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# Intent-Driven Behavioral Modeling During Cross-Border Epidemics

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***Abstract*—Modeling real-world social situations has proven to be one of the most daunting challenges in computational social science. With the exception of simplistic, single-domain scenarios, most computational models are quickly overwhelmed with the complexity and diversity of real-world scenarios. In this paper, we apply intent-driven modeling to a complex, real-world scenario. By mapping actors' intentions to their beliefs and goals, we are able to explain their actions and propose predictions of future actions. Specifically, we look at ways to help understand and explain complex group behaviors during epidemics in relation to national borders. Using an intent-driven socio-cultural behavioral model implemented with the help of Bayesian Knowledge Bases (BKBs), we explore the actions and reactions of actors in an epidemic setting, providing insight into behaviors affecting border security. Using these tools, we are able to employ dynamic, multi-domain modeling to explain the decisions and actions taken by actors in the scenario. We validate our methodology by modeling and analyzing migration behaviors during the 2009 H1N1 pandemic in Mexico.**

***Index Terms-- Socio-cultural Behavioral Modeling; Intent Model; Computational Social Science; Border Epidemics; Dynamic Social Models; Bayesian Knowledge Bases***

## I. INTRODUCTION

Computational models have been used in the social sciences since the earliest days of computing, but this use was restricted primarily to data and statistical analyses. Early efforts at computer simulation in social sciences were necessarily simplified and symbolic in nature [1]. Recently, a more robust use of the modeling capabilities has begun to emerge, particularly in the area of agent-based modeling [2]. Even these advanced models do not deftly handle dynamism - the constant changing of events, actors, and actors' beliefs and goals, inherent in a complex real-world scenario. Adequately representing cultural factors is also crucial because of the profound effect they have on individual/group behavior and decision making. A modeling framework to represent and relate socio-cultural factors from multiple domains, such as social, economic and political domains, to individual and group behavior is one of the critical challenges in computational social science.

One such complex real-world scenario is the behavior of populations during a cross-border epidemic. Dealing with epidemic or pandemic outbreaks in neighboring countries and resultant mass migration is a major concern for border security agencies across the world, including the US. Understanding how populations behave during epidemics and identifying triggers can help to evolve better border security and border health policies. Why do some people primarily maintain their current border-crossing behavior? Why do attempted border crossings increase or decrease? What prompts more individuals to try illegal crossings? Answering questions such as these can yield tremendous insight into expected behaviors in future or hypothetical scenarios. However, using typical epidemiology models to address border control issues during an epidemic faces two major hurdles: 1) modeling human decisions and actions is not their focus and 2) explaining behavior, and thus identifying the root causes for behavior, is not a capability they offer. Until the complex dynamics of group and individual behaviors can be analyzed and explained, border control during epidemic outbreaks can at best be only reactionary. By adding the power of intent-driven models to traditional epidemiology approaches, border control can become more of a proactive effort, even during the chaos of an epidemic outbreak.

In this paper we present an intent-driven model to represent and analyze behavior of populations during an epidemic and their propensity to flee to neighboring countries. Intent-driven models allow us to model actor intentions by representing their axioms (beliefs about themselves), beliefs (beliefs about others), goals and actions. By modeling actor and group intent, it is possible to address the complex interactions in cross-border epidemics. We incorporate socio-cultural factors from multiple domains, required for modeling such complex behaviors, by employing a probabilistic framework called Bayesian Knowledge Bases (BKBs)[3]. Apart from its capability to represent uncertain and incomplete information, it also supports a mathematically sound reasoning system that not only calculates likely outcomes from given evidence, but also provides explanations as to which events and evidence most profoundly affected the result. By incorporating cultural elements into the intent-driven model, we are able to model the different motivations that actors may have, as influenced by their cultural background. Culture affects actors' beliefs, goals and decisions, and thus is critical to properly represent the entirety of influences affecting actors' decisions. Including

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cultural influences in the model allows analysts and Subject Matter Experts (SMEs) the power and freedom to fully represent their intuitions, and to explore the model for explanations to emergent behaviors. We provide insight into actions taken during an epidemic, to reveal explanations for observed behavior, and to therefore sharpen our understanding of the likely impacts on border control during various outbreak scenarios.

We selected the 2009 H1N1 outbreak in Mexico as the scenario in this initial effort. Because this outbreak originated in a close neighbor to the US, it provides an interesting setting for studying both observed and hypothetical border impacts. In studying this scenario, we show the applicability of intent-driven models to understanding the events that transpired during the epidemic, and also explore the possible consequences of different decisions being taken during the outbreak. The paper is organized as follows. Section II provides a brief background on relevant modeling approaches. Section III provides a primer on the use of BKBs for representing cultural information and explains the relevance of culture to our simulation. Section IV describes the experimental validation including a detailed description of the scenario, results and analyses. Finally, in Section V, concluding remarks and future directions are discussed.

