The Effects of Personality in a Social Context

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Abstract

The contextuality of changing attitudes makes them extremely difficult to model. This paper scales up Quantum Decision Theory (QDT) to a social setting, using it to model the manner in which social contexts can interact with the process of low elaboration attitude change. The elements of this extended theory are presented, along with a proof of concept computational implementation in a low dimensional subspace. This model suggests that a society's understanding of social issues will settle down into a static or frozen configuration unless that society consists of a range of individuals with varying personality types and norms. **Keywords:** contextual models; quantum decision theory; attitude change; agent based modelling

Modelling Attitude Change in a Social Context

The ability to model and predict human responses to changing social conditions is fast becoming highly desirable in a world facing a number of global challenges. This social behaviour is frequently driven by their internally held *attitudes* of the individuals in a society (Ajzen, 2005; Fazio & Petty, 2008). For example, privately held attitudes play a critical role in people's personal choices about their health, education, social groups, and housing, as well as the importance they attribute to national issues such as the environment, immigration and state security. However, attitudes are highly contextual, and this makes them extremely difficult to model formally. People's attitudes are not static immutable objects, but change in response to persuasion (Seiter & Gass, 2010), and the attempt to maintain cognitive consistency (Cooper, 2007). We often express different attitudes and opinions in accordance with the social scenario we find ourselves in (Bond & Smith, 1996), and it is frequently the case that an explicitly expressed attitude is quite different from an internally held one (Greenwald & Banaji, 1995).

The Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986); and the Heuristic-Systematic Model (HSM) (Chaiken, 1987) are the two traditional models of attitude change, but both depend upon a number of poorly defined variables, which led Mosler, Schwarz, Ammann, and Gutscher (2001) to create a computational model of attitude change in order force a more accurate specification of the largely heuristic ELM. In essence, both models posit that some processes of attitude change require relatively high amounts of mental effort, resulting from situations where individuals are motivated to pay attention to a message, or have the cognitive capacities to consider it carefully. In these *high effort* or *high elaboration* processes, people's attitudes will be determined by an effortful examination of all relevant information, and so changing them will expend high amounts of cognitive energy. In contrast, other *low effort* or *low elaboration* processes of persuasion require relatively little mental consideration by the persuadee, resulting in attitudes determined by factors like emotions, 'gut feeling', liking, and reference to authority.

There are few analytical models capable of describing the dynamics of low elaboration attitude change. While high elaboration processes are more logical and considered, hence frequently following processes similar to first order logic, low elaboration processes are more difficult to control, and are frequently more open to subtle social influences. While it must be acknowledged that involuntary factors such as disgust can play a very important role in low elaboration attitude change (Griskevicius et al., 2013; Rozin, Haidt, & McCauley, 2008), these responses are themselves often mandated by previous social conditioning. It is very difficult to separate low elaboration attitude change from the social context (both current and historical) in which it occurs.

Furthermore, the underlying personalities of individuals in a society can reveal stark differences in how they will respond to their social context. For example, the Asch conformity experiments (Bond & Smith, 1996), while not directly applying to attitude change, revealed stark differences in the conformity of subjects when responding to a group of confederates who had been instructed to lie about a perceptual task. While a control group of subjects who performed the same task alone revealed an error rate of less than 1%, 75% of the experimental group of subjects gave an incorrect answer to at least one perceptual task. These incorrect responses often matched those of the lying confederate group. Interestingly, by performing post task interviews, Asch established that there was a wide range of individual responses to these tasks. Some individuals reacted confidently to their individual perceptions, whereas others became more withdrawn and hesitant. Some yielded easily to the group decisions, even to the point of actively believing that the group answer was the correct one. This suggests that the underlying personality of the subjects was a key factor affecting their likelihood of conforming with the group, or truly reporting their differing perceptual observations.

In this paper, we shall introduce a dynamical model of low elaboration attitude change, showing how it is possible to mathematically represent the manner in which the social context of an agent can affect their expressed attitudes. The model uses a cognitive state to represent an attitude, but is non-deterministic, with the probability of an agent acting taken to depend not just on this state, but also on: (1) the social context in which an agent finds themselves; and, (2) their underlying personality. A simple computational implementation will be discussed, and the way in which agent personalities affect individual attitude changes, and in turn affect the dynamics of the society as a whole will be explored.

