Fleur: Social Values Orientation for Robust Norm Emergence

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Abstract. By regulating agent interactions, norms facilitate coordination in multiagent systems. We investigate challenges and opportunities in the emergence of norms of prosociality, such as vaccination and mask wearing. Little research on norm emergence has incorporated social preferences, which determines how agents behave when others are involved. We evaluate the influence of preference distributions in a society on the emergence of prosocial norms. We adopt the Social Value Orientation (SVO) framework, which places value preferences along the dimensions of self and other. SVO brings forth the aspects of values most relevant to prosociality. Therefore, it provides an effective basis to structure our evaluation.
We find that including SVO in agents enables (1) better social experience; and (2) robust norm emergence.

Keywords: Agent-based simulation; norm adherence; preferences; social value orientation; Ethics

1 Introduction

What makes people make different decisions? Schwartz [23] defined ten fundamental human values, and each of them reflects specific motivations. Besides values, preferences define an individual's tendency to make a subjective selection among alternatives. Whereas values are relatively stable, preferences are sensitive to context and constructed when triggered [25].

In the real world, humans with varied weights of values evaluate the outcomes of their actions subjectively and act to maximize their utility [23]. In addition to values, an individual's social value orientation (SVO) influences the individual's behaviors [30]. Whereas values define the motivational bases of behaviors and attitudes of an individual [23], social value orientation indicates an individual's preference for resource allocation between self and others [8]. Specifically, social value orientation provides stable subjective weights for making decisions [17]. When interacting with others is inevitable, one individual's behavior may affect another. SVO revises an individual's utility function by assigning different weights to itself and others. Here is an example of a real-world case of SVO.

Example 1. **SVO.**

During a pandemic, the authorities announce a mask-wearing regulation and claim that regulation would help avoid infecting others or being infected. Although Felix tests positive on the pandemic and prefers not to wear a mask, he also cares about others' health. If he stays in a room with another healthy person, Elliot, Felix will put the mask on.

An agent is an autonomous, adaptive, and goal-driven entity [22]. Whereas many works assume agents consider the payoff of themselves, humans may further consider social preferences in the real world. e.g., payoffs of others or social welfare [5]. When humans are in the loop along with software, there are emerging need to consider human factors when building modern software and systems. These systems should consider human values and be capable of reasoning over humans' behaviors to be realistic and trustworthy.

In a multiagent system, social norms or social expectations [21, 2] are societal principles that regulate our behavior towards one another by measuring our perceived psychological distance. Humans evaluate social norms based on human values. Most previous works related to norms do not consider human values and assume regimented environments. However, humans are capable of deliberately adhering to or violating norms. Previous works on normative agents consider human values and theories on sociality [4, 31] in decision-making process. SVO as an agent's preference in a social context has not been fully explored.

Contributions We investigate the following research question.

RQ_{SVO}. How do the preferences for others' rewards influence norm compliance?

To address $\mathrm{RQ}_{\mathrm{SVO}}$, we develop Fleur, an agent framework that considers values, personal preferences, and social norms when making decisions. Our proposed framework Fleur combines world model, cognitive model, emotion model, and social model. Since values are abstract and need further definition, we start with social value orientations, the stable preferences for resource allocation, in this work. Specifically, Fleur agents take into account social value orientation in utility calculation.

Findings We evaluate Fleur via an agent simulation of a pandemic scenario designed as an iterated single-shot and intertemporal social dilemma game. We measure compliance, social experiences, and invalidation during the simulation. We find that the understanding of SVO helps agents to make more ethical decisions.

Organization Section 2 presents the related works. Section 3 describes the schematics of Fleur. Section 4 details the simulation experiments we conduct and the results. Section 5 presents our conclusion and directions for future extensions.

2 Related Works

Griesinger and Livingston Jr. [8] present a geometric model of SVO, the social value orientation ring as Figure 2. Van Lange [30] proposes a model and interprets prosocial orientation as enhancing both joint outcomes and equality in the outcomes. Declerck and Bogaert [6] describe social value orientation as a personality trait. Their work indicates that prosocial orientation positively correlates with adopting others' viewpoints and the ability to infer others' mental states. On the contrary, an individualistic orientation shows a negative correlation with these social skills. FLEUR follows the concepts of social preferences from [8].

