Modeling Belief Divergence and Opinion Polarization with Bayesian Networks and Agent-Based Simulation

A Study on Traditional Healing Use in South Africa

Kamwoo Lee(✉) and Jeanine Braithwaite

University of Virginia, Charlottesville, VA 22904, USA
{kl9ch,jeaninebraithwaite}@virginia.edu

Abstract. This study uses agent-based simulation with human settlement patterns to model belief revision and information exchange about health care options. We adopt two recent microeconomic theories based on Bayesian Network formulations for individual belief update then examine the macro-level effects of the belief revision process. This model tries to explain traditional healing usage at the village and regional level while providing a causal mechanism with a single conceptual factor, mobility, at the individual level. The resulting simulation estimates the dependency on traditional healing in villages in Limpopo, South Africa, and the estimates are validated with empirical data.

Keywords: Traditional healing · Belief divergence · Settlement patterns · Bayesian Networks · Agent-based modeling

1 Introduction

Traditional healing (TH) and its practitioners have long been considered an important supplement to the health care system in South Africa [1,7,14]. However, it is unclear to what extent individuals depend on TH and why some groups of people are more likely to use it than others. Even in the scientific literature, the estimated prevalence of TH use has wide discrepancies between studies. While it is frequently stated that 80% of people in African countries use traditional medicine practitioners for some part of their primary health care [2,10], other studies argue that the prevalence is negligibly low, anywhere between 0.1% and 2% [11,13].

Opinions towards TH are as polarized as the estimation itself. Some people vehemently advocate that modern or Western medicine is firmly rooted in a scientific paradigm and biomedical science explains the cause of disease while others believe that traditional medicine has long been successfully practiced, operating within a spiritual realm [15]. Although attitude polarization is a common, social phenomenon, it is puzzling why some groups of people are consistently inclined towards one side in the first place.

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This paper is an attempt to demonstrate how beliefs towards TH can diverge between groups of the general public in a systematic fashion across age, income, and geography. We hypothesize that people's mobility, which is closely related to all three factors, causes divergence when the information is inherently ambiguous like opinions about medical services. Since people with different mobility have different information flows, they give different credence to the same pieces of information they encounter. This discrepancy can eventually result in differing, or even opposing, opinions through polarization. We test this hypothesis by simulating continuous opinion exchanges in several geographic regions with people who approximate probabilistic inference. Starting with random levels of belief regarding traditional healers and hospitals, people revise their beliefs after listening to others and develop fairly regular and consistent opinions over time, based on age, income, and settlement patterns. The result of the simulation matches both our survey results and national statistics.

2 Background and Related Work

This paper draws together three separately researched topics and suggests a new combination of methods and subject matter. This section summarizes selected findings in these topics that comprise the foundation for the model of this study.

2.1 Traditional Healing in South Africa

The World Health Organization (WHO) defined traditional medicine (TM) as "the sum total of the knowledge, skill, and practices based on the theories, beliefs, and experiences indigenous to different cultures", while suggesting that TM is an important but underestimated form of health care [19]. It is arguable that TM can encompass all TH in South Africa because TH sometimes encompass supernatural counselling or even fortune telling. It is true that South African traditional healers play many different roles such as health care provider, spiritual advisor, and cultural heritage keeper. This paper particularly focuses on the primary health care function of TH and uses research findings and data of TM and TH interchangeably in this narrow functionality.

2.2 Belief Revision, Divergence, and Polarization

Belief revision is the process of changing beliefs in response to new information. The logic of belief revision is a relatively young field of research originated from philosophy and computer science [8]. Basically, a belief-revision rule defines how a person accepts and internalizes outside information when she or he encounters it. There are many logical representations for this process [6]. When assumed that believing is a probabilistic degree instead of a dichotomous conviction, one of the widely used methodologies to conceptualize belief revision is Bayesian frameworks [12].

It is not uncommon that two people change their beliefs in the opposite direction even when they observe the same set of information. Jern et al. [9] showed that the belief divergence can be expressed with a Bayesian network for a family of cases and that probabilistic inference of rational people can lead to divergence. Attitude polarization, a similar but different concept, is a phenomenon in which a disagreement becomes more extreme as people consider evidence about the issue. This is especially true when people encounter ambiguous evidence and interpret it to align with their existing beliefs. Through this process, people reinforce their previously-held beliefs, which further widens disagreement. Fryer Jr. et al. [5] introduced a model that represents polarization with Bayes' rule when information is ambiguous and open to interpretation.