## II. Background

Most current epidemiology models focus on predicting the spread of an epidemic [4][5], but do not attempt to explain the behaviors of individuals or groups of people exposed to an epidemic. Even those studies that do attempt to account for individual and group dynamics, through the use of social networks (SNs), do not provide explanations for those behaviors [6]. There has been work in other domains that have tried to model similar real-world scenarios. For example, Stabilization and Reconstruction Organizational Model (SROM) [7] has been used to represent and analyze large nation-scale social processes with regard to national reconstruction. However, it is not a generic model and cannot be easily mapped to other domains. In SROM, regions can be defined in sub-models, but then the interactions between them must be specified and are essentially static, resulting in a loss of dynamism and flexibility. There have also been attempts to model dynamism and to analyze the effects of changes in a social network [8][9]. Although they have provided some theoretical insights, they have not been transitioned to real-world problems. Attempts at implementing models to represent complex social situations have yielded insightful simulations [10], but are limited in their abilities to explain the causes for their emergent behaviors. Similarly, incorporating culture into models has met with limited success. Some models manage to be generic enough to be applicable to multiple domains [11], but that very generic nature has limited their ability to produce meaningful results, and certainly do not provide explanatory power. Other models successfully provide impressive depth and detail [12][13], but are not portable in the least. All of the effort invested into a particular domain is lost and cannot be transitioned into a new domain or area of interest. Even models specific to the epidemiology domain struggle to implement enough detail for useful analysis while not over-taxing computational resources. This leads to compromises in both rigor and detail [14]. To fully address the complexity of the social situations found in real-world problems, a model must be able to simultaneously handle dynamism and multi-domain information. In this paper we describe how our intent-driven model can provide these capabilities, while also providing explainability for outcomes.

## III. Our Approach

As previously mentioned, modeling actors' axioms, beliefs, goals and actions allow us to capture their intentions. However, modeling intent is a challenge because of the uncertainties involved. When deducing the intent of an actor, we must infer that intent from what we know of the actor's background, his belief system, his history and experience with related issues, his education, i.e. his *culture.* Such information is inherently uncertain and incomplete. To effectively work with information of this nature, a probabilistic reasoning framework is required. This is why Bayesian Knowledge Bases (BKBs) form the backbone of our model. Bayesian Networks (BNs) [15] are a special class of BKBs. In contrast to BNs, BKBs have the added capabilities to handle incomplete information and incorporate cyclic and even potentially contradictory information. Combined with their ability to support reasoning algorithms to provide explanations for predictions, their suitability for this problem is apparent.

BKBs are useful in representing individual (and group) intent by making use of the Adversarial Intent Inferencing (AII) framework [16][17][18]. As noted by Santos Jr. and Zhao [18], intentions are partial plans developed by an actor to achieve goals (or desires), based on personal information (beliefs) of the state of the world. This closely follows Bratman's Belief-Desire-Intention (BDI) model [19]. An AII model has been successfully used to capture adversary goals, intentions, biases, beliefs, and perceptions. We will leverage the modeling concept of AII which extends well to any situation where participants may have diverse (even conflicting) goals and intentions [20].

Equally, the AII model extends itself well to incorporation of cultural information which can impact intentions, decisions and actions [21][22]. What exactly do we mean by culture? Culture has many definitions and connotations, but one that closely approaches the meaning we are after is: "The totality of socially transmitted behavior patterns, arts, beliefs, institutions, and all other products of human work and thought. Culture is learned and shared within social groups and is transmitted by non-genetic means." [1] When we speak of cultural information and influences, we mean those influences mentioned in the definition above, as well as any other learned behaviors from one's environment. Cultural fragments representing certain aspects of an actor's goals, intentions, beliefs and cultural influences can be generated individually by multiple modelers/analysts and fused in to a single BKB [23] to represent the actor's overall behavior. Reasoning algorithms are then used to determine likely goals and actions, based on the available evidence. It is clear that by using the BKB fusion algorithm, the intent-based behavioral model allows multiple analysts to collaborate in building models for complex social

[1] http://dictionary.reference.com/browse/culture.

scenarios. This is critical in multi-domain models which require experts in various domains to work together.

A BKB is comprised of rules linking random variables (*rvs*) in an "if-then" fashion. Unlike BNs, BKBs do not require a complete specification of the probability distribution for all *rvs*, which is of tremendous benefit when dealing with real-world scenarios and their multitude of unknowns. BKBs are graphically represented as directed graphs with two types of nodes: (1) Instantiation-nodes (I-nodes) which represent the various states of *rvs* and (2) Support-nodes (S-nodes) which represent probability values in the rules. An example BKB fragment depicting the effect of a hypothetical border closure on migration decisions is shown in Figure 1.

We can also represent a BKB formally as a tuple. To understand the notation, we must first define a correlation graph as given in Santos Jr. & Santos [3].