Modelling Decisions in a Social Context

Our model takes *Quantum Decision Theory* (QDT) (Busemeyer, Pothos, Franco, & Trueblood, 2011; Busemeyer & Bruza, 2012) as its starting point, due to its implicit capacity to represent the effect of context upon a decision. QDT has been shown capable of providing a unified explanation for many of the so called 'violations' of rational decision theory that are exhibited by individual humans, and so offers a promising new approach to the modelling of human decision making in context. A recent work by the authors (Kitto & Boschetti, 2013) has introduced a social extension of the basic QDT model. It proposes a mechanism by which a society of agents self-organises into a set of ideologies representing their combined, and often contradictory, attitudes towards a social issue. This section will briefly introduce that model, but full details can be found in the longer paper.

The Basic QDT

We shall begin with a consideration of an agent A, called Alice, who is deciding whether or not to 'act' in response to a given social issue. Recognising that A's decision is likely to depend upon their social context, we shall represent her cognitive state as a vector $|A\rangle$ in a vector space,[1] the structure of which will depend upon the nature of the issue under consideration. If A has decided to act on this issue, then we shall denote this state of action as the vector $|1\rangle$, to represent a situation where it is *true* that she has *chosen to act* (in contrast to a state of inaction which we denote as $|0\rangle$).

These decisions only make sense with respect to a particular social context, and the probability of A acting could change with a new social setting. However, the quantum formalism can easily incorporate this contextuality due to its vectorial representation of the state $|A\rangle$. Thus, QDT represents the cognitive state of Alice, defined with respect to the context p as

$$|A\rangle = a_0|0_p\rangle + a_1|1_p\rangle, \text{ where } |a_0|^2 + |a_1|^2 = 1, \quad (1)$$

a situation that is illustrated in Figure 1(a). Pythagoras theorem is used to extract the probabilities of A acting (or not) in this context, with the probability of action given by $|a_1|^2$ and that of inaction similarly given by $|a_0|^2$. Thus, the *projection* of the state $|A\rangle$ onto the current context decides the probabilities of action for this model (Isham, 1995).

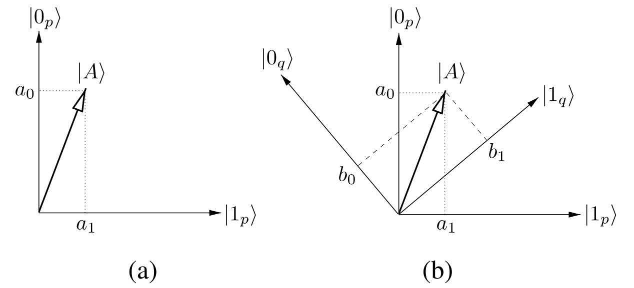

Figure 1: An agent attempts to decide whether or not to act. (a) Their probability of action is proportional to the length squared of the projection of their state onto the axes labelled $|0_p\rangle$ (no action) and $|1_p\rangle$ (action); (b) The changing context of a decision. The probability of the agent acting changes between the two depicted contexts, which can immediately be seen by the different lengths of the projections from the state $|A\rangle$ onto the two different 'act' axes $|1_p\rangle$ and $|1_q\rangle$.

With reference to Figure 1(a), we see that in the context p Alice is genuinely undecided. The cognitive state $|A\rangle$ represents an agent who has *yet to decide how to act* within some context, in contrast to the more standard modelling scenario where the agent has decided how to act, but we as modellers *do not know what that decision is*. Thus, the probabilities that arise in this model are fundamentally different from those of the more standard Kolmogorovian approaches (both Bayesian and frequentist), and this difference can have a profound effect with a change in context.

This can be seen with a consideration of figure 1(b), which is an elaboration of figure 1(a), and represents the changing probabilities of action that arise in the case of two different contexts, p and q. With reference to figure 1(b) we can quickly see that while our agent is highly likely to act in context q, this is not the case in context p, where A is much less likely to act (since by examination of the figure we can see that while $|a_0| > |a_1|$ in context p, $|b_1| > |b_0|$ in context q).

Social Framings of an Issue

This simple model can be naturally extended across a set of multiple agents which we shall call a *society* $\{|A\rangle, |B\rangle, |C\rangle \ldots\}$, all of whom are considering an issue, where each individual agent X is described with a cognitive state $|X\rangle$ which is expected to change in time.

We assume that agents can make decisions to act within one of two contexts, which we denote as *local*, and *global*.