Szekely et al. [26] show that high risk promotes robust norms, which have high resistance to risk change. de Mooij et al. [15] build a large-scale data-driven agent-based simulation model to simulate behavioral interventions among humans. Each agent reasons over their internal attitudes and external factors in this work. Ajmeri et al. [3] show that robust norms emerge among interactions where deviating agents reveal their contexts. This work enables agents to empathize with other agents' dilemmas by revealing contexts. Instead of sharing contexts, values, or preferences, FLEUR approximates others' payoff with observation. Serramia et al. [24] consider shared values in a society with norms and focus on making ethical decisions that promote the values. Ajmeri et al. [4] propose an agent framework that enables agents to aggregate the value preferences of stakeholders and make ethical decisions accordingly. This work takes other agents' values into account when making decisions. Mosca and Such [16] describe an agent framework that aggregates the shared preferences and moral values of multiple users and makes the optimal decisions for all users. Kalia et al. [10] investigate the relationship between norm outcomes and trust and emotions. Tzeng et al. [29] consider emotions as sanctions. Specifically, norm satisfaction or norm violation may trigger self-directed and other-directed emotions, which further enforce social norms. Dell'Anna et al. [7] propose a mechanism to regulate a multiagent system by revising the sanctions at runtime to achieve runtime norm enforcement. Agrawal et al. [1] provide and evaluate explicit norms and explanations. Winikoff et al. [33] construct comprehensible explanations with beliefs, desires, and values. Kurtan and Yolum [11] estimate privacy values with existing shared images in a user's social network. Tielman et al. [27] derive norms based on values and contexts. However, these works do not consider the differences between agents and the influences of an individual's behavior on others. Mashayekhi et al. [13] model guilt based on inequity aversion theory for an individual perspective on prosociality. In addition, they consider justice from a societal perspective on prosociality. Whereas Mashayekhi et al. [13] assume agents may be self-interested and their decisions may be affected by others' performance, FLEUR investigates the influence of social value orientations.

Table 1 summarizes related works on ethical agents. Adaptivity describes the capability of responding to different contexts. Empathy defines the ability to consider others' gain. The information share indicates information sharing among agents. The information model describes the applied models to process information and states. Among varied information models, contexts describe the situation in which an agent stands. Emotions are the responses to internal or external events or objects. Guilt is an aversive self-directed emotion. Explicit norms state causal normative information, including antecedents and consequences. Values and preferences both define desirable or undesirable states.

Table 1. Comparisons of works on ethical agents with norms and values.

Research	Adaptivity	Empathy	Information Share	Information Model
Fleur	✓	✓	✗	Preferences & Emotions & Contexts
Agrawal et al. [1]	✓	✗	✓	Explicit norms
Ajmeri et al. [3]	✓	✓	✓	Contexts
Ajmeri et al. [4]	✓	✓	✓	Values & Value preference & Contexts
Kalia et al. [10]	✓	✗	✗	Trust & Emotions
Kurtan and Yolum [11]	✓	✗	✗	Values
Mashayekhi et al. [13]	✓	✓	✓	Guilt
Mosca and Such [16]	✓	✓	✓	Preferences & Values
Serramia et al. [24]	✓	✗	✗	Values
Tielman et al. [27]	✓	✗	✓	Values & Contexts
Tzeng et al. [29]	✗	✗	✗	Emotions
Winikoff et al. [33]	✓	✗	✗	Values & Beliefs & Goals

3 Fleur

We now discuss the schematics of Fleur agents.

Figure 1 shows the architecture of Fleur. Fleur agents consists of five main components: cognitive model, emotion model, world model, social model, and a decision module.

3.1 Cognitive Model

Cognition relates to conscious intellectual activities, such as thinking, reasoning, or remembering, among which human values and preferences are essential. Specifically, values and preferences may change how an individual evaluates an agent, an event, or an object. In Fleur, We start with including human preferences. While preferences are the attitudes toward a set of objects in psychology [25], individual and social preferences provide intrinsic rewards. For instance, SVO provides agents with different preferences over resource allocations between themselves and others. Figure 2 demonstrates the reward distribution of different SVO types. The horizontal axis measures the resources allocated to oneself, and the vertical axis measures the resources allocated to others. Let

