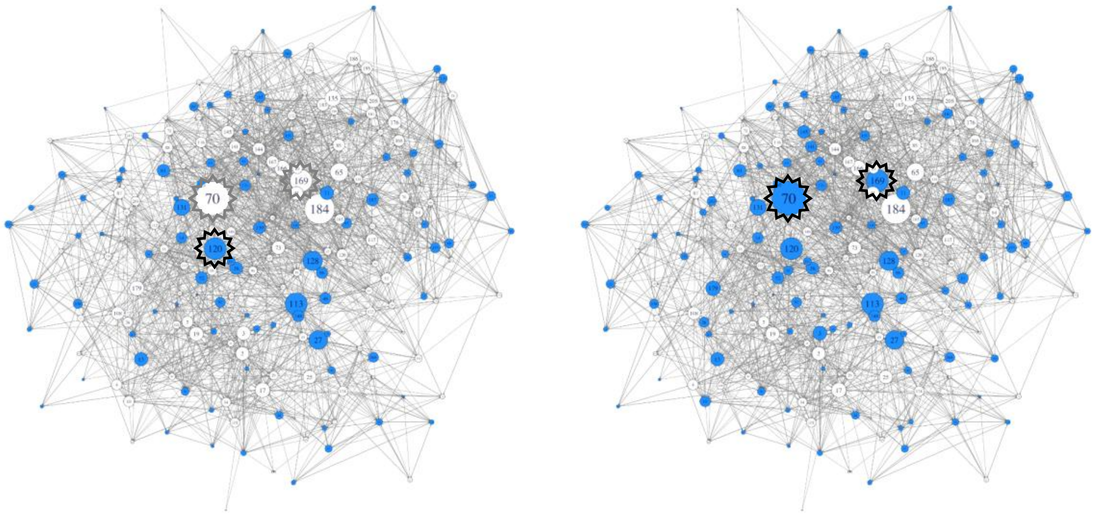


(e) Time (t_4) (f) Time (t_5)

Figure 6. An example of influence spreading and belief updating in the social network

At time t_1, the individual v^{70} is fed with a piece of positive information about the susceptibility to the disease. After revising his/her own degrees of belief, he/she spreads the piece of positive information via his/her social connections. Figure 6(b) illustrates the updated degrees of belief for all individuals at t_1, which are reflected to some extent by the changed colours of the nodes representing v^{70} and some of his/her direct social connections. With the aggregation of the prior belief distributions and the further arrivals of new information from t_2 to t_5, the dynamics of influence spreading and belief updating evolve as shown in Figure 6(c) to Figure 6(f). Obviously, the belief updating becomes more complex with an ever-increasing amount of information spreading, but the effects of social influence can still be observed from this illustrative simulation. For example, a few nodes connected to v^{169} turned to be green in Figure 6(d) from red in Figure 6(c) due to the receipt of the positive information. The negative information received by v^{113} in Figure 6(f) has resulted in a more mixed effect given that the information received earlier still spreads in the social network.

Correspondingly, Figure 7 shows the changing vaccination coverage from t_0 to t_5 due to the continuum of influence spreading and belief updating. The colour of the node indicates whether an individual is expected to have accepted vaccination. If the nodes are coloured to be blue, like individual v^{120} in Figure 7(a), v^{70} and v^{169} in Figure 7(b), it means that the individuals are expected to have taken vaccination since their degrees of belief on '*accept*' have exceeded their independent belief boundary.



(a) Time (t_0) (b) Time (t_5)

Figure 7. The Dynamics of vaccination coverage with social influence spreading

It is evident that a higher proportion of positive information or supportive evidence will be more or less strengthened in supporting vaccination acceptance through the social influence spreading.

4.3 Simulation-based sensitivity analysis

A series of simulation-based experiments are further conducted to examine whether individuals' socially influenced vaccination decision making are affected sensitively by two types of conditions: (1) the characteristics of influence spreading (including the content and amount of vaccine-related information) in the social network, and (2) individuals' initial beliefs and judgements on the decision criteria, which are formulated as weights and belief distributions in the integrated decision model. The simulation for each scenario was run 100 times in order to obtain reliable experimental results.