**Definition 1.** A *correlation-graph* is a directed graph $G = (I \cup S, E)$ in which $I \cap S = \emptyset, E \subset \{I \times S\} \cup \{S \times I\}$, and $\forall q \in S$, there exists a unique $a \in I$ such that $(q, a) \in E$. If there is a link from $q \in S$ to $a \in I$, we say that $q$ supports $a$.

For each S-node q in a correlation graph G, we denote $Pred_G(q)$ as the set of I-nodes pointing to $q$, i.e. $Pred_G(q) = \{a \in I | a \rightarrow q \in E\}$ and $Desc_G(q)$ as the I-node supported by $q$, i.e. the $a$ such that $q \rightarrow a \in E$. Two I-nodes, $\alpha_1$ and $\alpha_2$ are said to be *mutually exclusive* if they are different instantiations of the same random variable. Similarly, two sets of I-nodes $I_1$ and $I_2$ are mutually exclusive if there exists two I-nodes $\alpha_1 \in I_1$ and $\alpha_2 \in I_2$, such that $\alpha_1$ and $\alpha_2$ are mutually exclusive. For example, the sets of I-nodes $\{A = a_1, B = b_2\}$ and $\{A = a_2, B = b_2, C = c_1\}$ are mutually exclusive.

Given Definition 1, we can now provide a formal definition of a BKB, again from Santos & Santos [3].

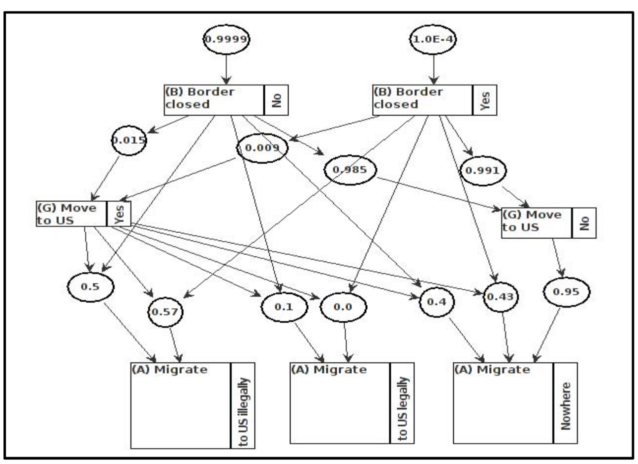


**Figure 1. Example BKB Fragment**

**Definition 2**. A BKB is a tuple $K = (G, w)$ where $G = (I \cup S, E)$ is a correlation–graph, and $w : S \rightarrow [0,1]$ such that

1. $\forall q \in S, Pred_G(q)$ contains at most one instantiation of each random variable.
2. For distinct S-nodes $q_1, q_2 \in S$ that support the same I-node, $Pred_G(q_1)$ and $Pred_G(q_2)$ are mutually exclusive.
3. For any complementary set of S-nodes $R \subseteq S$, $R$ is normalized: $\sum_{q \epsilon R} w(q) \leq 1$ where $w(q)$ is a weight function that represents the conditional probability $P(Desc_G(q) | Pred_G(q))$.

To re-iterate, we represent the intent of actors or entities using their cultural traits modeled probabilistically in BKBs. Based on the AII and BDI models, we categorize the *rvs* in the BKBs as:

1. Beliefs (B): represent what the actor or entity believes about other actors and entities.
2. Axioms (X): represent beliefs about self. In general, cultural details such as age, income and location can be thought of as axioms.
3. Goals (G): represent the aims and goals of the actor or entity.
4. Actions (A): represent the possible strategy or actions adopted by the actor or entity to achieve their goals.

All beliefs, including axioms, can influence other beliefs, goals and actions but can only be influenced by other beliefs. Likewise, goals can influence other goals and actions, but can only be influenced by beliefs and other goals. Finally, actions can only influence other actions, but can be influenced by all types of nodes in the AII model. Figure 1 shows a representative BKB fragment with the hierarchy of beliefs, goals and actions. The letters in parentheses indicate the type of *rv* represented, as proposed in Santos and Negri [16]. Generally, 'X' represents an axiom, 'B' represents a belief, 'G' represents a goal and 'A' represents an action.

As noted before, fusing fragments is necessary in order to integrate the numerous information nuggets into a single, coherent model. The method for fusing fragments (***Algorithm 1***) [23] can be described as follows. The input is a set of $n$ BKB fragments, $\{K_1, K_2, \ldots, K_n\}$ where $K_i = (G_i, w_i, \sigma_i, r(\sigma_i))$. Each fragment $K_i$ has an information source represented by $\sigma_i$, and $r(\sigma_i)$ is the reliability of source $\sigma_i$. The output is a new BKB, $K' = (G', w')$ with $G' = (I' \cup S', E')$, that is the fusion of the $n$ input fragments. For an I-node $\alpha$ in some fragment, let $R_\alpha$ be the random variable of which $\alpha$ is an instantiation.