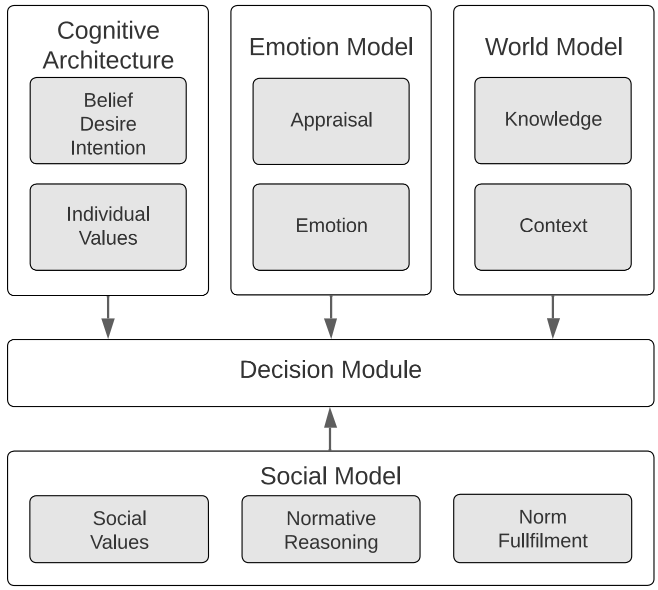

Fig. 1. FLEUR architecture.

$\overrightarrow{R} = (r_1, r_2, \ldots, r_n)$ represent the reward vector for a group of agents with size n. The reward for agent i considering social aspect is:

$$reward_i = r_i \cdot \cos\theta + r_{-i} \cdot \sin\theta \tag{1}$$

where r_i represents the reward for agent i and r_{-i} is the mean reward of all other agents interacting with agent i. Here we adopt the reward angle in [14] and represent agents' social value orientation with θ. We define $\theta \in \{90°, 45°, 0°, -45°\}$ as SVO $\in$ {altruistic, prosocial, individualistic, competitive}, respectively. With the weights provided by SVO, the presented equation enables the accommodation of social preferences.

In utility calculation, we consider two components: (1) extrinsic reward and (2) intrinsic reward. Whereas extrinsic rewards come from the environment, intrinsic rewards stem from internal stats, e.g., human values and preferences.

We extend the Belief-Desire-Intention (BDI) architecture [20]. An agent forms beliefs based on the information from the environment. The desire of an agent represents having dispositions to act. An agent's intention is a plan or action to achieve a selected desire.

Take Example 1 for instance. Since Felix has an intention to maximize the joint gain with Elliot, he may choose a strategy to not increase his payoff at the cost of others' sacrifice.

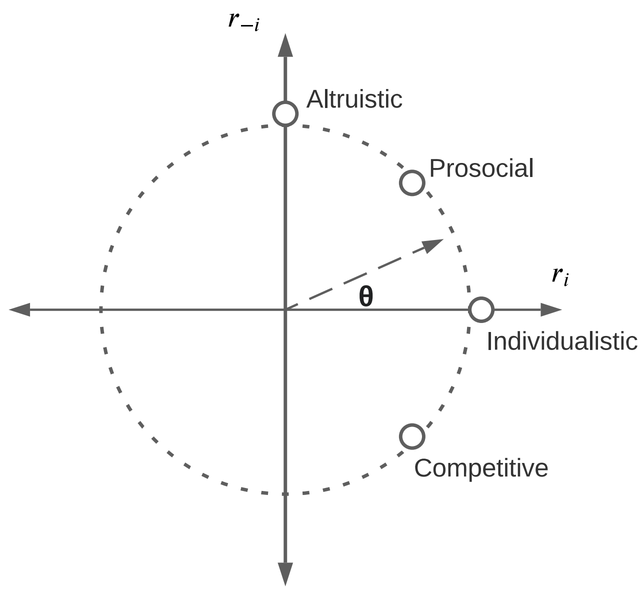

Fig. 2. Representation of Social Value Orientation [8, 14]. r_i denotes outcome for oneself and r_{-i} denotes outcomes for others.

3.2 Emotion Model

We adopt the OCC model of emotions [19]. Specifically, our emotion model appraises an object, an action, or an event and then triggers emotions. We consider emotional valence and assume norm satisfaction or norm violation yields positive or negative emotions if self behaviors align with the norms.