When modeling belief on traditional healing, we combine and extend the above-mentioned microeconomic models to incorporate both belief divergence and attitude polarization into macroeconomic dynamics. Our model extension allows us to follow the macroscopic effects of a sequence of belief revision provided by the microbehavioral insights in our real-world application.

2.3 Agent-Based Modeling of Spatial Dynamics

As outlined in Sect. 1, the main hypothesis of this research is that mobility and information flows drive polarization of opinion. Thus, it is necessary to incorporate spatial dynamics into the model. It is extremely difficult, if not impossible, to model the spatial pattern formation using purely mathematical abstractions. Agent-based models (ABM) can simulate autonomous agents with spatial interactions to allow macroscopic patterns to emerge from microscopic rules and make it possible to understand human behaviors and interactions that give rise to complex patterns [20]. Although, to our knowledge, ABM has not been applied in TH studies specifically, it has been widely used in health behavior and health care policy research [18]. One of the closest studies is the overview of possibilities of applying ABM to a wide range of complementary and alternative medicine research [4].

3 Study Area and Associated Data

The study villages are located in Vhembe district, Limpopo province, South Africa and are approximately 500 km Northeast of Johannesburg (Fig. 1). Vhembe district, and more broadly Limpopo province, is a suitable study area for traditional healing in the rural context since it is one of the most rural and poorest provinces in the country.

3.1 General Household Survey in South Africa

According to the General Household Survey (GHS) conducted by the national statistical office of South Africa [16], the percentage of households using TH as their primary health aid is quite low. When asked "If anyone in this household

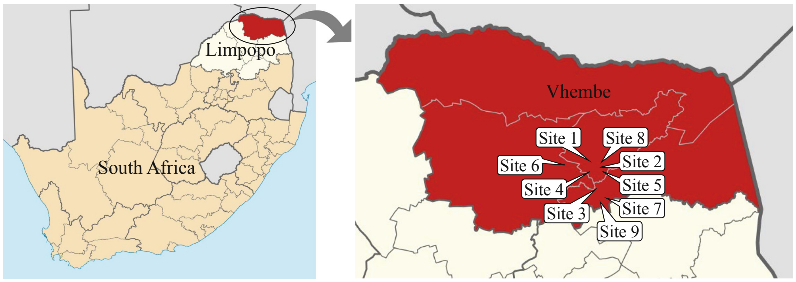


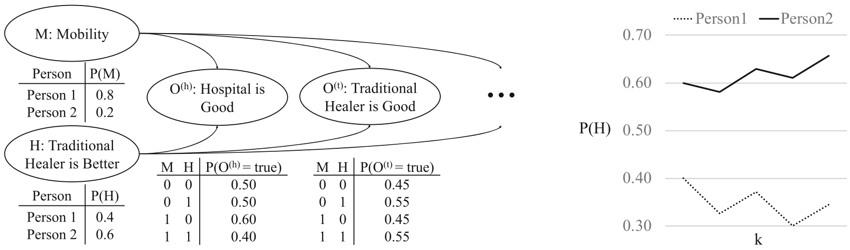
Fig. 1. Map of study area and nine survey sites in Vhembe district, Limpopo province, Limpopo province, South Africa (Source: Wikimedia Commons licensed under CC BY-SA)

becomes ill and decides to seek medical help, where do they usually go first?", less than 1% of household heads answered they would go to a "traditional healer" or a "spiritual healer" first. The Chi-Square test of independence on GHS 2017 data shows that income and geography related variables have significant relationships with the choice of health aid, such as "means of transport to nearest health facility" ($p < 10^{-7}$), "distance to the nearest transport" ($p < 10^{-4}$), "net household income" ($p < 10^{-4}$), and "roof material" ($p < 10^{-6}$).

3.2 Field Study in Limpopo

Our local utilization study took place in nine, mostly rural, traditional villages in Vhembe district during May 23–31, 2018 conducted by a joint research team from the University of Virginia, USA, and the University of Venda, South Africa (IRB protocol UVA IRB-SBS #2018-0156-00). We surveyed 112 people, whose ages were quite evenly distributed from 20 to 90, and the elderly formed a considerably large portion of our respondents compared to the national population-age composition. Since the percentage of people using TH is so low in the GHS, it is advantageous to focus on this admittedly biased sample to study TH user groups as it likely reflects a more sensible depiction of the prevalence of TH use in South Africa.

The main questions of the questionnaire asked for the choice of primary medical assistance. The two-step questions were "Do you primarily use traditional healers, western health centers, or both in conjunction?" and "If both, which would you visit first?". In summary, 8% of respondents answered "primarily traditional healers", 45% answered "primarily western health centers", and 44% answered "both". Among the respondents whose answer was "both", 37% and 51% responded that they would go first to traditional healers and western health centers, respectively. One noticeable finding of our study was that the dependency on TH was highly variable even among rural, traditional villages. When counted people who either primarily use TH or who use both but go to TH first, TH prevalence in each village ranges from 0% to 50%.