[1] Dirac notation being used here, which was invented as a shorthand for quantum physics (Isham, 1995). It explicitly allows us to represent a vector a using a *ket*, $|a\rangle$, with the transpose given as a *bra* $\langle a|$. This allows for an immediate recognition of the inner product between two vectors $\langle a|b\rangle$ (a *bra-ket*) and of the outer product $|a\rangle\langle b|$. We use it here to make explicit the difference between our agent A and her cognitive state $|A\rangle$, a distinction that will become important when the effects of social context are discussed. The vector space being used is a Hilbert space, which is a real or complex inner product space that is also a complete metric space with respect to the distance function induced by the inner product (Isham, 1995).

This is taken to represent the manner in which, while we frequently make internal or private decisions (as represented by a local frame), we must sometimes cast our choices within a societal domain (as represented by a global frame) when for example, we are required to vote in a general election. The local frames of the individuals in a society might be similar to a global understanding, or they might differ substantially, depending upon the agent and how they think about the world. Local frames might arise from a wide range of both external and internal factors, such as the socioeconomic status of an agent, their educational background, race etc. and so are likely to be highly complex, and multidependent variables. As a first approximation we shall model them as another basis in the two dimensional vector space already introduced for the states and global frame. This allows us to anticipate that global frames will result from an aggregation function applied to the local frames of every agent who somehow identifies with that ideology. At this point in time, we define identification by performing a distance measure; the global frame that most closely aligns with the local frame of the agent is the one to which the agent is deemed to belong. However, we note that this identification is not intrinsic to the theoretical model per se, rather it is expected to evolve as the model is applied to different social scenarios, and extended into a higher dimensional state space than the early 2D implementation discussed below. We currently use clustering for the definition of global frames via aggregation, but we anticipate that there are many potential methods for defining global frames, and that different ones will prove necessary for different issues (List, 2012)

Kitto and Boschetti (2013) claimed that this framework provides an opportunity to model low elaboration processes of attitude change nontrivially, due to its explicit recognition of the context in which an agent makes a decision. The QDT approach allows for the probability of an agent acting to vary over the full range $(0,1)$ in response to the range of angles that can be taken by the cognitive state of the agent within the Hilbert space that represents the issue currently under consideration. Thus, in order to evaluate Alice's probability of acting, we must take both her current cognitive state $|A\rangle$, *and* her current social context p (as represented by a global or local frame) into account.

We postulate that an agent who has made a decision is likely to feel a certain amount of *cognitive dissonance* (Cooper, 2007) as their internal cognitive state will not be aligned with their decision (unless their cognitive state was already aligned with the relevant frame from which they are currently considering an issue). This means that they will feel a certain amount of psychological discomfort, which will drive them to alter their view of the world to fit with their decision within the context that it was made. They can do this in the current model by adjusting either their cognitive state, or their local framing of the issue, to more accurately reflect their decision. However, the literature suggests that some people are more comfortable with cognitive dissonance than others; their *personalities* will therefore play a key role in how this adjustment occurs. For example, some agents will feel far less comfortable with uncertainty than others, and so be more affected by dissonance (Sorrentino & Roney, 2000; Sorrentino & Hewitt, 1984). In order to model these intuitions, we note that an agent whose cognitive state lies close to the axes representing their current frame will be more certain about their likely future actions than one whose cognitive state lies between those axes (i.e. has the cognitive state forms a 45° angle between choosing to act and choosing not to act in the frame p). This leads us to introduce a measure of the *uncertainty* that an agent experiences about their likely future decisions, using binary entropy $H_b(P) \equiv -P\log_2 P - (1-P)\log_2(1-P)$, which is a function taking its minimum values at $P = 0$ and $P = 1$, and its maximum at $P = 1/2$. Here, the probability P is defined with reference to the probability of the agent acting (or not) within the given context. Referring to Figure 1(a), we can rewrite the binary entropy of our agent within the context p using a set of geometric variables

$$H_b(P(\theta)) = -|a_1|^2.\log_2(|a_1|^2) - |a_0|^2.\log_2(|a_0|^2) \qquad (2)$$

where θ is the angle between the $|1_p\rangle$ basis state and the state of the agent $|A\rangle$. This entropy measure is then used in a model of the two different drives for cognitive consistency that we hypothesise are experienced by an agent making a decision in a social context:

1. A desire for internal cognitive consistency. This drives agents to align their cognitive state with the local frame within which they are currently considering an issue.