4.3.1 The effects of the characteristics of information spreading

The characteristics of information spreading, especially the content of the information, obviously influence individuals' decision making in a social environment (MacDonald et al., 2015; Xia & Liu, 2014; Schöbel et al., 2016).

(1) The content of information

Here, we first consider four simple scenarios under the settings in Table 5 in terms of the content of information, which is either positive (i.e., supportive) or negative (i.e., unsupportive) in terms of facilitating vaccination acceptance. In each of the scenarios, a new piece of information regarding criterion $C_{1,1}$ ('Susceptibility') will be spread from one individual separately in the network at time steps t_1 and t_2.

Table 5. Different settings on the content of information

	Positive (P) /Negative (N)	
	t_1	t_2
$s_{1.1}$	N	N
$s_{1.2}$	N	P
$s_{1.3}$	P	N
$s_{1.4}$	P	P

In the first scenario $s_{1.1}$, a randomly selected individual receives a piece of negative information or unsupportive evidence on criterion $C_{1,1}$ (i.e., '*Susceptibility*' to the disease) at time t_1, and then another piece of negative information targeting on the same criterion at time t_2. The other parameters in the integrated decision model are initialised as discussed in Section 4.2, and they remain consistent for each of the four scenarios.

It shows in Figure 8 that the estimated vaccination coverage varies considerably across the four different scenarios.

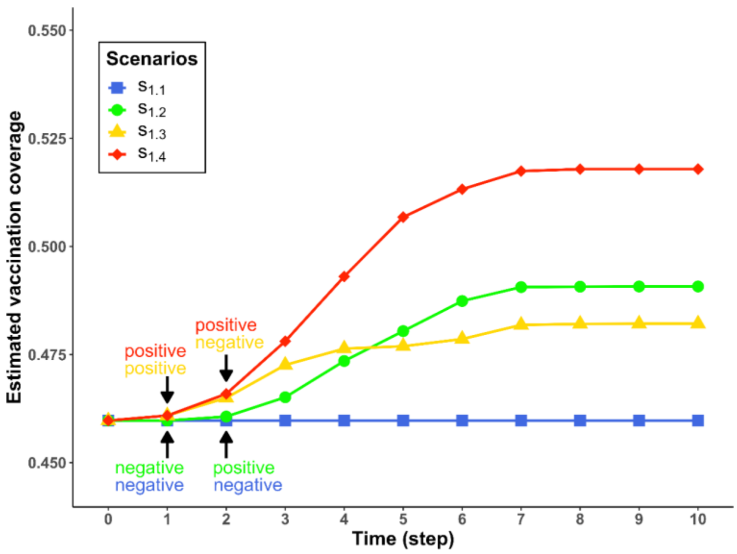


Figure 8. Effects of the content of information on vaccination coverage

It is quite straightforward from comparing the scenarios $s_{1.1}$ and $s_{1.4}$ that positive information motivates significantly individuals' voluntary vaccination decisions and raise the overall estimated vaccination coverage in the social network. However, it looks from the scenarios $s_{1.2}$ and $s_{1.3}$ that the early-arrived positive information can stimulate the intention of accepting vaccination initially, although the late arrival of negative information counteracts the positive effect and vice versa.

(2) Increasing amount of positive information

We can further analyse how the estimated vaccination coverage changes with the increasing amount of positive information. The settings for the increasing amount of positive information are listed in Table 6. For example, in the scenario $s_{2.5}$, a new piece of positive information associated with a specific decision criterion will start to spread across the social network at each time from t_1 to t_5. In contrast, there is only one piece of positive information spreading at t_1 in the scenario $s_{2.1}$.

