Pushing meat to the backseat?

How does the introduction of cognitive dissonance in Opinion Dynamics Modelling affect the spread of opinions regarding the importance of meat?

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1. Introduction

1.1 Background

The focus of this thesis is on how positive attitudes and opinions towards sustainable practices and sustainable diets could spread through social networks. It focuses in particular on opinions surrounding the importance of meat consumption, since meat consumption currently has a relatively high environmental impact compared to plant-based alternatives. Therefore, meat-based diets are often considered inefficient in terms of its resource use and conversion into animal protein. (Buttlar & Walther, 2019; Carlsson-Kanyama, 1998; Stoll-Kleemann & Schmidt, 2017). For the year of 2005, the IPCC estimated the livestock sector was responsible for roughly 14.5 % of all anthropogenic greenhouse gas emissions (Gerber et al., 2013). Greenhouse gas emissions are linked to additional pressure on food production due to negative feedback loops between food production, the environment and greenhouse gas emissions. Therefore, a connection could be made between unsustainable meat consumption practices and potential food security issues (de Bakker & Dagevos, 2012; Ferk, Grujic, & Kresic, 2018).

Poore & Nemecek (2018) stated that the production of animal products (including dairy and aquaculture) use approximately 83% of all farmland, while producing around 37% of our protein intake and 18% of our calorie intake (Poore & Nemecek, 2018). This is likely due to the fact that in order to produce animal products, livestock needs to be fed first, which depending on production practices can lead to feed-food competition (van Hal et al., 2019). Feed-food competition occurs when the production of food for human consumption clashes with the production of feed for livestock (van Hal et al., 2019). This is illustrated by the example that approximately 40% of all arable land is used for feed cultivation for cattle (Mottet et al., 2017). Nutrient-wise, it would be theoretically more efficient to use arable land for food crop cultivation (Godfray et al., 2010; van Hal et al., 2019). Furthermore, depending on production practices meat production can have negative influences on fresh water availability, soil quality, biodiversity and levels of greenhouse gas emissions (Aleksandrowicz et al., 2016; de Bakker & Dagevos, 2012; Ferk et al., 2018; Scarborough et al., 2014; Tilman & Clark, 2014).

However, it is important to note that not all meat production and consumption is inherently wasteful. There is a lot of diversity in the production efficiency and environmental impact of meat production, depending on the type of meat and its production practices. Livestock fed on inarable grassland or human food waste do not result in feed-food competition and can be an important source of farmers' income, especially in poorer communities (Godfray et al., 2010).

Besides the potentially detrimental impact on the environment, high levels of meat consumption have the potential to increase health risks. High carnivorous diets, such as the modern Western diets, have been linked to obesity (Ferk et al., 2018). Furthermore, a higher risk of non-communicable diseases is associated with the consumption of processed and red meats (Aleksandrowicz et al., 2016; Springmann et al., 2016; Tilman & Clark, 2014). A reduction in animal product consumption in our diets is likely to have dual positive environmental and health effects (Springmann et al., 2016; Tilman & Clark, 2014; Westhoek et al., 2014). According to Springmann et al. (2016) changing towards less meat-based diets in line with certain dietary guidelines, could reduce global mortality by 6-10% and food–related GHG emissions by 29-70% compared to a reference scenario in 2050.

However, what exactly can be considered a sustainable diet with sustainable food practices? The Food and Agriculture Organization of the United Nations (FAO) define sustainable diets as "*those diets with* *low environmental impacts, which contribute to food and nutrition security, and to healthy life for present and future generations. Sustainable diets are protective and respectful of biodiversity and ecosystems, culturally acceptable, accessible, economically fair and affordable; nutritionally adequate, safe and healthy; while optimizing natural and human resources"* (Burlingame & Dernini, 2011). In order to fulfill the FAO definition and the promise of sustainable diets in the future, replacing or omitting part of our meat consumption is likely to be key. Reducing meat intake can be speculated to optimize natural resources while increasing food security, leading to positive health benefits, and reducing the impacts on ecosystems and biodiversity (Aleksandrowicz et al., 2016; Scarborough et al., 2014; Tilman & Clark, 2014). This link between diets, their environmental pressures and health consequences are represented in the diet-environment-health trilemma. The diet-environment-health trilemma, states that the dietary practices people partake in can either accelerate or alleviate environmental and health concerns (Hawkins, 2019; Stubbs et al., 2018).

If a shift away from meat consumption is desirable, some behavior change on the individual level is required to take place. Changing consumers' food behavior is known to be a challenge (Perry & Grace, 2015; Sanchez-Sabate & Sabaté, 2019). Therefore, in order for behavior changes to take place, social mechanisms are often required to break through current dietary practices. Consequently, it is important to understand what social pressures can incite behavior changes in people's food practices. How do positive attitudes and opinions regarding meat consumption practices spread through social networks? Social sciences provide us with some qualitative understanding of the mechanisms underlying behavior changes in consumption practices surrounding meat. This thesis focuses on three of these social mechanisms: social influence, cognitive dissonance and idealism. And attempts to quantify these concepts somewhat using Opinion Dynamics Modelling (ODM) and contribute to the understanding of the theoretical spread of opinions within social networks. This thesis follows Sun & Müller (2013) in their approach of incorporating social influence in ODM and proposes its own approach to incorporate cognitive dissonance and idealism in ODM.

1.2 Research question

How does introducing cognitive dissonance impact the spread of opinions concerning the importance of meat in ODM?

1.3 Thesis sub questions

- What are the barriers and drivers in the reduction of meat consumption?
- What is Opinion Dynamic Modeling (ODM)?
- How are opinion weights influenced over time under the standard social influence model in ODM?
- How are opinion weights influenced over time by adding and implementing the social concept of cognitive dissonance in conjunction with social influence using ODM?
- How are opinion weights influenced over time, when adding idealists to cognitive dissonance model using ODM?

2. Drivers and barriers for reducing meat consumption.

A reduction in meat consumption seems to be desirable from a societal viewpoint, especially at the level of the average consumer (Stubbs et al., 2018). The main categories of arguments for individuals to reduce their meat consumption are health, sociocultural, environmental, ethical and economic reasons.

Food and its consumption are heavily embedded in its social and cultural context, and are predominantly assumed to be based on people's habits and routines, rather than on completely conscious decisions (Macdiarmid, Douglas, & Campbell, 2016; Stubbs et al., 2018; Tosun & Gürce, 2018). Therefore, changing consumers' food practices is known to be a challenge (Perry & Grace, 2015; Sanchez-Sabate & Sabaté, 2019). Habits are acquired through repetition and are unconscious and automatic. Thus, established habits take effort and energy to change, and often people are unwilling and unable to make big and drastic changes quickly (Tosun & Gürce, 2018). Therefore, a reduction in meat consumption does not seem likely to be quick and instantaneous. Often a form of social pressure is necessary to introduce the beginnings of change. Often our belief systems have to be contradicted repeatedly. That is why the focus of this thesis is on the effect of introducing social influence, cognitive dissonance and idealism on attitudes towards sustainable diets in ODM models.

Despite obstacles for adopting meat curtailment strategies, there seems to be an increase in local and individual interest to adopt a more environmentally friendly lifestyle (Carlsson-Kanyama, 1998). Some consumer groups seem to have higher inclinations to reduce their meat consumption than others. Young, female westerners from Asian and European countries appear to be the most willing to reduce meat consumption due to environmental concerns (Sanchez-Sabate & Sabaté, 2019). While men are less likely to reduce meat consumption, possibly due to social norms and stereotypes such as "real men eat meat" (de Boer et al., 2017; Graça et al., 2015). For now, it seems only a limited group relates to the environmental concerns regarding meat reduction (Sanchez-Sabate & Sabaté, 2019). This could be due to a lack of awareness of the connection between dietary practices and their potential impact on the environment (Corrin & Papadopoulos, 2017; Stubbs et al., 2018). As well as a skewed perception of the negative individual impact one's dietary choices has on sustainability a larger scale (Stubbs et al., 2018). Besides ignorance about the impact of meat production, there remains some skepticism about the scientific evidence of the impacts of meat consumption (Macdiarmid et al., 2016; Stubbs et al., 2018). However, there is an upward trend in awareness and the willingness to pay for environmentally responsible food products (Peschel, et al., 2016). So, while environmental concerns are not yet dispersed through the entire population, it seems to have become more prevalent, at least in some consumer groups (Stubbs et al., 2018).