3.3 World Model

The world model describes the contexts in which Fleur agents stand and represents the general knowledge Fleur agents possess. A context is a scenario that an agent faces. Knowledge in this model are facts of the world. In Example 1, the context is that an infected individual, Felix, seeks to maximize the collective gain of himself and a healthy individual, Elliot. In the meantime, Felix acknowledges that a pandemic is ongoing.

3.4 Social Model

The social model of an agent includes social values, normative reasoning, and norm fulfillment. Social values define standards that individuals and groups employ to shape the form of social order [28], e.g., fairness and justice. Agents use the normative-reasoning component to reason over states, norms, and possible outcomes of satisfying or violating norms. Norm fulfillment checks if a norm has been fulfilled or violated with the selected action. Sanctions may come after norm fulfillments or violations.

3.5 Decision Module

The decision module selects actions based on agents' payoffs and individual values. We apply Q-Learning [32], a model-free reinforcement learning algorithm that learns from trial and error, to our agents. Q-Learning approximates the action-state value $Q(s, a)$ (Q value), with each state and action:

$$Q'(s_t, a_t) = Q(s_t, a_t) + \alpha * (R_t + \gamma \max_{a'} Q(s_{t+1}, a) - Q(s_t, a_t)) \tag{2}$$

where $Q'(s_t, a_t)$ represents the updated Q-value after performing action a at time t and s_{t+1} represents the next state. α denotes the learning rate in the Q-value update function, and R_t represents the rewards received at time t after acting a. γ defines the reward discount rate, which characterizes the importance of future rewards. Agents observe the environment, form their beliefs about the world, and update their state-value with rewards via interactions. By approximating the action-state value, the Q-Learning algorithm finds the optimal policy via the expected and cumulative rewards.

Algorithm 1 describes the agent interaction in our simulation.

Algorithm 1: Decision loop of a FLEUR agent

Initialize one agent with its desires D and preference P and SVO angle θ;
Initialize action-value function Q with random weights w;
for t=*1*,T **do**
    Pair up with another agent pn to interact with;
    Observe the environment (including the partner and its θ) and form beliefs b_t;
    With a probability ϵ select a random action a_t
      Otherwise select $a_t = argmax_a Q(b_t, a; w)$
    Execute action a_t and observe reward r_t;
    Observe the environment (including the partner) and form beliefs b_{t+1};
    Activate norms N with beliefs b_t, b_{t+1}, and action a_t;
    if $N\,! = \varnothing$ **then**
        Sanction the partner based on a_t and its behavior;
    end
end

4 Experiments

We now describe our experiments and discuss the results.

4.1 Experimental Scenario: Pandemic Mask Regulation

We build a pandemic scenario as an iterated single-shot and intertemporal social dilemma. We assume that the authorities have announced a masking regulation. In each game, each agent selects from the following two actions: (1) wear a mask, and (2) not wear a mask. Each agent has its inherent preferences and social value orientation. An agent forms a belief about its partner's health based on its observation. During the interaction, the decision an agent makes affects itself and others. The collective behaviors among agents determine the the dynamics in a society. Each agent receives the final points from its own action and effects from others: $R_{sum} = P_{i\_self} + P_{i\_other} + S_j$. P_{i_self} denotes the payoff from the action that agent i selects considering the reward distribution in Figure 2 and self-directed emotions. P_{i_other} is the payoff from the action that the other agent performs. S_j denotes the other-directed emotions from others towards agent i.

Table 2. Payoff for an actor and its partner based on how the actor acts and how its action influence others. Column Actors show the points from the actions of the actor. Column Partners display the points from the actions to the partner.

Health		Actions			
		Mask		No mask	
Actor	Partner	Actor	Partner	Actor	Partner
healthy	healthy	0.00	0.00	0.00	0.00
healthy	infected	1.00	0.00	−1.00	0.00
infected	healthy	0.00	1.00	0.00	−1.00
infected	infected	0.50	0.50	−0.50	−0.50

Table 3. Payoff for decisions on preferences

Type	Decisions	
	Satisfy	Dissatisfy
Preference	0.50	0.00

4.2 Experimental Setup

We develop a simulation using Mesa [12], an agent-based modeling framework in Python for creating, visualizing, and analyzing agent-based models. We ran the simulations on a device with 32 GB RAM and GPU NVIDIA GTX 1070 Ti.