Table 1. The settings of the increasing amount of positive information

	Information on which criterion				
	t_1	t_2	t_3	t_4	t_5
$s_{2.1}$	$C_{1,1}$				
$s_{2.2}$	$C_{1,1}$	$C_{1,2}$			
$s_{2.3}$	$C_{1,1}$	$C_{1,2}$	$C_{2,1}$		
$s_{2.4}$	$C_{1,1}$	$C_{1,2}$	$C_{2,1}$	$C_{2,2}$	
$s_{2.5}$	$C_{1,1}$	$C_{1,2}$	$C_{2,1}$	$C_{2,2}$	$C_{2,3}$

It is evident in Figure 9 that the amount of positive information significantly affects the upward trends of the estimated vaccination coverage in the social network. The estimated vaccination coverage rates seem to be unsatisfactory without the continuing stimulation of new positive information, e.g., in the scenarios $s_{2.1}$ and $s_{2.2}$.

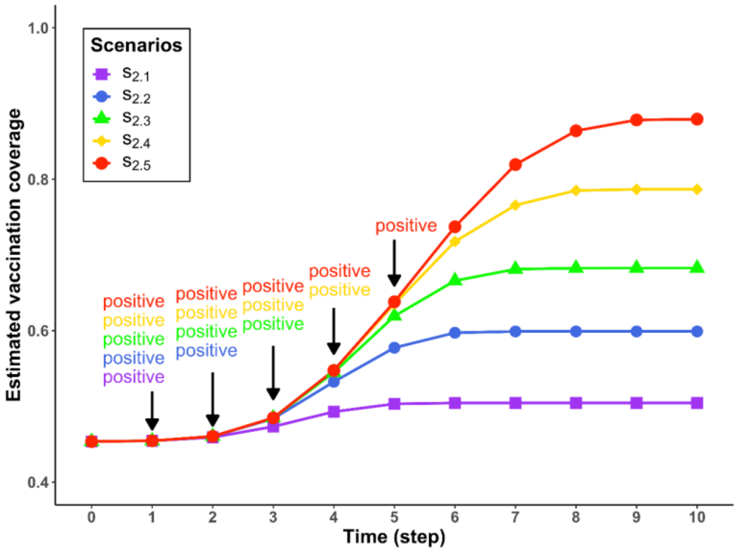


Figure 9. Effects of the increasing amount of positive information on vaccination coverage

The simulation results in this section demonstrated that it is important to spread positive information and share supportive evidence continuously in order to achieve sufficiently high vaccination coverage in a social network, although how to effectively manage the characteristics of information spreading for vaccination may need to involve health organisations, healthcare professionals, decision scientists, social media analysts, etc.

4.3.2 The sensitivity analysis of the criterion weights

As discussed previously, not all the criteria are equally important in affecting individuals' vaccination decision making. Some individuals may value the safety of vaccines while others may be more concerned about the physical effects caused by infections. In this sense, it is important to analyse the effects of criterion weights in the socially influenced vaccination decision-making process. Here we mainly investigate the sensitivity of vaccine coverage in terms of different combinations of weights for the main criteria and sub-criteria in the decision criterion hierarchy.

(1) Different weights of the main criteria

There are two main criteria at the upper level of the criterion hierarchy in Figure 1, i.e., '*Perceived risk of disease*' (C_1) and '*Vaccine-specific issues*' (C_2). Their normalised weights are denoted by w_1 and w_2 respectively. In this section, five scenarios are considered for simulation analysis. The first two scenarios $s_{3.1}$ and $s_{3.2}$ consider the situation that individuals are generally more concerned with the disease. Therefore, w_1 is initialised randomly from the interval [0.6, 1] or [0.8, 1] respectively whilst the remaining weight is allocated to w_2. The next two scenarios $s_{3.3}$ and $s_{3.4}$) take into consideration the contrary situation. It is assumed in the last scenario $s_{3.5}$ that people have an equal preference on the importance of the two main criteria. The experimental settings for these five scenarios are listed in Table 7(a) and 7(b).