**Algorithm 1:** BAYESIAN-KNOWLEDGE-FUSION($K_1, K_2, \ldots, K_n$) [23]

Let $G' = (I', S', E')$ be an empty correlation graph

1. for all fragments $K_i$ with i ← 1 to n
2. for all S-nodes $q \in S_i$
3. Let $\alpha \leftarrow Head_{G_i}(q)$
4. Let the source I-node for $q$ be $s = (S_{R\alpha} = \sigma_i)$
5. Add $q$, all nodes connected to $q$ in $G_i$, and the corresponding edges to $G'$

6. Add $s$ to $G'$ along with an S-node supporting it
7. Let $\rho$ be a normalizing constant
8. for all S-nodes $q'$ supporting some source node $s$
9. Let $\omega'(q') \leftarrow r(s)/\rho$
10. return $K' = (G', \omega')$

Note that for an S-node $q$, $Head_{G_i}(q)$ is the I-node it points to. To compute the normalizing constant $\rho$, we compute for each random variable $R$, the sum of the reliabilities of all source nodes supporting an instantiation of $R$. We then set $\rho$ to the maximum of these sums.

In our model, we make use of two key calculations: belief updating [23] and variable contributions. In belief updating, given some state of the world (based on evidence, events or facts), we calculate the posterior probability of a target *rv* having a particular instantiation or state. Belief updating can be used to identify probable states and their statistical probabilities. This will change as new information, in the form of new fragments or new evidence, is introduced into the model. Belief updating is one of the key tools used in probabilistic networks for addressing the dynamism of the real-world.

BKBs model the causal chains linking evidence, events, goals and other *rvs*. We can identify variables that are responsible for observed phenomena by retracing the causal chain to the source *rvs*, and consequently provide explanations. In doing this, we select a target variable in the BKBs and then calculate how much other variables contribute towards its value. It is these contributions that provide the foundation for explainability in our intent-driven model. This contribution is essentially the percentage of probability mass that the *rv* contributes to the target *rv*'s belief updating calculation. To calculate the contribution by an *rv r* for a target *rv q*, denoted as $c_q^t(\mathrm{r})$, for the BKB $B_t$, we look at all possible worlds or inference graphs [3] where q has the specified states. Out of these worlds, the probabilities of those worlds containing r are summed to calculate the contribution. From [24], the method for calculating the contribution is given in ***Algorithm 2*** below.

**Algorithm 2:** CONTRIB-COMPUTE($B_t$; t; q)

1. Determine $\mathrm{W}_{\mathrm{q}}^{\mathrm{t}}(\mathrm{r}) = \{(\mathrm{w}_{\mathrm{q,i}}^{\mathrm{r}}(\mathrm{q}), \mathrm{p}_{\mathrm{q,i}}^{\mathrm{t}}(\mathrm{r}))\}$
   ► $w_{q,i}^t i(r)$: world containing r in which q is true
   ► $p_{q,i}^t(r)$: probability of $w_{q,i}^t(r)$
2. $\mathrm{c}_{\mathrm{q}}^{\mathrm{t}}(\mathrm{r}) = \sum_{\mathrm{i}=1}^{\mathrm{m}} \mathrm{p}_{\mathrm{q}}^{\mathrm{t}}(\mathrm{r})$
   ► Contribution of r towards q

All of the above builds toward the ultimate goals of explicitly modeling the uncertainty and incompleteness of available socio-cultural data, incorporating multi-domain details, consolidating the diverse views of analysts/modelers and providing predictions backed by explainability.

## IV. Experimental Validation

In order to validate our intent-driven model, we needed to find a sufficiently complex scenario that would also enable us to test the effectiveness of our ability to explain outcomes produced by the model. Thus, we needed a historical setting where our calculations could be compared to actual outcomes, and that had enough recorded information to model and validate behavior. We selected the 2009 H1N1 outbreak in Mexico. The outbreak alerted U.S. citizens and government officials alike to the potential dangers of epidemics in border regions. Beyond simply raising awareness, the outbreak instilled something more akin to panic in many individuals.[2,3] The H1N1 outbreak caused much concern worldwide, with many fearing a truly devastating pandemic. However, in the end, the fatality rate was comparable to that of the common flu. [4] Secondly, with heightened awareness came the corresponding desire for a better understanding of what went on during the 2009 pandemic and of what might be expected in similar incidents in the future. Although the pandemic did not lead to catastrophic cross-border events like mass migrations, analyzing the 2009 pandemic can yield some useful insights to help plan for similar, but perhaps worse, future events. Finally, with the generous media coverage and the relatively recent occurrence of the outbreak, an abundance of data, including both disease-related statistics and cultural information, were available for incorporation into our model.