(a) (a) Bayesian network configuration

(b) (b) belief divergence

Fig. 2. Illustration of suggested Bayesian Network (a) and an example of belief divergence after encountering two $O^{(h)}$ and two $O^{(t)}$ opinions (b).

3.3 Human Settlement Patterns

Including the settlement pattern is necessary to differentiate people in our model. Since it is almost impossible to obtain such settlement pattern data in rural areas in developing countries, an alternative source of information is utilized. A synthetic population density data source – the high resolution settlement layer (HRSL) – provides estimates of human settlement distribution at a resolution of 1 arc-second (approximately 30 m) for the year 2015. This dataset was created using computer vision techniques to detect objects from satellite images and was validated with the national census data and the World Bank Living Standards Measurement Study (LSMS) surveys [3].

4 Proposed Model

The simulation model proposed in this paper formulates attitude polarization as a result of belief divergence and reinforcement of such belief. Divergence and reinforcement are treated as separate mechanisms but in the same Bayesian network formulation. After introducing the Bayesian network formulation, this section delineates parameters and interactions of agents in the model.

4.1 Bayesian Network Formulation for Individual Belief Revision

At the individual level, a Bayesian network is represented by conditional probability distributions of random variables with causal relationships. The three types of variables in our proposed model are:

1. Hidden fact in question (H): Traditional healer is better than hospital
2. Mobility of an agent (M): Mobility of an agent is high
3. Opinion (O_k^{type}): At time k, an agent hears from another agent either that a hospital is good (type h) or that a traditional healer is good (type t)

Figure 2 shows the causal relationships and conditional probabilities of the variables. Here, the fact that an agent hears an opinion about a hospital or a traditional healer obviously depends on the effectiveness of the hospital or the healer. Also, one's mobility affects the chance of listening to other agents' opinions about hospitals, which are usually more remote than traditional healers. Intuitively, agents with high mobility think that they can judge the reality about remote hospitals better than agents with low mobility because they have more chances to listen to many opinions. However, everyone has the same chance to listen to opinions about traditional healers regardless of their mobility because the healers are close to them. The opinions about traditional healers are less clear due to the nature of healing procedure. All conditional probability on observation nodes are close to 0.5, which means that opinions about medical aid are inherently not clear and the advantage of agents with high mobility is only slightly higher.

Once the building blocks of the Bayesian network are constructed, it can be expanded for a recursive update as follows:

$$\begin{aligned} P(H|O_{1:k}) &= \frac{P(O_k|H)}{P(O_k|O_{1:k-1})} \times P(H|O_{1:k-1}) \\ &= \frac{\left\{P(O_k|M,H) \cdot P(M|H,O_{1:k-1}) + P(O_k|M^c,H) \cdot P(M|H^c,O_{1:k-1})\right\}}{P(O_k|O_{1:k-1})} \times P(H|O_{1:k-1}) \end{aligned}$$

where the denominator $P(O_k|O_{1:k-1})$ is constant relative to H, and the numerator can be calculated and then normalized. $P(H|O_{1:k-1})$ is a previous belief on the hidden fact before encountering O_k and, the base case is $P(H)$ which we give normally distributed random value with mean 0.5 and standard deviation 0.1. $P(M|H,O_{1:k-1})$ and $P(M|H^c,O_{1:k-1})$ can be updated recursively, too as follows:

$$\begin{aligned} P(M|H,O_{1:k-1}) &= \frac{P(O_{k-1}|M,H)}{P(O_{k-1}|M,O_{1:k-2})} \times P(M|H,O_{1:k-2}), \\ P(M|H^c,O_{1:k-1}) &= \frac{P(O_{k-1}|M,H^c)}{P(O_{k-1}|M,O_{1:k-2})} \times P(M|H^c,O_{1:k-2}). \end{aligned}$$

With this recursion, agents fine-tune their beliefs. It is worth noting that the model does not assume any human bias at this point. Since perfectly rational probabilistic inference can cause divergence due to the nature of the hidden fact and the mobility, the simulation takes advantage of this structure. As shown in Fig. 2, two perfectly rational people can reach different conclusions after encountering the same set of opinions. The beliefs of person 1 and person 2 have changed from 0.40 to 0.34 and from 0.60 to 0.66, respectively, after observing two $O^{(h)}$ and two $O^{(t)}$ opinions.