We evaluated Fleur via a simulated pandemic scenario where agents' behaviors influence the collective outcome of the social game. A game-theoretical

Table 4. Payoff for decisions on norms

Actor	Partner	
	Wear	Not-Wear
Wear	0.10	−0.10
Not-Wear	0.00	0.10

setting may be ideal for validating the social dilemma with SVO and norms. However, real-world cases are usually non-zero-sum games where one's gain does not always lead to others' loss. In our scenario, depending on the context, the same action may lead to different consequences for the agent itself and its partner. For instance, when an agent is healthy and its partner is infected, wearing a mask gives the agent a positive payoff from the protection of the mask but no payoff for its partner. Conversely, not wearing a mask leads to a negative payoff for the agent and no payoff for its partner. The payoff given to the agent and its partner corresponds to the X and Y axis in Figure 2. When formalizing social interactions with SVO in game-theoretical settings, the payoffs of actions for an agent and others are required information.

We incorporated beliefs and desires, and intentions into our agents. An agent observes its environment and processes its perception, and forms its beliefs about the world. In each episode, agents pair up to interact with one another and sanction based on their and partners' decisions (Table 4).

Context. A context is composed of attributes from an agent and others and the environment as shown in Table 2. We frame the simulation as a non-zero-sum game where one's gain does not necessarily lead to the other parties' loss.

Preference. In psychology, preferences refer to an agent's attitudes towards a set of objects. In our simulation, we set 40% of agents to prefer to wear and prefer not to masks individually. The rest of the agents have a neutral attitude on masks. The payoffs for following the preferences are listed in Table 3.

Social Value Orientation. Social value orientation defines an agent's preference for allocating resources between itself and others. We consider altruistic, prosocial, individualistic, and competitive orientations selected from Figure 2.

4.3 Hypotheses and Metrics

We compute the following measures to address our research question $\mathrm{RQ}_{\mathrm{SVO}}$.

Compliance The percentage of agents who satisfy norms
Social Experience The total payoff of the agents in a society
Invalidation The percentage of agents who do not meet their preferences in a society

To answer our research question $\mathrm{RQ}_{\mathrm{SVO}}$, we evaluate three hypotheses that correspond to the specific metric, respectively.

$H_{Compliance}$: Preferences for others' rewards positively affect norm compliance with prosocial norms

$H_{Social\ Experience}$: The distribution of preferences for others' rewards positively affect social experiences in a society

$H_{Invalidation}$: Preferences for others' rewards negatively affect the tendency to meet personal preferences

4.4 Experiments

We ran a population of $N = 40$ agents in which we equally distributed our targeted SVO types: altruistic, prosocial, individualistic, and competitive. Since each game is a single-shot social dilemma, we consider each game as an episode. The training last for 500,000 episodes. In evaluation, we run 100 episodes and compute the mean values to minimize deviation from coincidence. We define our five societies as below.

Mixed society A society of agents with mixed social value orientation distribution

Altruistic society A society of agents who make decisions based on altruistic concerns

Prosocial society A society of agents who make decisions based on prosocial concerns

Selfish society A society of agents who make decisions based on selfish concerns

Competitive society A society of agents who make decisions based on competitive concerns

We assume all agents are aware of a mask-wearing norm. Agents who satisfy the norm receive positive emotions from themselves and others, as in Table 4. Conversely, norm violators receive negative emotions. Table 5 summarizes results of our simulation.

Figure 3 displays the compliance, the percentage of agents who satisfy norms, in the mixed and baseline-agent societies. We find that the compliance in the altruistic and prosocial-agent society, averaging at 69.70% and 70.25%, is higher than in the mixed (63.34%) and agent societies have no positive weights on others' payoff (65.10% and 54.08% for selfish and competitive-agent societies, respectively). The differences in the results of altruistic and prosocial-agent societies are statistically significant with medium effect ($p < 0.001$; Glass' $\Delta > 0.5$). Conversely, the competitive-agent society has the least compliance, averaging at 54.08%, with $p < 0.001$ and Glass' $\Delta > 0.8$. The results of the selfish-agent society (65.10%) shows no significant difference with $p > 0.05$ and Glass' $\Delta \approx 0.2$.