Another argument category for individual people to reduce meat consumption are the perceived individual health benefits (Corrin & Papadopoulos, 2017; De Backer & Hudders, 2015; Hayley et al., 2015; Tobler et al., 2011; Tosun & Gürce, 2018). Consumers who adopt completely vegetarian diets are often motivated by health motives. Vegan and flexitarian diets on the other hand seem to be motivated by health reasons as well as environmental reasons (Tobler et al., 2011). There is a significant positive correlation between vegetarian lifestyles and the awareness of facts and scientific knowledge about nutritional values. Non-vegetarians on the other hand, are more uncertain about the association between health benefits and the vegetarian diets (Corrin & Papadopoulos, 2017). Some consumers belief eating no meat is unnatural and some form of animal protein and meat is essential to a healthy diet, and are more likely to be inclined to be skeptical about health benefits from a more plant-based diet. One could speculate that these beliefs could be connected to an anthropocentric viewpoint of the world, where people feel naturally entitled to meat. This may stem from human-animal dominance ideologies (Graça et al., 2015). When people are not aware of potential health benefits and are skeptical about the scientific evidence behind claims plant-based diets are no less healthy then carnivorous diets, people are less likely to reduce their meat consumption (Stubbs et al., 2018).

The individual decision to reduce meat consumption is often underlined by financial or economic motives as most consumption decisions are (Corrin & Papadopoulos, 2017; Macdiarmid et al., 2016; Malek et al., 2019; Tosun & Gürce, 2018). The consumption of meat is in certain cases associated with a higher social status and is thus can be viewed as a form of conspicuous consumption (Tosun & Gürce, 2018). Malek (2019) found that a reduction in meat intake in Australian diets, were mostly the result of financial restraints, rather than being a form of anti-consumption due to environmental, ethical or health reasons. On the other hand, adopting vegetarian diets were often associated with environmental or ethical concerns rather than financial concerns.

Perceiving the consumption and production of meat as unethical is also indicated to be a frequent motivator for reducing an individual's meat intake (Corrin & Papadopoulos, 2017; De Backer & Hudders, 2015; Malek et al., 2019; Rothgerber, 2015; Stubbs et al., 2018; Tobler et al., 2011). This motivator is captured in what is called the meat paradox. The meat paradox contrasts the human pleasure and the animal suffering derived from eating meat (Buttlar & Walther, 2019). These conflicting feelings during meat consumption can lead to cognitive dissonance and identity incongruity. Cognitive dissonance can occur when a person is confronted with conflicting beliefs, attitudes or opinions (Li et al., 2020). Cognitive dissonance, as defined in this thesis, is "*the feelings of unease and discomfort when behavior and perceptions of self-identity are misaligned, often instigated by being presented new information or different beliefs through social connections*". Inconsistent cognitions can cause a state of uncomfortable tension or anxiety that the individual is driven to reduce. The larger the discrepancy between two beliefs or perceptions, the more discomfort an individual experiences, which increases their motivation to reduce the discrepancy. Especially when this new information and opinions contradict with the perception of oneself and threaten an individual's self-esteem (Covey, 2009). For example, people can have difficulty matching their meat-eating behavior with other values they express or perceptions they hold of themselves. For instance, the belief that you are an animal lover is inconsistent with the animal suffering in meat production. Of course, cognitive dissonance can also occur as a result of environmental or health arguments. Alleviating cognitive dissonance can be done by two broad categories of action. Either people can actually change one of their beliefs to achieve congruency, or apply a variety of moral disengagement strategies to make the two conflicting cognitions congruent with each other (Alfnes et al., 2010; Buttlar & Walther, 2019).

These moral disengagement strategies attempt to make inconsistent beliefs and behavior consistent with each other again. These strategies include avoiding to recognize the issue or responsibility, denial of information, downplay their individual impact, and pro-meat justifications (Rothgerber, 2014). An example of someone employing moral disengagement strategies is individuals avoiding explicit content videos of animals in slaughterhouses. Or one might downplay the environmental impact of their meat consumption, by expressing skepticism towards scientific evidence. Another might avoid individual responsibility by stating why they should reduce their meat intake, when other people are not reducing their meat intake either. This in order to avoid having to change their beliefs or behavior. However, employing these moral disengagement strategies takes effort as well, especially when these beliefs are conflicting on a regular basis. So, in order to reduce cognitive dissonance, people can either change their behavior and beliefs or employ moral disagreement strategies that allow them to continue their current behavior (Alfnes et al., 2010; Buttlar & Walther, 2019; Rothgerber, 2015). Therefore, cognitive dissonance can act both as a barrier and as a driver of change in dietary practices depending on the path chosen to alleviate cognitive dissonance.

Attitudes about changing food practices are complicated by the social and cultural importance of diets and meat, as well as the processes of preference formation during childhood. Many drivers and barriers for meat reduction are either sociocultural or indirectly influenced by someone's sociocultural background. What is perceived as ethical or not is often underlined by the sociocultural background as well as upbringing. The consumption of meat is often tied together with (family) tradition and seen as a social, highly pleasurable experience (Corrin & Papadopoulos, 2017; Macdiarmid et al., 2016). Meat consumption is in essence a social practice and has social meaning. Consumption of meat, or the lack thereof often ties into a person's identity (de Boer et al., 2017). People seem to attach a value to meat on top of the nutritional value (Graça et al., 2015; Macdiarmid et al., 2016). The construct of meat attachment shows this especially well. Meat attachment indicates the positive attachment a person has towards meat. High meat attachment can hinder and obstruct shifts towards lower meat consumption, because people feel a strong bond with the consumption of meat (Graça et al., 2015). People's opinions and behavior are also influenced by their social networks and the interactions within these networks. Peer pressure and peer group behavior have the potential to be both obstacles and drivers towards a reduction of meat in people's diets. Since people are influenced by their peers and do not like to diverge far from their peer groups (Macdiarmid et al., 2016; Malek et al., 2019).

It seems that economic, health, ethical and environmental motives for reducing meat consumption are heavily underlined by its sociocultural context. The spread of sustainable practices and the spread of motives of sustainable practices seems most likely through social mechanisms, such as social influence, cognitive dissonance, and self-identity tied to idealism. In this thesis the focus is on how these social mechanisms in particular theoretically influence opinion distributions in social networks in ODM.

3. Opinion dynamics modelling (ODM)

Opinion dynamics modelling (ODM) is a method used to model the influence of social interactions on the opinions or beliefs held within social networks. Within ODM it is assumed opinions develop over time due to social diffusion processes in which participants of social groups interact with each other and share their beliefs (Schenk, 2014). It shows how individual opinions can change and progress under pressure of various social mechanisms and how that affects the collective opinion in society (Das, Kamruzzaman, & Karmakar, 2018). In other words, people's behavior and opinions are not isolated from social mechanisms. People evaluate the judgement and behavior of the people around them and this might lead them to change their own expressed opinions and behavior (Huang, Tzou, & Sun, 2011). Opinion dynamics models can be either discrete or continuous between 0 and 1 (Huang et al., 2011; Monica & Bergenti, 2017). Discrete models are often used when a finite number of behavioral options and opinions are possible, i.e. political elections with a limited number of candidates. Continuous models are often used to represent opinions on a single issue, where opinions are variable on a scale of strongly disagree to agree, i.e. the importance of sustainable food consumption or the importance of meat consumption (Monica & Bergenti, 2017). One of the most established approaches in continuous ODM are the bounded confidence models, independently developed by Hegselmann and Krause (in their HK-model) and by Deffuant and Weisbuch (in their DW-model). In these bounded confidence models limits are placed on which opinions can influence each other (Li et al., 2020; Liu et al., 2017).