The H1N1 outbreak in Mexico originated on 18 March 2009[5], though the first related death was not until 12 April 2009.[6] The virus spread rapidly through Mexico and the US, with fatalities appearing much earlier in Mexico. By 27 April, confirmed cases of H1N1 had also been reported in Canada and Spain.[7] By 25 July 2010, the World Health Organization (WHO) reported that over 214 countries worldwide had confirmed cases of H1N1, claiming at least 18,398 lives.[8] This was apparently after the outbreak had peaked, but the pandemic was not declared at an end until 10 August 2010.[9]

### A. Experimental Setup

As the initial groundwork for our simulation of the pandemic in Mexico, we chose to model the Mexican population and focus on changes in their border crossing behaviors and intent. By building BKB cultural fragments to represent various sectors of the Mexican populace, we constructed our model fed by inputs from a set timeline representing various other events and actions/decisions taken by other actors in the scenario, such as the Mexican and US governments, and international organizations such as the European Union (EU) and the WHO. In total, a team of researchers used information from dozens of newspaper articles, news websites, government and non-governmental organizations, open sources and general knowledge, to build 23 BKB fragments and 22 rvs. The probabilities in the BKBs

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[2] P. Curson, "Hysteria at fever pitch," The Australian, 29 April 2009, p. 12

[3] http://www.cbsnews.com/stories/2009/04/30/politics/otherpeoplesmoney/main4979595.shtml

[4] http://www.reuters.com/article/2009/09/16/us-flu-deaths-idUSTRE58E6NZ20090916

[5] http://www.who.int/csr/don/2009_04_24/en/index.html

[6] http://www.washingtonpost.com/wp-dyn/content/article/2009/04/25/AR2009042501335.html

[7] http://www.who.int/csr/don/2009_04_27/en/index.html

[8] http://www.who.int/csr/don/2010_07_30/en/index.html

[9] http://www.bloomberg.com/news/2010-08-10/who-declares-swine-flu-pandemic-over-as-immunity-to-h1n1-virus-has-spread.html

represent the subjective view of the researcher, informed by the data sources. However, when statistical information was available, it was used to generate the probabilities.

The Mexican populace was modeled by two main demographic details: age and location. Age was broken down into three groups that corresponded well with reported vulnerability to H1N1[10]: young (0-17), middle-aged (18-64), and old (65+). These breakouts were relevant because there was a widespread belief that the middle-aged group were disproportionately vulnerable, which would likely affect their decisions and behavior. Consequently, we expect the behavior for the middle-aged group to be markedly different from that of the other two age groups. A cultural fragment for the middle-aged group (given in Figure 2) represents the commonly held view that H1N1 was more lethal for this group[12]. Note that the probability values represent the intuition of the SME that built the BKB, based on his/her expertise, experience and available facts. We also implemented a high-level regional model, dividing the Mexican state into three geographic areas: the north, the south, and the interior. We subsequently modeled the H1N1 epicenter as located in the interior, as the earliest outbreaks were reported in the Federal District of Mexico and San Luis Potosi[11], both in central Mexico. To incorporate diverse behaviors of the Mexican population, we built BKB fragments to represent cultural influences of demographic examples of typical Mexicans, such as middle-aged and interior, or elderly and north. At the same time, we fused in fragments representing individual details, such as region of residence in relation to the epicenter of the outbreak. All of these cultural and individual details can influence decision making.

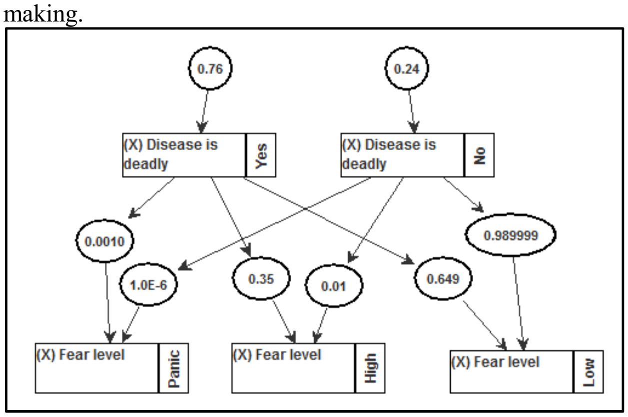


**Figure 2 Cultural fragment for middle-aged population[12]**

Once a representative individual is created by fusing relevant cultural fragments, we proceed with building the scenario, by fusing in BKB fragments representing events from the scenario timeline. An example of an "event fragment" (given in Figure 3) represents the event T8 in the timeline (Table 1) when the availability of the vaccine led to a change in