Table 7. Different weight settings for the main decision criteria

(**a**) Interval of criterion weight

	w_1	w_2
$s_{3.1}$	[0.6,1]	$1 - w_1$
$s_{3.2}$	[0.8,1]	$1 - w_1$
$s_{3.3}$	$1 - w_2$	[0.6,1]
$s_{3.4}$	$1 - w_2$	[0.8,1]
$s_{3.5}$	0.5	0.5

(**b**) The content of information

	Positive information on which sub-criterion			
	t_1	t_2	t_3	t_4
$s_{3.1}$-$s_{3.5}$	$C_{1,1}$	$C_{1,2}$	$C_{2,1}$	$C_{2,2}$

It can observed in Figure 10 that the estimated vaccination coverage in the network is quite sensitive to the weights of the main decision criterion, given the arriving sequence and content of information remain the same.

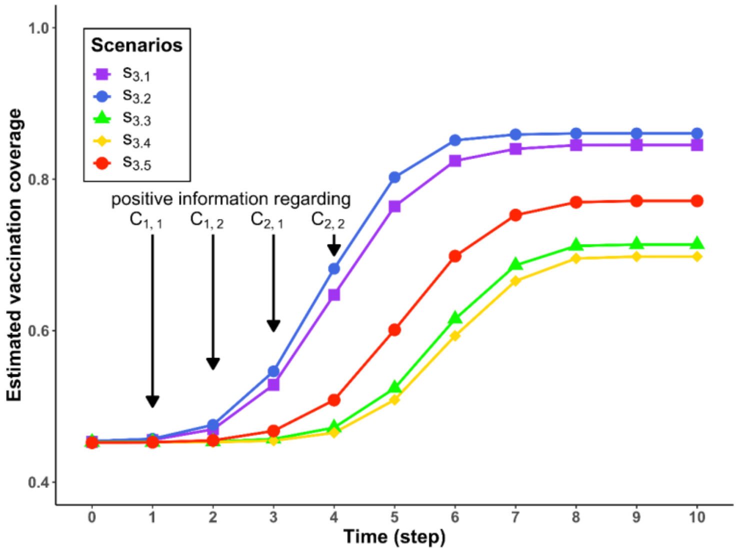


Figure 10. Effects of the weights of the main criteria on the vaccination coverage

If there is one dominating criterion (i.e., being much weighted by individuals), the influence of information spreading on the other main criterion seems to be limited in the social network.

(2) Different weights of the sub-criteria

In this experiment, we compare individuals' preferences on the sub-criteria at the lower level in the criterion hierarchy to investigate the sensitivity of weights with respect to vaccination coverage. The two sub-criteria selected for analysis are $C_{1,1}$ '*Susceptibility*' and $C_{1,2}$ '*Severity*'.

The explanations on the settings of the five scenarios are similar to the above-mentioned experiment for the main criteria. The weight settings together with the content of information are listed in Table 8(a) and 8(b).

Table 2. Different weight settings for the sub-criteria

(**a**) Interval of sub-criterion weight

	$w_{1,1}$	$w_{1,2}$
$s_{4.1}$	[0.6,1]	$1-w_{1,1}$
$s_{4.2}$	[0.8,1]	$1-w_{1,1}$
$s_{4.3}$	0.5	0.5
$s_{4.4}$	$1-w_{1,2}$	[0.6,1]
$s_{4.5}$	$1-w_{1,2}$	[0.8,1]

(**b**) The content of information

	Positive information on which sub-criterion			
	t_1	t_2	t_3	t_4
$s_{4.1}$-$s_{4.3}$	$C_{1,1}$	$C_{1,2}$	$C_{2,1}$	$C_{2,2}$
$s_{4.4}$-$s_{4.5}$	$C_{2,1}$	$C_{2,2}$	$C_{2,1}$	$C_{2,2}$

It can be seen in Figure 11 that the sensitivity of vaccination coverage to the different weight settings for the sub-criteria is not as significant as that in the previous experiment for the main criteria.