It is assumed that people interpret each ambiguous opinion and then make inferences about the interpreted opinions. Even though people lose some information since only the interpretation of the opinions is retained, it has been shown that this is optimal if agents sufficiently discount the value of time as shown by [5].

4.2 Parameters of Agents

Individual mobility for the simulation is parameterized as the following formula:

$$\text{mobility} = a \cdot \frac{1}{\text{age}} + b \cdot log(\text{family income}) + c \cdot \sqrt{\text{available cars}} + \varepsilon,$$

where a, b and c are constants that are calibrated during the initial simulation test-runs. The reasoning behind this formulation is that mobility of a person decreases with age and increases with income or the number of available cars around. We take the log of income and the square root of the number of available cars to better differentiate population by utilizing the fact that income and density of cars are more normally distributed on logarithmic scale and square-root scale, respectively, while the original distribution is highly skewed. ε is a small random value with a fraction of the standard normal distribution which reflects individual peculiarity and simulation randomness.

The agents in the simulation are populated according to the HRSL. The distributions of age and family income are from the Limpopo data in the GHS 2017, and the demographic characteristics are randomly assigned in each run of simulation. It is assumed that the decisions for people under 20 are made by adult members of the population group. The number of vehicles around is estimated from the population density and statistics of the South African Department of Transport [17] assuming that the number of vehicles in a village is proportional to the number of residents.

4.3 Interactions of Agents

In this model, agents are simulated to exchange their opinions about hospitals and traditional healers. Each person regards other people's opinion as evidence about the quality of the medical practitioners and makes probabilistic inferences about the question whether traditional healers are better than hospitals. If the probability is greater than 0.5, one concludes that the traditional healers are better and if it is less than 0.5, one reaches the other conclusion. Over time, agents keep revising their beliefs while they hear opinions of others. Since expression can be ambiguous, it is assumed that 50% of opinions needs to be interpreted and agents retain the interpreted opinions in their mind.

5 Results

This section presents the analysis of simulation runs and validation. The parameters of agents are calibrated with the responses in three villages of our field study described in Sect. 3.2. The study responses from the remaining 6 villages are used to validate the model. The national statistics is also used for the validation.

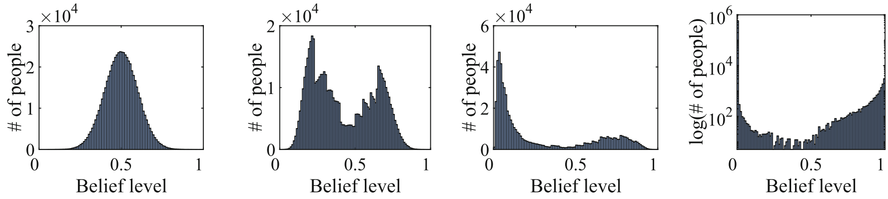


Fig. 3. Beliefs on traditional healing are diverging gradually from initial normal distribution. Note that the last figure is displayed in logarithm scale for a better depiction.

5.1 Simulation

The simulation demonstrates how the initial random beliefs about traditional healing changes over time and how the prevalence of TH use asymptotically approach the current real-world distributions, which range from 0% to 50% of the biased population in our study areas (Sect. 3.2) and 1% of the total population in Limpopo province (Sect. 3.1). Our results show that the opinions of agents diverge and eventually polarize. Each simulation runs until opinions of people do not change for sufficient time. Since each run begins with random beliefs and random demographic characteristics, the end result is different for every run. The final outputs of the simulation are the average and confidence interval out of 100 simulation runs. The simulation parameters are calibrated using study responses from village 3, 4, and 5 to capture a wide range of responses for TH use. The fixed parameters are used for simulations for the remaining of villages as well as Limpopo province.

Figure 3 illustrates the divergence of beliefs. The initial bell curve splits right after the start of the simulation, and then ends up with polarized beliefs on both sides. Even though the numbers are much higher on the left side, neither side of the curve moves after some point in time. One could casually conjecture that more rural, isolated areas use more TH. But this may not necessarily be true. The variances of TH use are high in very rural, isolated areas depending on the initial demographic distribution and interactions among them. For example, village 7 is one of the most isolated areas, but the usage of TH is found to be relatively low in our field study. Our simulation shows that very isolated areas have high variance of TH use depending on the initial demographic characteristics and initial beliefs of small population.