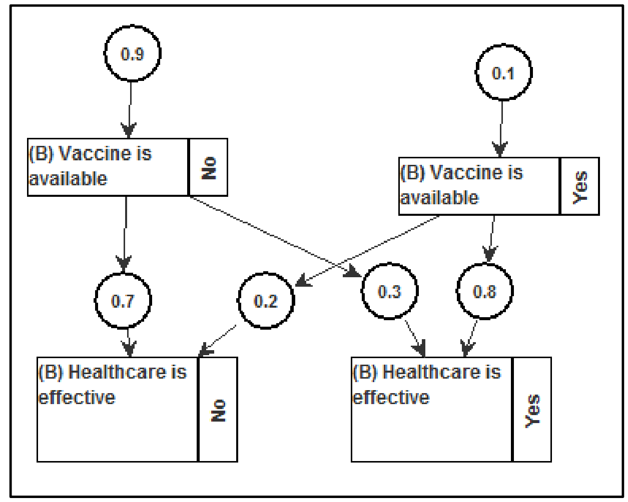


**Figure 3 Event fragement[13]**

belief that healthcare is more effective[13]. Our model currently begins at the time of the first reported H1N1 case in Mexico, and continues until the WHO declared the pandemic over. We make use of 10 rough time steps (Table 1), representing significant events in the pandemic development. Additional granularity will be added in future work as the model matures.

Of primary interest are the changes in the migration patterns. In the BKBs, the intent to migrate is represented by the *rv (A) Migrate* and has five states "*to US legally*", "*to US illegally*", "*Nowhere*", "*within MX*" and "*Internationally*". "*Internationally*" indicates the action of migrating to Mexico's southern neighbors and "*Nowhere*" indicates the action of not migrating. First, we must understand how migration is linked to the pandemic events in our model. In plain terms, the migration behavior is linked indirectly to the pandemic via two key *rvs*: *(X) Fear level* and *(G) Escape pandemic*. Consequently, migration behavior during the pandemic is influenced by individual goals to flee the pandemic, which in turn are formed by an individual's fear level.

## *B. Results and Analyses*

Due to space constraints, we will limit our discussions to the most interesting results from the experimental simulation. To begin with, it is most useful to look at the migration behavior for middle-aged Mexicans, as they are easily the most populous group.[14] While we established the relative ratio between illegal and legal migrations to the US based on factual sources,[15,16] we were unable to find reliable numbers for Mexican migration to southern neighbors. Consequently, it is important to focus primarily on the changes in probability values and thus migration behavior, rather than the actual probabilities produced by our model.

[10] http://www.who.int/csr/disease/swineflu/notes/h1n1_vaccine_20090713/en/index.html
[11] http://www.who.int/csr/don/2009_04_24/en/index.html
[12] http://www.suite101.com/content/who-needs-an-h1n1-swine-flu-shot-a187205

[13] http://www.cdc.gov/h1n1flu/vaccination/public/vaccination_qa_pub.htm
[14] https://www.cia.gov/library/publications/the-world-factbook/geos/mx.html
[15] http://migrationinformation.org/USfocus/display.cfm?id=767
[16] http://pewhispanic.org/files/reports/126.pdf

**Table 1. Timeline for H1N1 pandemic scenario.**

| Time Step | Physical date | Additional information |
|---|---|---|
| T1 | Mar 17, 2009 | First case of H1N1 reported in Mexico – business as usual |
| T2 | Apr 12 | First deaths attributed to H1N1 – epidemic outbreak evident |
| T3 | Apr 24 | WHO sends experts to Mexico to work with health authorities |
| T4 | Apr 27 | EU advises Europeans not to travel to US or Mexico unless the need is urgent WHO elevates the pandemic alert from phase 3 to 4 |
| T5 | Apr 29 | WHO raises the pandemic level from 4 to 5 |
| T6 | May 1 | Mexico shuts down most parts of the country for five days to avoid spread of H1N1, advising citizens to stay in their homes |
| T7 | Jul 13 | H1N1's disproportionate effect on healthy young adults reported by WHO; businesses and government have reopened |
| T8 | Oct 5 | UN asserts rich countries to make more vaccine available to poorer countries; residents no longer advised to stay home |
| T9 | Dec 30 | The pandemic appears to be declining |
| T10 | Aug 10, 2010 | WHO declares H1N1 pandemic is over |

In Figure 4, we readily observe that the highest level of migration is illegal migration to the US, with legal migration to the US and other international migration being roughly equal. This conforms to our preliminary research mentioned above. You may also notice that only 9 time steps are included in the plots, while Table 1 lists 10 time steps. The first time step was omitted in the interest of brevity, due to the vast difference in scale and resolution in transitioning from the relative calm of pre-pandemic behavior to the chaos of full-scale pandemic. As the model is refined in future work, this transition should be smoother and more conducive to analysis.