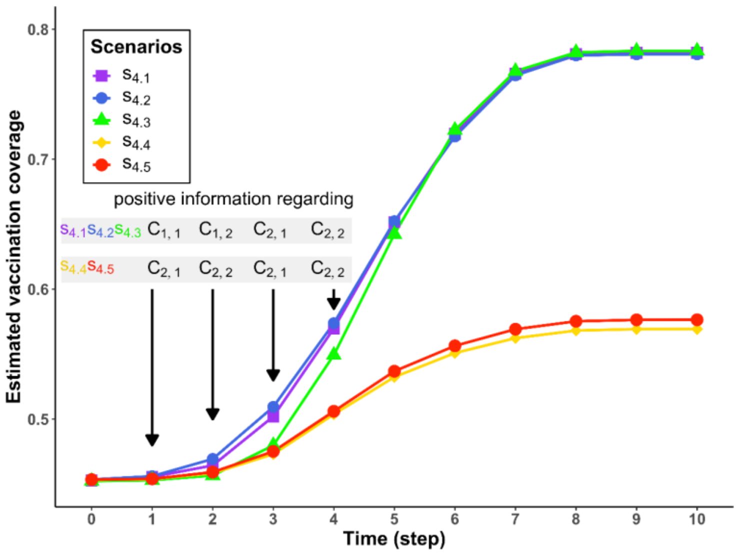


Figure 11. Effects of the weights of the sub-criteria on the vaccination coverage

That is because an individual's vaccination intention is aggregated recursively from the lower-level decision criteria to the top-level decision criterion in the integrated decision model, and some sub-criteria may only play a limited role in affecting individuals' vaccination decision making. In reality, some individuals in a social community may place great emphasis on certain decision criteria, and providing them with the redundant information on other decision criteria is less effective to affect their vaccination decision behaviours.

5. Conclusions and discussion

The benefits of vaccination have been emphasised extensively in terms of increasing the probability of immunisation as well as reducing the medical burden of infectious diseases. Thus, understanding the voluntary vaccination decision-making process in a social environment is prominently important for disease control departments to develop effective strategies and interventions of vaccine-preventable diseases.

In this paper, an integrated model exploiting the joint strength of multiple criteria belief modelling and social network analysis is developed to characterise socially influenced vaccination decision making in an innovative way. In the proposed model, each individual's beliefs and subjective judgements on vaccine uptake are formulated as belief distributions in the framework of MCDA, and the spread of influence in the social network is further incorporated into the information aggregation process for supporting informed vaccination decision analysis. In order to demonstrate the effectiveness and practicality of the integrated decision model, we conducted a series of simulation-based analyses. The results revealed that the population-level vaccination decision behaviours and vaccination coverage are determined primarily by individuals' beliefs and judgements on the decision criteria, and are also affected sensitively by the characteristics of influence spreading (including the content and amount of vaccination-related information) in the social network. Practically, spreading positive information and sharing supportive evidence at the right time, preferably continuously can improve the vaccination coverage in the social network significantly. Through incorporating social network analysis into the MCDA model of voluntary vaccination decisions coherently, this exploratory work can be beneficial to better understand population vaccination behaviours and vaccination coverage from the perspectives of individuals' socially influenced vaccination decision making, which can further provide actionable insights and decision support on infectious disease control and prevention.

It was evident from the simulation-based analysis that the strength of social interactions among individuals has a considerable impact on the information spreading, population-level decision behaviours and vaccination coverage. However, in this research the friendship level in the social network data was used as a rough proxy of the strength of social influence in the context of vaccination decision making. In addition, the social network was relatively small. In our future research, real-world and large-scale datasets will be collected in order to obtain a holistic view over the biased beliefs of individuals (e.g., preferences on specific decision criteria) as well as the features of social networks (e.g., heterogeneous or homogenous communities, different metrics of social influence).

During the period of finalising this paper, the novel coronavirus disease (Covid-19) is still unfolding rather than relieving as spikes are being seen continuously across different countries. However, the prospects of putting an end to the pandemic have changed utterly, as several vaccines have hit the headlines across the globe with very promising results from clinical trials. It is hoped that this exploratory research will shed some light on understanding socially influenced vaccination decision-making behaviours, and the analytical findings can be helpful to underpin Covid-19 vaccination strategies and facilitate vaccine deployment, such as through promoting public confidence in the importance, safety and effectiveness of Covid-19 vaccines and making use of social influence on individuals' vaccination decision making.

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