There are 25% of agents in the mixed-agent society are competitive agents. Specifically, they prefer to minimize others' payoff. A competitive infected agent may choose not to wear a mask when interacting with other healthy agents in this scenario. In the meantime, the selfish agents would maximize their self utility without considering others. Therefore, the behaviors of selfish and competitive agents may decrease compliance in the mixed-agent society.

Table 5. Comparing agent societies with different social value orientation distribution on various metrics and their statistical analysis with Glass' Δ and p-value. Each metric row shows the numeric value of the metric after simulation convergence.

		Compliance	Social Experience	Invalidation
S_{mixed}	Results	63.40%	0.4483	0.2960
	p-value	–	–	–
	Δ	–	–	–
$S_{altruistic}$	Results	69.70%	0.5543	**0.3340**
	p-value	< 0.001	< 0.001	< 0.001
	Δ	0.6602	0.6116	0.4635
$S_{prosocial}$	Results	**70.25%**	**0.5656**	0.3228
	p-value	< 0.001	< 0.001	< 0.05
	Δ	0.7178	0.6771	0.3263
$S_{selfish}$	Results	65.10%	0.4695	0.2690
	p-value	0.2180	0.4245	< 0.05
	Δ	0.1781	0.1221	0.3293
$S_{competitive}$	Results	54.08%	0.2208	0.2888
	p-value	< 0.001	< 0.001	0.5412
	Δ	0.9772	1.3131	0.0884

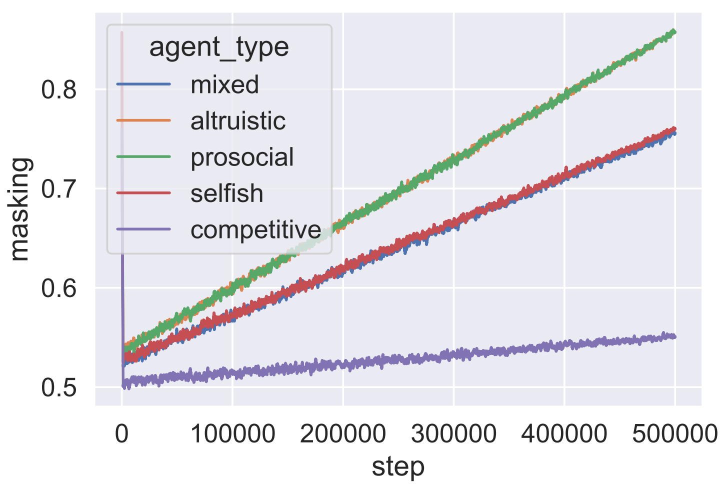

Fig. 3. Compliance in training phase: The percentage of norm satisfaction in a society.

Figure 4 compares the average payoff in the mixed and baseline-agent societies. The social experience in the altruistic and prosocial-agent society, averaging at 0.5543 and 0.5656, is higher than in the mixed (0.4483) and agent societies have no positive weights on others' payoff (46.95% and 22.08% for selfish and

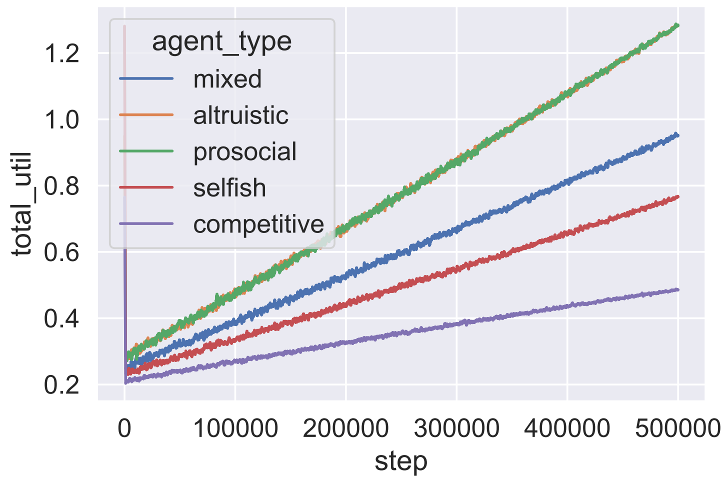

Fig. 4. Social Experience in training phase: The total payoff of the agents in a society.

competitive-agent societies, respectively). The differences in the results of altruistic and prosocial-agent societies are statistically significant with medium effect ($p < 0.001$; Glass' $\Delta > 0.5$). On the contrary, the competitive-agent society has the least social experience, averaging at 0.2208, with $p < 0.001$ and Glass' $\Delta > 0.8$. The results of the selfish-agent society (0.4695) shows no significant difference with $p > 0.05$ and Glass' $\Delta < 0.2$.