2. A desire to 'fit in' with the society and its current norms. This desire is expressed by a pull of agent's local frame towards the current global frame (or ideology) to which they belong, which serves to reframe their understanding of the issue.

Defining Θ as the angle between the agent's current state $|A\rangle$ and the decision to act in the global frame to which they currently belong we introduce a function which measures the uncertainty of the agent A with respect to both frames:

$$H(|A\rangle, \theta, \Theta) = w_i(A)H_b(P(\theta)) + w_s(A)H_b(P(\Theta)) \qquad (3)$$

where the weights $w_i(A)$ and $w_s(A)$ refer to agent A's need for internal consistency and social conformity respectively. These weights can be set to range over a population of agents, indicating a rough parameterisation of a society's social make-up. This measure can naturally be extended to consider the uncertainty of the whole society of N agents:

$$H_{b_{Tot}} = \sum_{i=1}^{N} H(|i\rangle, \theta_i, \Theta_i) \qquad (4)$$

$$= \sum_{i=1}^{N} [w_i(i)H_b(P(|i\rangle,\theta)) + w_s(i)H_b(P(|i\rangle,\Theta))] \qquad (5)$$

which should decrease as the agents achieve cognitive consistency and so settle into a set of stable *ideologies*, or global attitudes about the world.

Time Evolution

The weights $w_i(A)$ and $w_s(A)$ can be considered as personality variables, and they will affect each agent's future actions, in addition to their current cognitive comfort (as is represented by (3)). At present, we update agent states and local frames slightly differently according to the frame in which the decision was initially made.

Local Decisions If the decision was in the local frame, then only the cognitive state of the agent is updated (within the local frame). Thus, an agent who has chosen to act within a certain framing of a problem will shift their state towards the decision ('yes' or 'no') that they made in that context. The size of this shift is defined as dependent upon two factors: (1) the personality profile of the agent (given in this case as w_i, as it represents the desire of an agent to align their cognitive state with their local frame); (2) the angle θ. Writing θ_0 for the angle between the agent's state and the $|0_p\rangle$ axis, and θ_1 for the angle between their state and the $|1_p\rangle$ axis, the new angle between the agent's state and the frame will become:

$$\text{if } A \text{ decides} \begin{cases} \text{to act: } \theta_1(|A\rangle_{t+1}, w(A)) = \theta_1(|A_t\rangle) \times w(A) \\ \text{not to act: } \theta_0(|A\rangle_{t+1}, w(A)) = \theta_0(|A_t\rangle) \times w(A) \end{cases} \tag{6}$$

where $w(A)$ depends upon the comfort of A with holding an attitude that is dissonant from their decision. Thus, for this update process $w(A) = w_i(A)$. Agents who decide to act will thus experience a rotation of their cognitive state by a certain distance dependent upon their personality towards the $|1_p\rangle$ axis (recall that θ is the distance between the $|1_p\rangle$ axis and the current state of the agent $|A\rangle$), and agents who decide not to act will experience a rotation of their cognitive state in the opposite direction.

Global Decisions If the decision was made in the global frame, then both the cognitive state of the agent and their local frame are updated (with reference to their global frame). Thus, in addition to the update of the cognitive state that is represented in equation (6), the local frame of the agent will shift towards the global axis that represents the decision made by the agent. The amount by which the local frame shifts is given by an equivalent version of equation (6), thus the new angle between the local frame and the global frame is given by (6), but with $w(A) = w_s(A)$.

Implementation

A proof of concept model has been implemented in MATLAB, which allows for an investigation of the timewise behaviour of this new agent based modelling paradigm. Space does not permit a full explanation of this implementation, however, we direct the interested reader towards the actual MATLAB script[2] which implements the basic pseudocode shown in Figure 2.

While the model that we have presented is admittedly very simple, it does exhibit a number of key features which one could reasonably expect should be found in an agent based model of attitude change. For example, Kitto and Boschetti (2013) describes the manner in which a population self-organises into a set of ideologies, which evolve and update in time. As predicted, the entropy (4) has a tendency to decrease in time. It is also possible to guide the behaviour of the population, through shifting a global frame, and to then watch the system reorganise into a new semi-stable configuration. In this paper we shall instead focus upon one key feature that has not yet been described, namely, the importance of personality in driving the attitude changes of a society of individuals.