Through various social diffusion processes it is assumed that if opinions stabilize over time, there are three general structures of stabilized opinions in opinion dynamics (see the figure 1 below). The first stabilized structure is fragmentation, where opinions close together converge into multiple opinion camps. The second stabilized structure is polarization, where opinions converge into two opposing opinion camps. The third stabilized structure is consensus, where all opinions converge to the same opinion over time. (Li et al., 2020).

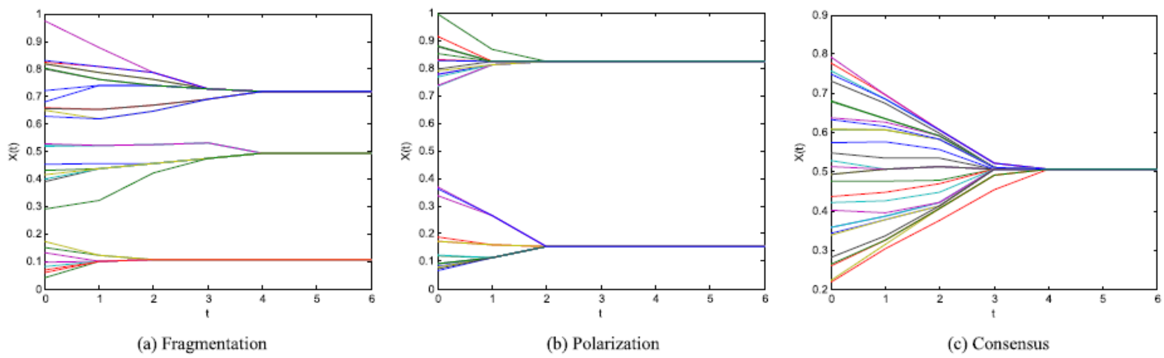


Figure 1 Types of structures of stabilized opinions (Li et al., 2020)

Opinion dynamics modelling (ODM) is applied for various purposes and in various fields (Liu, 2017). One can also apply ODM to opinions on sustainable practices. These opinions on sustainable practices are often assumed to be related to actions taken towards creating more sustainable practices. In our case we take a look at how social mechanisms influence the beliefs and opinions people hold about the importance of meat consumption. The rationale being that the attitudes and opinions people hold over the importance of meat consumption are related to the weights people attach to meat in their utility functions and in turn their meat consumption. The social mechanisms focused on in this thesis are social influence, cognitive dissonance, idealism, and the interaction of those mechanisms. In order to focus on the influence of those mechanisms, stable unchanging social networks are assumed for a given period of time and the same actors, where all agents meet exactly once over the time period.

When modelling social influence, this thesis follows the example of Sun & Müller (2013). Sun & Müller (2013) use a version of a bounded confidence model, an adapted version of the Deffuant-Weisbuch (DW) model. Each modeled agent is assigned an initial opinion or belief. This initial opinion can be influenced and changed by interactions with other agents. Whether or not an agent adjusts their opinion after meeting another agent in the social network depends on the size of the difference in opinions. If the difference in opinion is larger than social influence threshold d, no adjustment of opinions take place. If the difference in opinion is smaller than threshold d, opinions can be socially influenced and adjusted accordingly. The size of the adjustment depends on how strong the social influence is, which is represented by convergence parameter μ (Sun & Müller, 2013).

For modelling cognitive dissonance, this thesis proposes its own approach to incorporate cognitive dissonance in ODM. When new information and opinions that contradict our current opinions are encountered through social connections, cognitive dissonance can occur. Individuals are motivated to reduce the feelings of unease and discomfort experienced due to cognitive dissonance (Covey, 2009). To reduce these feelings of unease and discomfort two broad categories of action can be undertaken. Either someone is willing to change their existing beliefs and opinions to relieve the discrepancy and reduce cognitive dissonance. Or an individual keeps their existing attitudes and opinions, by employing a variety of moral disengagement strategies to discredit or avoid the newly encountered conflicting attitudes and opinions (Alfnes et al., 2010; Buttlar & Walther, 2019; Rothgerber, 2014). Repeated exposure to cognitive dissonance on the same issues increases the likelihood of adjusting existing attitudes and opinions, due to the fact that employing moral disengagement strategies takes effort.

When the mechanisms of social influence and cognitive dissonance are combined, it is assumed contradicting opinions relatively close to existing opinions are more likely to lead to a change in existing beliefs through social influence. People are assumed to find it easier to change their opinions in smaller steps, rather than drastically. People generally find it difficult to make big and drastic changes (Tosun & Gürce, 2018). Encountering more extreme opinion differences, will also lead to cognitive dissonance, but is more likely to lead to the employment of moral disengagement strategies. This is because it can be difficult for people to admit that their self-identity and attitudes do not line up and make larger behavioral and belief changes (de Boer et al., 2017; Tosun & Gürce, 2018). However, we assume that repeated exposure to large opinion differences, does increase the probability of changing existing opinions and attitudes through social influence. Since, repeatedly having to employ moral disengagement strategies takes effort as well.

Our approach to incorporating cognitive dissonance in opinion dynamics takes a different perspective from the approach of Li et al. (2020). In the model of Li et al. (2020) cognitive dissonance is assumed to be reduced by employing only the following two moral disengagement strategies: updating social connections with people with similar beliefs and breaking social connections with people with differing beliefs. There are definitely scenarios where this model is applicable, especially regarding opinions on controversial or deal-breaking issues. However, there are also scenarios where people will deviate from these two particular moral disengagement strategies. Besides altering social connections, there are other moral disengagement strategies that can be applied. Furthermore, not all issues are controversial enough to disconnect with people that disagree with you. Or rather, there are certain scenarios and issues, where the exchange of opinions and attitudes is unavoidable. Take food practices, as stated earlier, they are inherently social. One is unlikely to break social ties based on someone not sharing the same opinions over food practices or their opinions regarding the importance of meat consumption. Avoiding the topic all together can be hard as it is interwoven in many social events, both in the personal and professional area (such as birthday and business dinners). So, for food practices it seems almost impossible to edit your social connections in a way that you are never confronted with differing opinions than your own. Therefore, we take a different approach to modeling cognitive dissonance in opinion dynamics than Li et al. (2020). We assume that besides employing moral disengagement strategies a person can also decide to alter their opinions and attitudes. Furthermore, we assume a wider variety of moral disengagement strategies is possible and do not distinguish between all the potential disengagement strategies, but rather look at the probability someone chooses to employ them to reduce cognitive dissonance (and thus keep their existing beliefs) or not (and alter their existing beliefs).

In the final model idealism is added to the previous cognitive dissonance model. The idealists in our model are assumed to only be open to social influence and cognitive dissonance from other idealists, while still being able to influence non-idealists through the mechanism of cognitive dissonance.

4. Models and assumptions

4.1 General building blocks and assumptions

The model assumes a set of ten agents (A = {A_1, A_2, …, A_{10}}) and 10 discrete timesteps. The opinions of these agents are expressed by opinion weights g_{cit}, where opinion weight g_{cit} represents the opinion of agent $A_i \in A$ in timestep t (t = {1, 2, …, 10}). The opinion weight g_{ci1} at t=1 represents the initial opinions the agents hold before social interactions. Opinions are assumed to be on a continuous scale. The opinion g_{cit} represents the importance of meat to agent A_i. The higher the value of opinion g_{cit}, the higher their attachment to meat is. Over the course of t=2 to t=10, every agent will meet all other agents in the social network exactly once. During every timestep an agent meets another agent they have not met in previous timesteps or rounds. Therefore, during every round from t=2 to t=10, 5 encounters occur. This can be seen as a representation of a small community of 10 members, where every agent is connected to each other and meets one member per round. Whenever an agent encounters another agent, opinions are exchanged and the possibility of social influence occurs. The exact barriers to social influence between two agents vary per model. In the first model, social influence is only obstructed by a social influence threshold d. Social influence threshold d, indicates what size of opinion difference can still be considered small. In the first model only agents with small opinion differences can influence each other. In the second model, the concept of cognitive dissonance is added to the first model. Lastly, in the third model, idealism is introduced. Agents who are considered idealists, can only be influenced by other agents that are considered idealists. The sequence of meetings in every timestep is fixed between positions, but every agent, characterized by g_{cit}, is randomly assigned a position every run of the model. Thus, reducing undue influence of position or sequence effects if the model is run multiple times, similar to taking multiple small community samples.