The mixed-agent society shows similar results as the selfish-agent society. Although 50% of the mixed-agent society agents are altruistic and prosocial, the competitive agents would choose to minimize others' payoff without hurting their self-interests. Since the selfish agents do not care about others, they would act for the sake of their benefit. The selfish and competitive behaviors diminish the social experiences in society.

Figure 5 compares invalidation, the percentage of agents who do not meet their preferences in the mixed and baseline-agent societies.

The invalidation in the altruistic and prosocial-agent society, averaging at 33.40% and 32.28%, is higher than in the mixed (29.60%) and agent societies have no positive weights on others' payoff (26.90% and 28.88% for selfish and competitive-agent societies, respectively). The differences in the results of altruistic and prosocial-agent societies are statistically significant with small or medium effect ($p < 0.001$; Glass' $\Delta > 0.2$). On the contrary, the selfish-agent society has the least invalidation, average at 26.90%, with $p < 0.05$ and Glass' $\Delta > 0.2$. The results of the competitive-agent society (28.88%) shows no significant difference with $p > 0.05$ and Glass' $\Delta < 0.2$.

While agents who consider others' rewards positively achieve better compliance and social experiences, these achievements are based on their sacrifice of

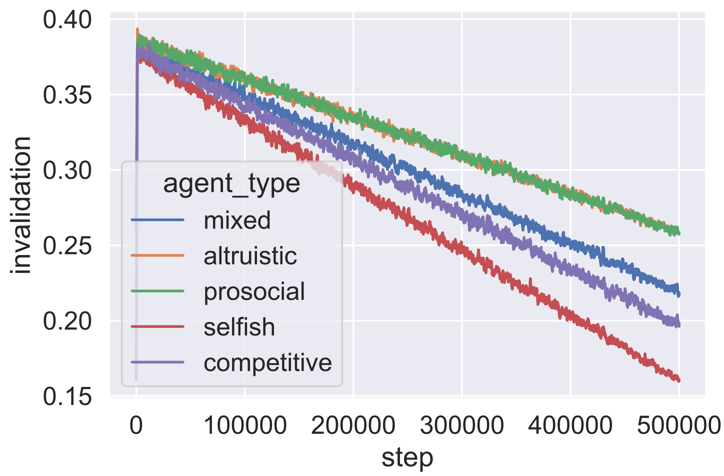

Fig. 5. Invalidation in training phase: The percentage of agents who do not meet their preferences in a society.

preferences. The altruistic and prosocial agent societies have the most percentage of agents who do not meet their preferences.

4.5 Threats to Validity

First, our simulation has a limited action space. Moreover, different actions may have the same payoff in some contexts. Other behaviors may better describe different types of SVO, yet our focus is on showing how SVO influences normative decisions.

Second, we represent actual societies as simulations. While differences in preference and SVO among people are inevitable, we focus on validating the influence of SVO.

Third, to simplify the simulation, we assume fixed interaction, whereas real-world interactions tend to be random. An agent may interact with one another in the same place many times or have no interaction. We randomly pair up all agents to mitigate this threat and average out the results.

5 Conclusions and Directions

We present an agent architecture that integrates cognitive architecture, world model, and social model to investigate how social value orientation influences compliance with norms. We simulate a pandemic scenario in which agents make decisions based on their individual and social preferences. The simulations show that altruistic and prosocial-agent societies comply better with the mask norm and bring out higher social experiences. However, altruistic and prosocial agents trade their personal preferences for compliance and social experiences. The results between the mixed and selfish-agent societies show no considerable difference. The competitive agents in the mixed-agent society may take the responsibility.

Future Directions

Our possible extensions include investigating an unequal distribution of SVO in Fleur and applying real-world data in the simulation. Other future directions are incorporating values into agents, and revealing adequate information to explain and convince others of inevitable normative deviations [1, 18, 34].

Acknowledgments

STT and MPS thank the US National Science Foundation (grant IIS-2116751) for support.

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