[2] Available at http://www.per.marine.csiro.au/staff/Fabio.Boschetti/quantumPeople.html .

```
Number of global frames = G
Number of agents = N
For i=1..N
 Assign coherence & consistency variables
 If RandomPersonality = 0 then
  conformity = 0.5 and consistency = 0.5
 If RandomPersonality = 1 then
  consistency & conformity range over [0-1]
 Assign cognitive states & local frames randomly
For each timestep
 Find the position of the global frames (use k-means)
 For each agent
  Calculate which global frame the agent belongs to
  Probabilistically choose to act or not in one frame
  If acting in local frame then update cognitive state
  If acting in global frame then update cognitive
   state and local frame
  Calculate entropy of the agent
  Calculate total entropy of system
```

Figure 2: Pseudocode for the computational implementation.

The Importance of a Personality Spread

Two different seeding strategies have been utilised to initialise the consistency and conformity parameters ($w_i(A)$ and $w_s(A)$) for each agent within the computational model. A random distribution is possible, where each agent is seeded with parameters that randomly range from 0 to 1, or alternatively all agents can be seeded with a fixed personality distribution. This allows for an investigation of the effect that varying personality spreads can have upon a population.

Random Personality When agents are seeded with a random personality mix the time evolution of the system is predictably at its most erratic. While the entropy of the system has a tendency to decrease throughout a run, the agents tend not to find a stable configuration, and the system remains in a state of flux and change; states, local, and global frames can all move throughout a run.

Figure 3 shows a set of shots from a typical run for this scenario, along with the entropy plot as it gradually decreases through time, subject to some stochastic variance as agents realign their local frames. Two global frames were specified, and their location at each timestep found using a k-means style algorithm. Agent's cognitive states are represented using black lines, global frames by the large dots above the cognitive states, and local $|1\rangle$ frames as small black spots.

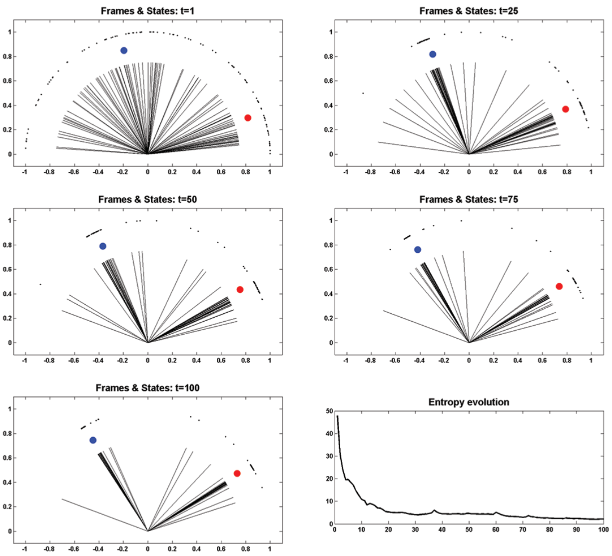

Figure 3: A typical run of a system initialised with agents of random personality spread. Note that the entropy of the system has a tendency to decrease in time, but that it never fully minimises or stablises.

Figure 4 shows a collection of entropy plots for two, three, and four global frames, all initialised with a random mix of personality parameters. Note that in all cases the entropy decreases, but that the system shows more erratic behaviour when more global points of view are available for the agents to align with. The limited nature of the current computational implementation (which has only been performed for two dimensions) means that arbitrarily adding more frames to what is a very small space does not result in realistic behaviour, however, work is currently in progress to extend this model to a higher dimensional state space, and this would allow for the interaction of far more social contexts to be investigated.

Fixed Personality In contrast, when the personality mix of the agents is fixed at $w_i(A) = 0.5,\ w_s(A) = 0.5$ the system exhibits a far more stable time evolution pattern, and becomes fixed in a static configuration around timestep 25. Figure 5 shows a typical run for this scenario. Note that the entropy minimises very early during a run, as the agents settle into a stable scenario that does not need to re-adjust. All agents can find a state and local frame that minimises (3), and the system rapidly settles down. This dynamics is also evident for for higher numbers of global frames.