Round 2	t=2
1	2
3	4
5	6
7	8
9	10

Round 3	t=3
1	3
5	2
7	4
9	6
10	8

Round 4	t=4
1	5
7	3
9	2
10	4
8	6

Round 5	t=5
1	7
9	5
10	3
8	2
6	4

Round 6	t=6
1	9
10	7
8	5
6	3
4	2

Round 7	t=7
1	10
8	9
6	7
4	5
2	3

Round 8	t=8
1	8
6	10
4	9
2	7
3	5

Round 9	t=9
1	6
4	8
2	10
3	9
5	7

Round 10	t=10
1	4
2	6
3	8
5	10
7	9

Table 1: Order of encounters

4.2 Model 1: The social influence model

Model 1 assumes that social influence takes place in an encounter between agent A_i and agent A_j when the opinion difference is sufficiently small, as determined by social influence threshold d. This assumes people influence each other as long as the absolute opinion difference (Δ) is smaller than social influence threshold d. This model is based on the approach of Sun and Müller (2013) of modelling social influence. The model checks, whether the difference between opinions g_{cit} and g_{cjt} of agents A_i and A_j respectively, falls under or is equal to social influence threshold d. If $\Delta \leq d$, social influence will take place. Since the opinions are on a continuous scale of 0 to 1, the maximum difference between two opinions is equal to 1. Therefore, it is assumed $0 \leq d \leq 1$. As the threshold of social influence increases, a lower degree of fragmentation and a higher degree of consensus is expected, all other things being equal. The strength of the social influence is indicated by convergence parameter μ. Convergence parameter μ indicates the percentage of the opinion difference between agents A_i and A_j, that agent A_i will adjust their opinion with. If $\mu > 0.5$, the agents will adjust their opinion by more than 50% of the difference, and thus end up in reverse opinion positions. To rule this out, it is assumed convergence parameter $0 \geq \mu \geq 0.5$. This ensures that a convergence parameter μ of 0.5 is the maximum, in which case a complete consensus is reached between the two agents. The higher convergence parameter μ, the higher the consensus reached between agents on an individual level.

Mathematically, the formula for the opinion in the next timestep or round is $g_{ci(t+1)} = g_{ci(t)} + \mu(g_{cj(t)} - g_{ci(t)})$. This leads to the following opinion tree for agent A_i (see figure 2). The square nodes in this opinion tree have a similar function as square nodes in decision trees; they indicate a determined outcome based on the parameter values given. Circular nodes represent chance nodes, when the result of an uncertain outcome is decided. Agent A_j faces the same opinion tree as A_i, but reversed.

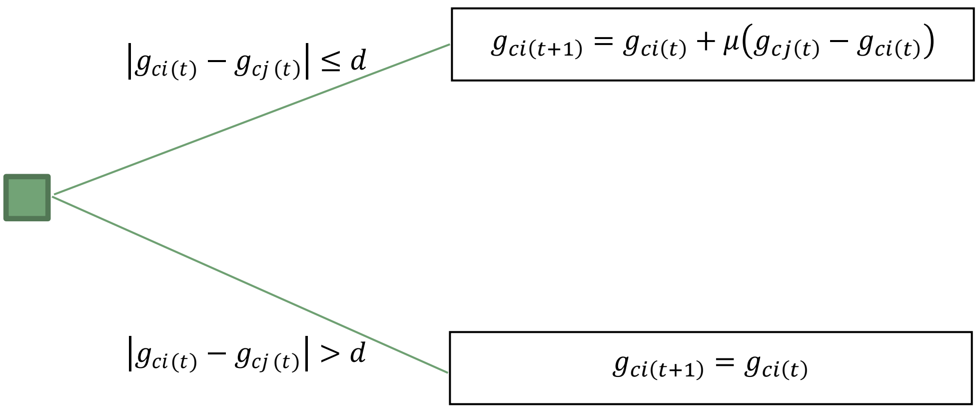


Figure 2: Opinion tree of model 1: the social influence model.

4.3 Model 2: The cognitive dissonance model

Model 2 combines the social mechanisms of cognitive dissonance and social influence. As shown earlier, cognitive dissonance is in this thesis defined as "*the feelings of unease and discomfort when behavior and perceptions of self-identity are misaligned, often instigated by being presented new information or different beliefs through social connections*". In this thesis it is assumed that when cognitive dissonance occurs, an agent will either adjust their current opinion by allowing social influence or they will employ moral disengagement strategies and keep their current opinions. The likelihood of an individual employing moral disengagement strategies is lower for encounters with small opinion differences ($\Delta < d$) compared to encounters with large opinion differences ($\Delta \geq d$). Smaller belief changes are assumed to be easier for people (Tosun & Gürce, 2018). Therefore, we assume that the effort of changing opinion weights for small opinion differences is relatively low compared to large opinion differences. The likelihood of employing moral disengagement strategies for small opinion differences (P_s) is the same for all time steps. The likelihood of employing moral disengagement strategies for large opinion differences ($P_l^{1+\alpha N}$) (see next paragraph for an explanation of α and N) can become smaller after previous exposure to large opinion differences. Since it is assumed moral disengagement strategies take increasing effort over time as an agent is repeatedly challenged. I.e. denying individual responsibility, when confronted with other people's behavior. Furthermore, it is assumed that seeing many differing opinions, opens one up for the assumption that no one is completely right. This might make it easier to admit flaws in earlier held beliefs or open the door for realizing they themselves might not be completely right either If no moral disengagement strategies are employed, social influence according to the approach of Sun and Müller (2013) takes place. To show that the effort of changing beliefs for small opinion differences are initially always lower compared to changing for large opinion differences, it is assumed $P_s < P_l$ in the first round (where N is always 0)

If two agents with small opinion differences ($\Delta \leq d$) encounter each other, the likelihood of employing moral disengagement strategies is P_s. P_s is a probability, therefore $0 \leq P_s \leq 1$. The probability of social influence occurring as described by Sun and Müller (2013) is $1-P_s$. If two agents with large opinion differences ($\Delta > d$) encounter each other, the likelihood of employing moral disengagement strategies is $P_l^{1+\alpha N}$. P_l is a probability, therefore $0 \leq P_l \leq 1$. N is the number of times extreme opinions were encountered in the previous timesteps or rounds and α is the influence of repeated exposure to extreme opinions. In this model no distinction is made between extreme opinion differences below or above an agent's current opinion. This is done on the assumption, that exposure to extreme opinions in either direction opens an agent up for the possibility that an issue might not be completely black and white, and therefore their own opinion might be up for a reevaluation. Another reason why no distinction is made between to keep the model more comprehensive. A model tries to translate a complex real-life situation into a representation of the essentials. Adding the direction of the extreme opinion encounters, would likely add an additional P parameter to the model, and increase its complexity. Furthermore, since opinions can move over time it is also possible for some opinions which used to be above the current opinion to end up below the new opinion, or vice versa. Since the model showed the desired and expected effects of cognitive dissonance without adding this additional parameter, it was decided not to add this distinction between extreme encounters. Depending on the initial opinion distribution and social influence threshold chosen, the highest N for an individual agent often fluctuates between 4 and 8 times until the final round. Since $\alpha > 0$ is assumed, $1+\alpha N$ is increasing in α and $P_l^{1+\alpha N}$ is decreasing in α. Hence the higher α and the sooner extreme encounters happen the stronger the influence of α on an agent's final opinion. If α is very high, the likelihood of employing moral disengagement strategies in cases of large opinion differences ($P_l^{1+\alpha N}$) becomes closer to zero with each additional extreme opinion encounter. This could lead to a situation where social influence will always take place when opinion differences are large in later rounds, where $N \geq 1$, depending on the value of α. To avoid this previous scenario and to avoid that in later timesteps ($P_l^{1+\alpha N} \leq P_s$), in the scenarios run for this thesis it is assumed $0 \geq \alpha \geq 0.15$. This keeps the effect of $1+\alpha N$ mostly under and only in some cases slightly bigger than a quadratic power of 2 in the most extreme cases. $1+\alpha N$ reflects the increasing cost of moral disengagement strategies over time and the increased openness towards large opinion differences as they are encountered more often. Hopefully, simultaneously keeping the effect of $1+\alpha N$ limited. The closer P_s is to 0, P_l is to 1 and α is to 0, the more the second model resembles the first model of social influence alone. The second model is represented by the opinion tree in figure 3.