If we follow the timeline in order and analyze the results in Figure 4, we see a level of illegal immigration to the US set during T2, followed by a gradual decline in that immigration for the next two time steps. This corresponds to an outbreak with an initial panic, followed by an event in T3 (WHO sending experts to Mexico) that helps control that panic. In T4, the EU's recommendation to restrict travel did not have a large influence on migration behavior in our model, but the WHO raising the pandemic level in T5 clearly did. Likewise, in T6, T7, T9, and T10, the change in migration follows our intuition for the events transpiring in those time steps. However, T8 seems to be a problem. In T8, a vaccine is announced, which would logically calm fears and therefore reduce panic migration. What is the cause of the apparent increase? Note that legal and international migrations follow this same pattern, so we will not examine them separately here.

As mentioned earlier, our system models Mexican citizens from three regions: north, interior, and south. We first look at migrations from the north for an explanation of this behavior. To explore the factors affecting the illegal migration *rv*, we conduct contribution analysis. Figure 5 shows the percentage of probability mass various *rvs* contributed to the posterior probability for illegal immigration to the U.S. from the north region of Mexico. It is very evident that the three highest contributors to illegal immigration are also increasing in impact from T7 to T8, and most importantly, are all *rvs* which encourage migration. In fact, they are all related in our model. As an individual begins to believe H1N1 is particularly deadly for him, his fear level begins to increase and, consequently, his desire to escape the pandemic increases. Clearly, the impact of learning of the disease deadliness has carried on to have a significant impact in T8 before beginning to wane. What is not clear is why that impact continued to increase. When looking at contributions, we often eliminate those factors that have a minimal effect on the target *rv*. On closer examination of the data, we see that the *rvs (B) Government advises staying home* and *(B) Government shutdown* strongly depressed the tendency to migrate in T6. These variables do not appear in Figure 5, because they are set as evidence and therefore, their contributions do not change. In T7, the government reopened, which allowed some impact from the *rv (X) Disease is deadly*, but not the full effect. Only when *(B) Government advises staying home* is reset in T8 does the full impact of *(X) Disease is deadly* show. Subsequent decreases are due to waning of the pandemic. A useful lesson learned from this analysis is that contribution analysis is a valuable tool to understanding causes within a BKB model, but it is important to analyze what contributions are there, and what contributions are absent. As noted above, disappearing contributions can have a significant impact to changing conditions.

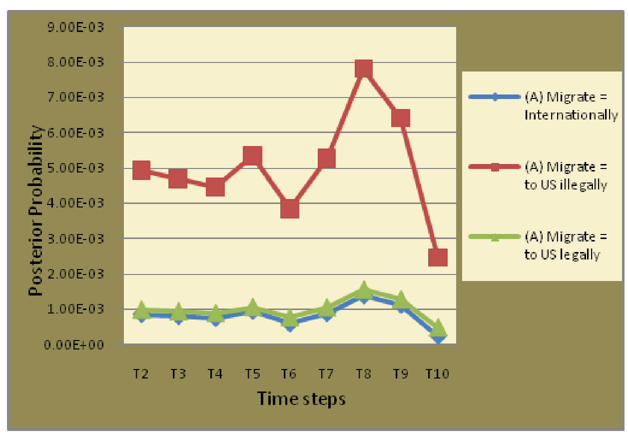


**Figure 4. Pandemic migration for middle-aged Mexicans**

A quick look at Figure 6 shows that the only significant illegal migration is from the north, which also makes geographic sense. Hence, contribution analysis for interior and south regions will not yield any interesting insights and is therefore not given here. We now analyze the impact on migration behavior due to the unique feature of the H1N1 contagion: its deadly effect on middle-aged people. Therefore, we would expect that if we were to look at the migration for old or young Mexicans, we would not see such a large increase in T8, as they did not perceive H1N1 to be as deadly to them. Looking at Figure 7, we see exactly that for old Mexicans. The level of migration (all types) at T8 is not greater than the maximum level reached during previous time steps. These results are promising, and encourage us to continue strengthening the model for future research.

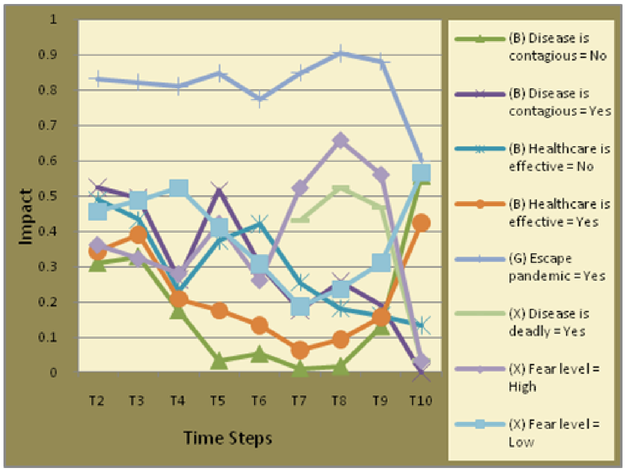


**Figure 5. Contributions for Illegal Migration from the North**

Our modeling experience with the H1N1 scenario provided us with some insights and issues to be mindful of while working with BKB fragments. Introducing new event fragments to a model must be done with caution. New events fused late in the timeline must not introduce *rvs* that would logically have existed earlier. We learned this lesson when we