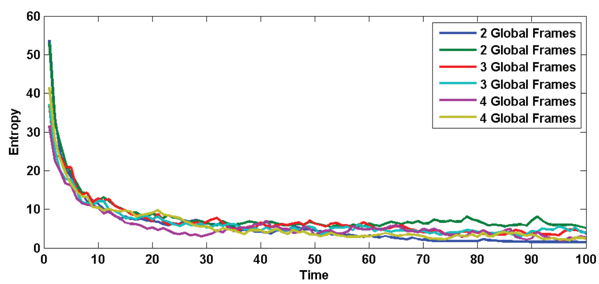

Figure 4: A collection of entropy plots for differing numbers of global frames, initialised with a random mix of personality.

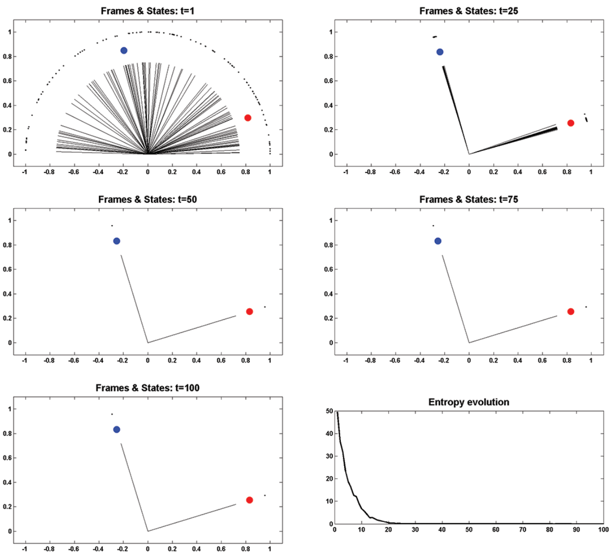

Figure 5: A typical run of a system seeded with a population of fixed personality type. (In this case $w_i(A) = 0.5$ and $w_s(A) = 0.5$.) The system quickly stabilises into a configuration where all agents are of one, or the other, state of mind. This behaviour is observed for all fixed personality profiles.

Evolution Requires Consistency and Cohesion

This brief discussion highlights the need for a society to contain a range of personality types. A society of individuals who all have the same personality mix quickly becomes static in this model, it settles down into a scenario where the attitudes of the agents, and their framing of those attitudes, do not change in time. This situation becomes even more dramatic when the society is seeded with individuals who have nonzero values *only* for conformity *or* for consistency. In both of these scenarios the model does not evolve at all, it remains in the same state as the one that it was initialised in.

This behaviour plausibly reflects the behaviour of societies in general. Difference of opinion and a varying response to the social context are both key and essential features of a society, and yet such behaviour does not tend to be well captured by current modelling technology. Thus, the contextualised apparatus of QDT offers an interesting new perspective on the modelling of social behaviour that we feel holds promise for future extension and expansion to a more realistic set of scenarios.

Conclusions

We begin our conclusion with something of a caveat. The model presented here does not utilise the standard complex Hilbert space of quantum theory, nor even the standard Schrödinger based time evolution equation of that model. Indeed, while the dynamics of equation (6) are unitary (Isham, 1995), they are not a part of the standard formalism of quantum theory. We propose that QDT is the first of a class of contextual models of human cognition, but do not expect that a straightforward application of the quantum formalism will suffice to model every contextually dependent cognitive system.

The geometric nature of the model presented here provides a dramatic departure from more standard state based modelling methodologies. In particular, the interaction between the cognitive state of the agent ($|A\rangle$) and of the basis in which they choose to make their decision (as represented by the basis $\{|0\rangle, |1\rangle\}$) means that in a different social context, the agent is highly likely to make a different decision as to how to act. Thus, in adopting a framework inspired by QDT, a very new approach to the treatment of context has been obtained. Furthermore, as the model presented here is developed, we anticipate that it will become necessary to progress to a complex space in order to represent the full range of personality variables and their associated cognitive states. In particular, the interference effects that are apparent in QDT, are not implemented in the current simple form of this model. In summary, it is the *contextuality* of human decision making in a social context that is captured by this model, but more cognitive effects are likely to be possible within this framework.

However, this initial step is important. Uncertainty dominates in scenarios where contextuality arises, but it is a cognitive effect apparent in the minds of the agents themselves, not in that of the modeller (Payne, Bettman, & Schkade, 1999), and this is not well captured by our current probabilistic approaches. We have shown one viable approach towards capturing contextual social effects, based upon QDT. A proof of concept computational model was discussed, and a set of varying personalities was shown to be essential for the dynamical evolution of the model. Thus, a way forwards presents, and future work will seek to develop this exciting new approach.

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