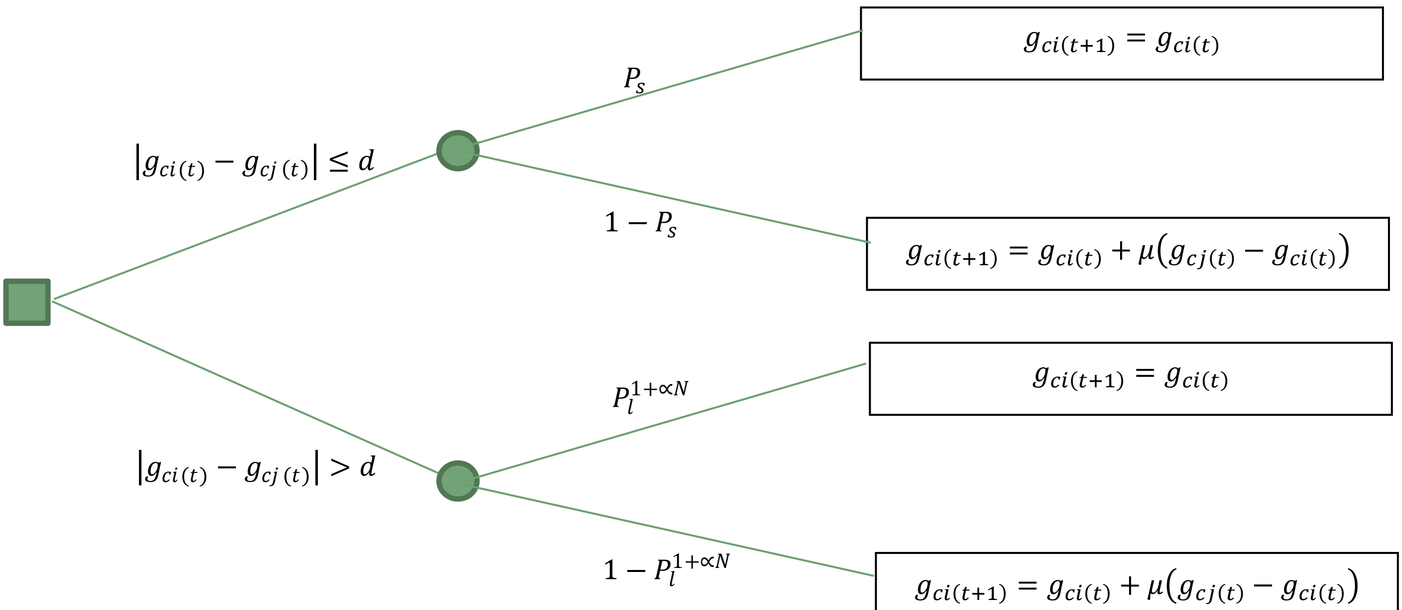


Figure 3: Opinion tree of model 2: the cognitive dissonance model.

4.4 Model 3: The idealism model

Model 3 builds on the cognitive dissonance model by adding a simplified idealism clause. In the idealism model, it is assumed idealists will not experience cognitive dissonance when encountering agents who are non-idealists. The rationale behind this is that in these scenarios, idealists are not susceptible to the arguments or peer pressure to increase meat consumption by people outside of their belief group. This might be because their core values surrounding ethics or sustainability prevent cognitive dissonance to adjust their beliefs upwards when the pressure comes from an in their eyes unreliable source, i.e., non-idealists. Therefore, it is assumed the cognitive dissonance an idealist experiences from not considering non-idealists' beliefs, is lower than the cognitive dissonance that would be experienced by deviating from their core values. Thus, an idealist can never be influenced by a non-idealist.

An agent is considered an idealist if their opinion weight g_{cit} is below or equal to idealist threshold ι ($g_{cit} \leq \iota$). It is assumed they can only potentially be influenced by an encounter if agent A_j also holds a belief below or equal to idealist threshold ι ($g_{cjt} \leq \iota$). If an idealist encounters another idealist, the interaction follows the second model of cognitive dissonance. So, idealists can only be potentially influenced by other idealists. If an idealist encounters a non-idealist, the idealist will keep their current belief. People who are considered non-idealists ($g_{cit} > \iota$), can be influenced by both idealists and non-idealists in a similar manner to model 2 of cognitive dissonance. It is assumed $0 \geq \iota \geq 1$. See figure 3, for a visual representation of the idealism model.