5.2 Validation

The model results are validated with our study responses and the GHS 2017 results. It is not reasonable to compare the percentages of TH use between our study responses and the simulation since the sample of our study is biased as discussed in Sect. 3.2 while the simulation reflects the whole population distribution of Limpopo. Thus, in the simulation, we keep track of the same sub-population group divided by age and income in each village (Fig. 4). We, then, compare the

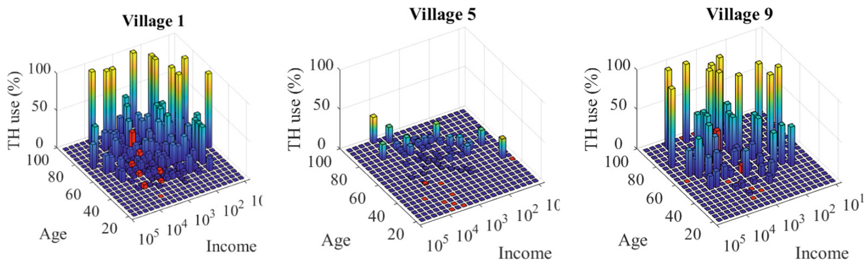


Fig. 4. Average TH use of sub-population groups divided by age and income in each village out of 10 simulation runs. For instance, in Village 1, the percentage of TH use for the sub-group with age 80–83 and income 2500–3900 Rand/month is 12% from this set of simulation runs. The red bars represent the sub-groups of which we keep track for the comparison between the simulation result and the field study. (Color figure online)

Table 1. Comparison of simulation results with field study and GHS

Category	Name	Field study and GHS		Simulation	
		Avg TH use	95% CI	Avg TH use	95% CI
Village 1	Vhutanda	50.0%	(25.4%–74.6%)	26.9%	(21.6%–32.2%)
Village 2	Khwevha	7.1%	(1.3%–31.5%)	11.9%	(6.5%–17.3%)
Village 3	Tshivhulana	36.4%	(15.2%–64.6%)	27.9%	(18.3%–37.4%)
Village 4	Ha-Gelebe	11.8%	(3.3%–34.3%)	8.0%	(3.4%–12.6%)
Village 5	Muledane	0.0%	(0.0%–29.9%)	0.8%	(0.0%–1.9%)
Village 6	Vuvha	28.6%	(11.7%–54.6%)	6.4%	(3.2%–9.5%)
Village 7	Thandani	6.7%	(1.2%–29.8%)	20.9%	(13.3%–28.4%)
Village 8	Univen	0.0%	(0.0%–56.2%)	0.1%	(0.0%–0.2%)
Village 9	Davhana	31.3%	(14.2%–55.6%)	30.8%	(23.3%–38.4%)
Province	Limpopo	1.05%	(0.30%–1.95%)	1.77%	(0.89%–2.64%)

average TH use of that sub-population group with our study responses. For the comparison with GHS, we run the same model on Limpopo province HRSL data and compare the TH use of the whole population.

Since both survey data and simulation result are estimation, we check the average and confidence interval (CI) of both estimates. Table 1 shows the validation results. The average TH use in the simulation falls within the 95% CI of the average TH use in most villages of our field study. It is notable that the simulation average of Limpopo province is also within the tight CI of GHS average. Conversely, the average TH use in the field study and GHS is within the CI of simulation average in the majority of villages and Limpopo province. Village 8 does not represent this geographic location because it is a university campus. It is included for only presentation purpose. The average TH use in Village 6 is significantly different between our field study and simulation. We will discuss this matter in the discussion section.

6 Discussion and Conclusion

This paper proposed a causal mechanism that explained the distribution and variance of TH use in Limpopo region, South Africa. It is surprising that mobility alone can explain much of the variance in this abstract micro-macro model since there could be many other factors that affect TH use such as cultural backgrounds, education, and types of illness [13]. This is in part because people in our study areas shared much of the same cultural experience, and we regarded many cultural variables as constant. Another reason could be that the focus was on the health care function of traditional healing. If people had been asked whether they use TH for other reasons, the distribution could have been much different. Other roles of TH such as supplementary health care, spiritual mentoring, and forecasting the future are beyond of the scope of this research. This research only emphasizes the primary health care function of TH.

Several limitations remain, and many extensions are possible. In validation, the simulation estimate was much lower than the average study responses in Village 6. Our conjecture is that the ratio of vehicles to population is different from region to region, especially in very isolated villages. To solve this, we need more accurate data. One very effective and efficient way is to use an object detection methods on satellite images and count the number of vehicles in each village. On the macro level, the result may seem similar to a regression analysis. But this research study is more than just identifying factors that are related TH usage. We tried to explain the belief changing process, which could be applicable to other aspects of development as well. By explaining the causal link between the individual level and the macroscopic phenomenon, it enables policy makers to develop individual level interventions for systematically marginalized populations since the model can serve as a test bed to conduct dynamic experiments.

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