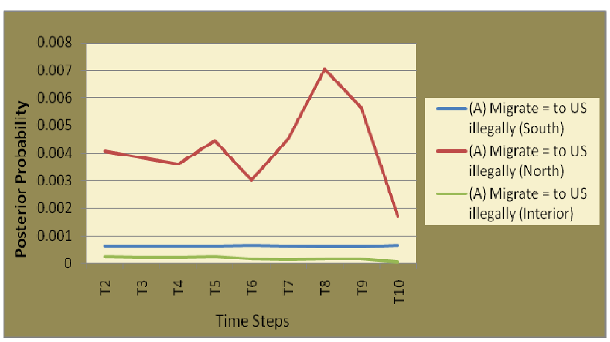


**Figure 6. Illegal migrations to the US by middle-aged Mexicans**

recognized we could not easily compare results from T1. The *rv* for regions was introduced in T2 when pandemic escape became an issue. The pandemic event was new, and thus could be logically introduced at the time of the pandemic outbreak. However, the regions existed throughout the simulation and should be introduced from T1, thus allowing regional migration comparisons for the entire timeline. Testing the fragments is also an important issue. Early testing of individual fragments prior to fusing can save time and effort spent debugging the much more complex results of fused BKB fragments. In general, a fragment can be treated as a black box, with inputs ($Pred_G$) and outputs ($Desc_G$) on the outer edges of the fragment. Based on expectations for the behavior of the fragment, one can project either increases or decreases in the outputs when the input S-nodes are varied. If the behavior deviates from expectations, either the fragment was "wired" incorrectly, or expectations must be revisited and likely revised. This seems an insignificant aid for small fragments, but is a boon for large, complex fragments.

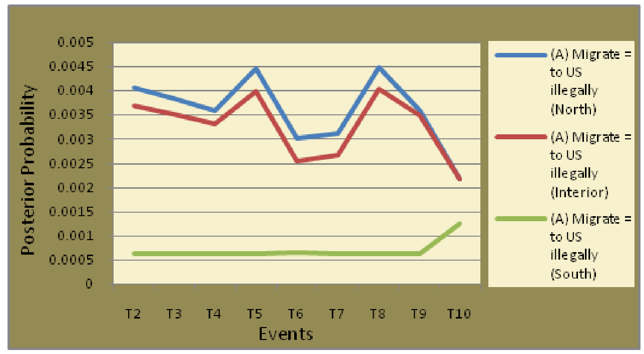


**Figure 7. Illegal migrations to the US by old Mexicans**

## V. CONCLUSION AND FUTURE WORK

In this paper, we presented an intent-based framework to develop socio-cultural models to understand complex group behaviors during pandemic scenarios. Our particular focus has been to model and understand cross-border population migration dynamics during a pandemic. The central modeling principle that we espouse in our behavioral framework is the critical need to model multi-domain cultural information. Using BKBs we tackle two critical challenges in socio-cultural modeling: 1) explicitly model the inherent uncertainty and incompleteness of cultural information, and 2) utilize reasoning algorithms to provide analyses and explanations. We modeled the 2009 H1N1 pandemic in Mexico using critical social, cultural, economic and demographic factors. We analyzed the migratory trends seen during the pandemic. We also provided the explanations for these trends by calculating the contributions by various factors and identifying the important ones. Furthermore, we demonstrated the capability of the intent framework to incorporate multi-domain information. This in turn requires SMEs to work together by providing input to various aspects of the model. We also demonstrated how the SMEs can build parts of the model, in the form of cultural fragments, and combine them using the fusion algorithm.

There are a number of interesting future directions for the work described in this paper. One of our future goals is to incorporate social networks to represent social relations between individual actors. Social relations are crucial to understand how opinions, ideas and panic spread in a population, and how they should be adequately modeled in our intent model. We will leverage our previous work in Culturally Infused Social Networks (CISNs) [22] to incorporate information about family, friendship and professional networks. CISNs provide a generic methodology to incorporate cultural information to capture the nuances of social relationships. It will also provide us the capability to model the multi-scalar nature of social systems. For example, the intent of an actor to migrate has a bearing on how his community or neighborhood behaves, which in turn affects how people in the town behave and so on. Modeling ripple effects of events across multiple scales is a capability that CISNs provide. With regards to the actual H1N1 modeling, we have produced a solid foundation upon which to progress our analysis of the potential causes and effects of cross-border migration during an epidemic. We will analyze "what-if" situations such as expected migratory behaviors of the Mexican population if US border security becomes stringent and severe restrictions are placed on legal immigration. This is one of the strengths of our methodology that we would like to highlight in future work. As we incorporate additional capabilities, the complexity of the model will increase tremendously, as will our ability to analyze and explain.

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