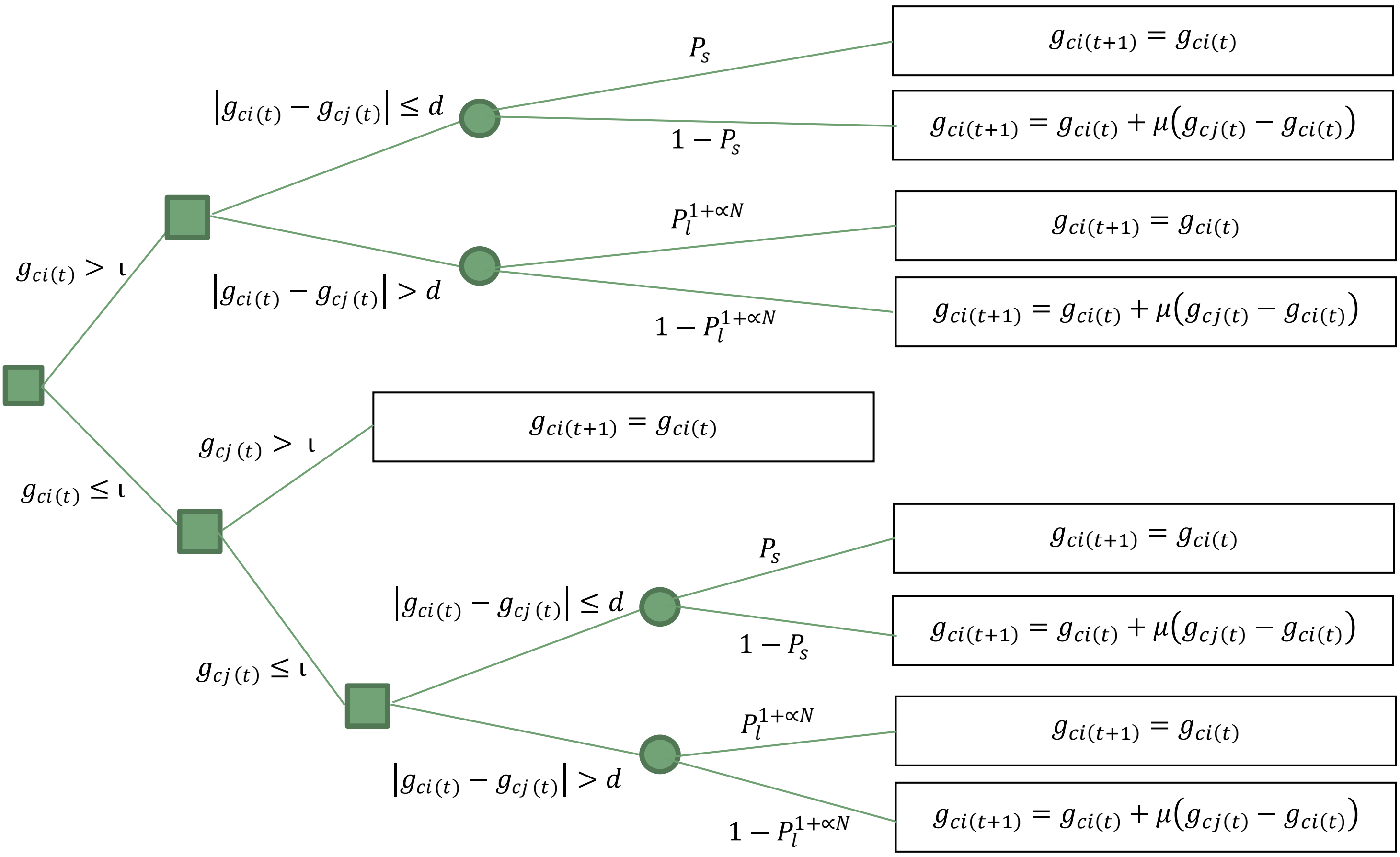


Figure 4: Opinion tree of model 3: the idealism model.

5. Results social influence model

5.1 General assumptions

In order to generate the results for this social influence model, 20 different scenarios were run. A scenario, looks at how the simulation model behaves under different parameter values and initial distribution types. Each scenario in these results chapters consists of 30 runs. A run of a particular scenario, executes the model with the parameters for that scenario once. Each run consists of 10 rounds or timesteps. Executing a run results in 10 observations per timestep. The scenario cumulates all observations of the individual 30 runs. Therefore, a scenario has 300 observations per timestep.

Before an individual run is executed, the positions of the initial distribution values are randomized. This is done to avoid undue influences of the position of specific values on the end results for the scenario, which looks at the observations of all 30 runs together. Each individual run is independent of all other runs. Therefore, as the number of runs increases, a possible slight dependence within runs is minimized further and further with each additional run. In the case of a scenario, which is run 30 times, each single observation in the final distribution is at most influenced by 9 out of the 300 final distribution observations. Thus, by looking at the observations of all 30 runs of each scenario together, independence of observations can be assumed. This independence of observations in the final distribution is necessary to compare the final distribution of one scenario with the final distribution of another scenario. Figure 5, gives an overview of the possible range of values used for each parameter in the different scenarios. Figure 6 gives an overview of all 20 scenarios executed for the social influence model. Figure 7 and 8, show the four different types of initial distributions used in the scenarios.

The Q-Q plots and detrended Q-Q plots for the observations in the final distribution (t=10), indicated the data was non-normally distributed or that the error of the datapoints was not randomly distributed around 0. Furthermore, the final distributions between scenarios cannot automatically be considered similar in shape and variance looking at the Q-Q plots, detrended Q-Q plots and histograms of the final distributions of each scenario. The non-normality of the data and unequal variances between final distributions of scenarios place limits on the available tests. To compare the final distributions (t=10) between scenarios two sample Kolmogorov-Smirnov tests were done. The Kolmogorov-Smirnov test compares whether two samples are likely drawn from the same distribution, by testing the maximum distance between distribution A and distribution B, when plotted on a cumulative distribution function. Contrasted to other some other tests, this can compare the distributions of two samples to each other. Rather than testing whether both samples come from one of the standard distributions, such as the normal or chi-squared distribution. The Kolmogorov-Smirnov test looks at both differences in location and shape between the two distributions. The null-hypothesis is that both samples come from the same distribution, i.e., the samples do not have a statistically significantly different distribution. Note that this test does not indicate the characteristics of the common distribution. Because this test does not exclude any types of differences, the test is less powerful than tests looking at whether samples come from a specific type of common distribution. However, if two samples do not follow a well-known distribution they can still be compared with a Kolmogorov-Smirnov test.

	Social influence threshold d	Convergence dispersion parameter μ
Low	0.1	0.15
Standard	0.3	0.3
High	0.5	0.45

Figure 5: Range of parameter values used in the social influence scenarios (model 1).

	Type of distribution	Model	Differing parameter values
Scenario 1	Even distribution (type 1)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 2	Polarized distribution (type 2)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 3	Low meat attachment distribution (type 3)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 4	High meat attachment distribution (type 4)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 5	Even distribution (type 1)	1	Low d (d = 0.1)
Scenario 6	Even distribution (type 1)	1	High d (d = 0.5)
Scenario 7	Polarized distribution (type 2)	1	Low d (d = 0.1)
Scenario 8	Polarized distribution (type 2)	1	High d (d = 0.5)
Scenario 9	Low meat attachment distribution (type 3)	1	Low d (d = 0.1)
Scenario 10	Low meat attachment distribution (type 3)	1	High d (d = 0.5)
Scenario 11	High meat attachment distribution (type 4)	1	Low d (d = 0.1)
Scenario 12	High meat attachment distribution (type 4)	1	High d (d = 0.5)
Scenario 13	Even distribution (type 1)	1	Low μ (μ = 0.15)
Scenario 14	Even distribution (type 1)	1	High μ (μ = 0.45)
Scenario 15	Polarized distribution (type 2)	1	Low μ (μ = 0.15)
Scenario 16	Polarized distribution (type 2)	1	High μ (μ = 0.45)
Scenario 17	Low meat attachment distribution (type 3)	1	Low μ (μ = 0.15)
Scenario 18	Low meat attachment distribution (type 3)	1	High μ (μ = 0.45)
Scenario 19	High meat attachment distribution (type 4)	1	Low μ (μ = 0.15)
Scenario 20	High meat attachment distribution (type 4)	1	High μ (μ = 0.45)

Figure 6: Overview of scenarios for the social influence model

Type 1		Type 2		Type 3		Type 4
0.1		0.1		0		0.15
0.2		0.15		0.05		0.3
0.3		0.2		0.1		0.45
0.4		0.25		0.15		0.7
0.5		0.3		0.2		0.75
0.5		0.7		0.25		0.8
0.6		0.75		0.3		0.85
0.7		0.8		0.55		0.9
0.8		0.85		0.7		0.95
0.9		0.9		0.85		1

Figure 7: Overview of the even distribution (type 1), the polarized distribution (type 2), the low meat attachment distribution (type 3), and the high meat attachment distribution (type 4).

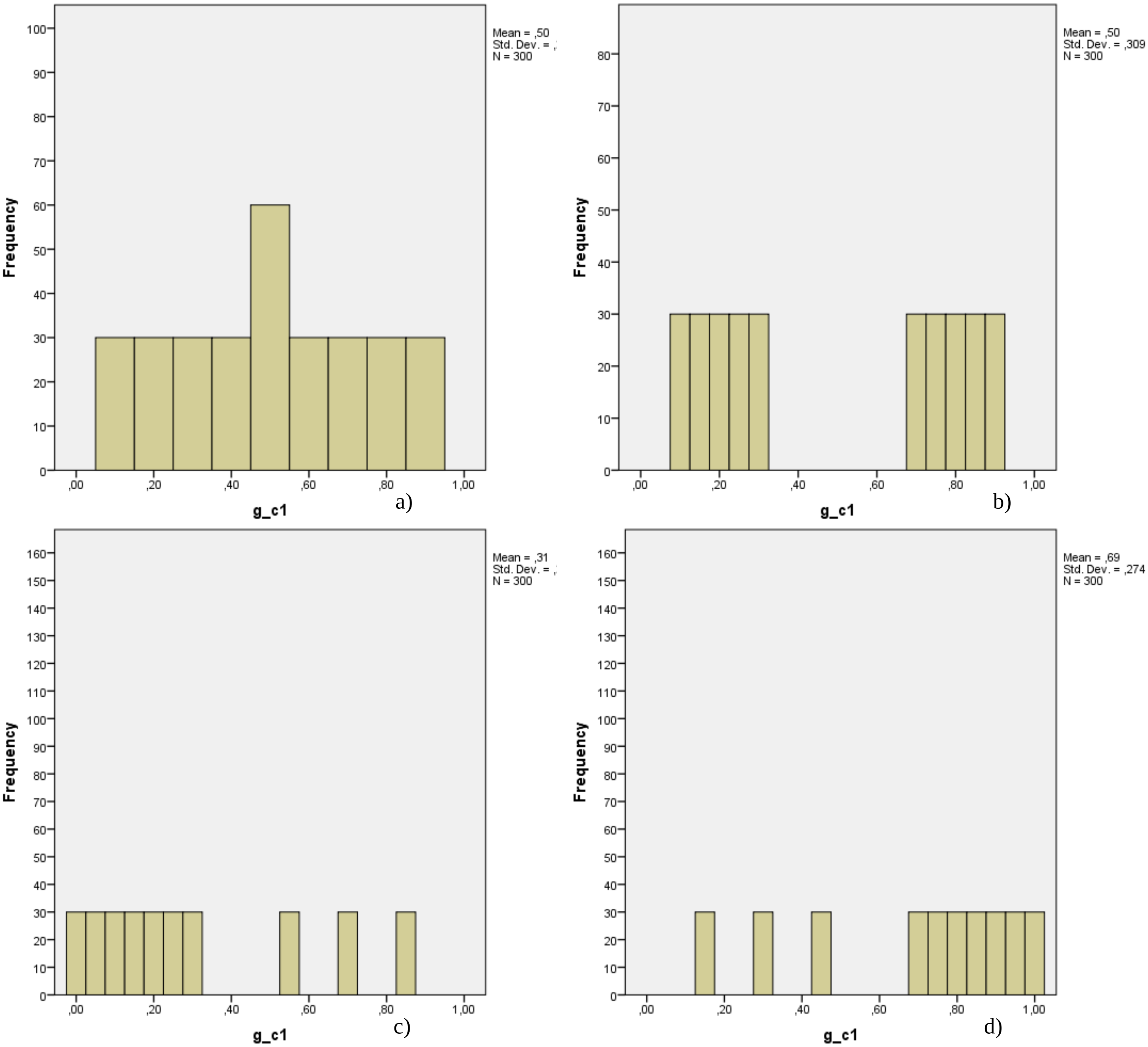


Figure 8: Histograms of the initial distributions: even distribution (a), polarized distribution (b), low meat attachment (c), high meat attachment (d)

5.2 Standard scenarios

5.2.1 Standard even distribution

- Scenario 1:
  - Standard threshold d (d = 0.3)
  - Standard convergence parameter μ (μ =0.3)
  - Even distribution (type 1 distribution)

Figure 9, shows the scatterplot of all datapoints of scenario 1 and a histogram of the final distribution. As one can see all runs started with the same initial distribution. In the following timesteps the mechanism of social influence led to an adjustment of opinions for certain agents. The patterns in the scatterplot and the histogram indicate that, under this scenario, opinions in the final distribution were converging towards a consensus around the mean. With occasionally some fragmentation happening at the extremities. The convergence towards a consensus around the mean might also be indicated by a lower standard deviation in the final distribution (0.152) compared to the initial distribution of opinions (0.245). Figure 10, shows two examples of individual runs of scenario 1. Note that in the first run there is stronger convergence with a couple of fragmented outliers, while the other run does not necessarily show fragmentation in the outliers, but the consensus around the mean seems a little less strong. This shows that there is always some variation in the final distribution of individual runs, and multiple runs are necessary in order to be able to compare final distributions between scenarios. There is too much variation in singular runs otherwise.

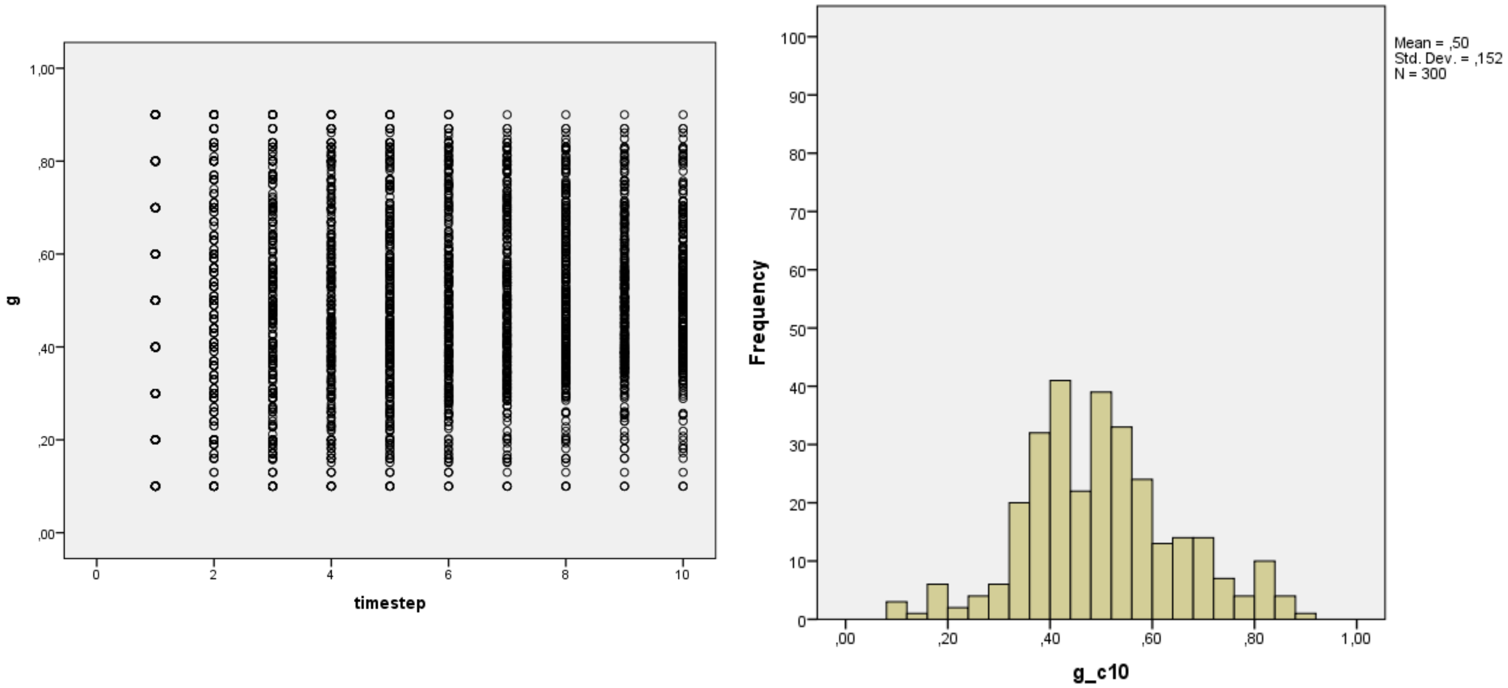


Figure 9: Scatterplot of all datapoints and the histogram of the final distribution for scenario 1: Standard even distribution

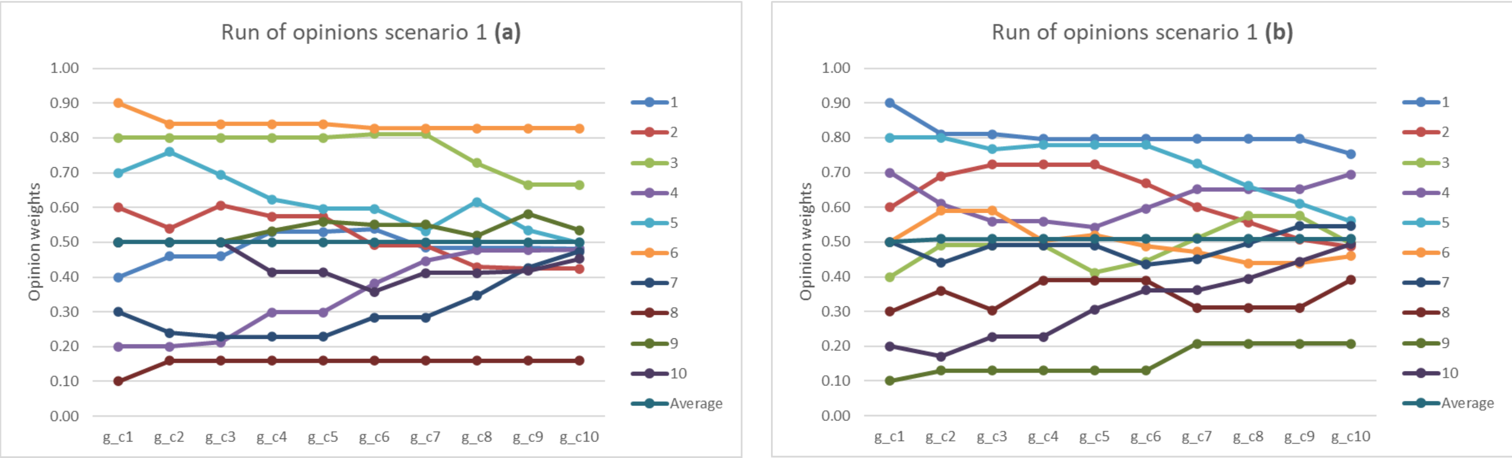


Figure 10: Two examples of a run of scenario 1 (Standard even distribution).

5.2.2 Standard polarized distribution

- Scenario 2:
  - Standard threshold d (d = 0.3)
  - Standard convergence parameter µ (µ =0.3)
  - Polarized distribution (type 2 distribution)

In figure 11, both a scatterplot of all datapoints of scenario 2 and a histogram of the final distribution can be found. From these two graphs, it seems as if the initial polarization is enhanced further by the model of social influence as we can see a further polarization of the opinions at the two extremities. The difference becomes clearer when we compare the histogram of the final distribution (figure 11) to the histogram of the initial distribution (figure 8b). Scenario 2, seems to result in an increased polarization of opinions. See figure 12 for a visualization of an example of a singular run of scenario 2.

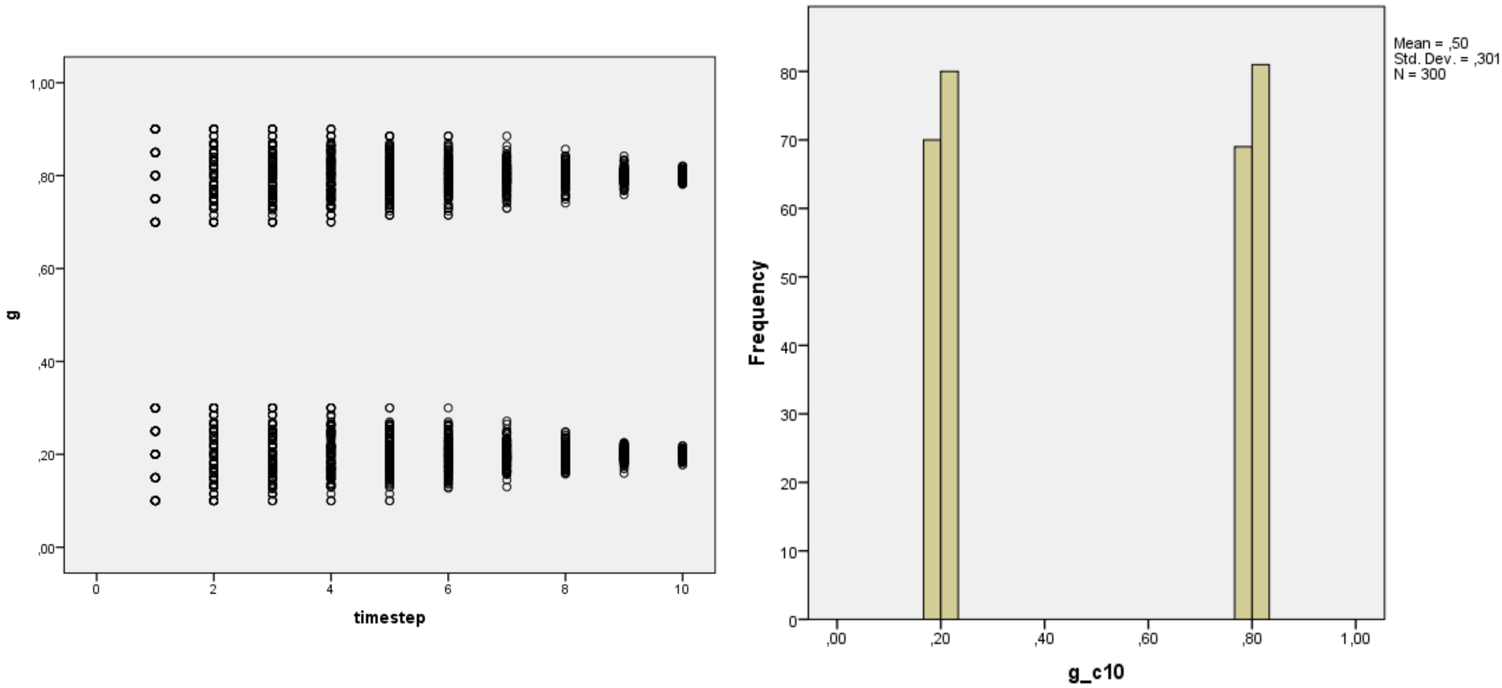


Figure 11: Scatterplot of all datapoints and the histogram of the final distribution for scenario 2: Standard Polarized distribution

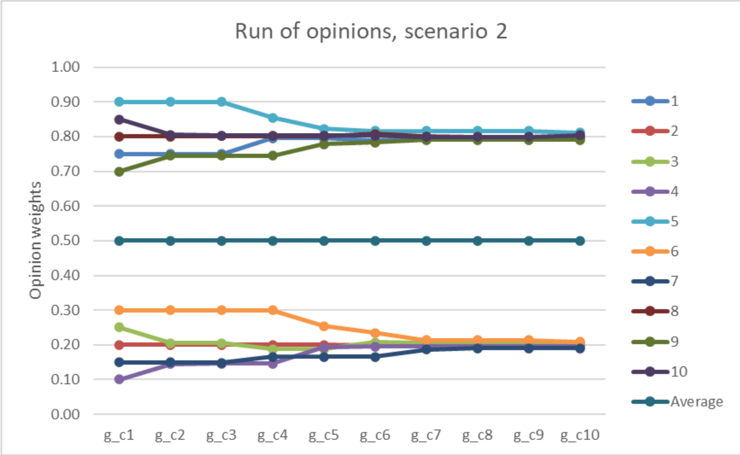


Figure 12: An example of a run of scenario 2: Standard polarized distribution

5.2.3 Standard spread skewed towards low meat attachment

- Scenario 3:
  - Standard threshold d (d = 0.3)
  - Standard convergence parameter μ (μ =0.3)
  - Skewed distribution towards low meat attachment (type 3 distribution)

In figure 13 a scatterplot of all datapoints of scenario 3 can be found, as well as a histogram of the final distribution. This shows that the majority opinions converge together and the minority opinions also seem to converge and cluster together, resulting in two polarized positions, where the majority converge towards an opinion that indicates a low attachment to meat. See figure 14, for a sample of a run of scenario 3. When comparing the histogram of the final distribution (figure 13) to the histogram of the initial distribution (figure 8c), we see an increased clustering of the majority opinion, which might be the reason the standard deviation in the final distribution (0.246) is slightly lower than in the initial distribution (0.274). In figure 14, two examples of a run of scenario 3 can be seen. In the first run, one of the minority opinions joins the majority consensus, while in the second example of a run, all minority opinions converge together. Showing the some of the diverseness of individual runs.

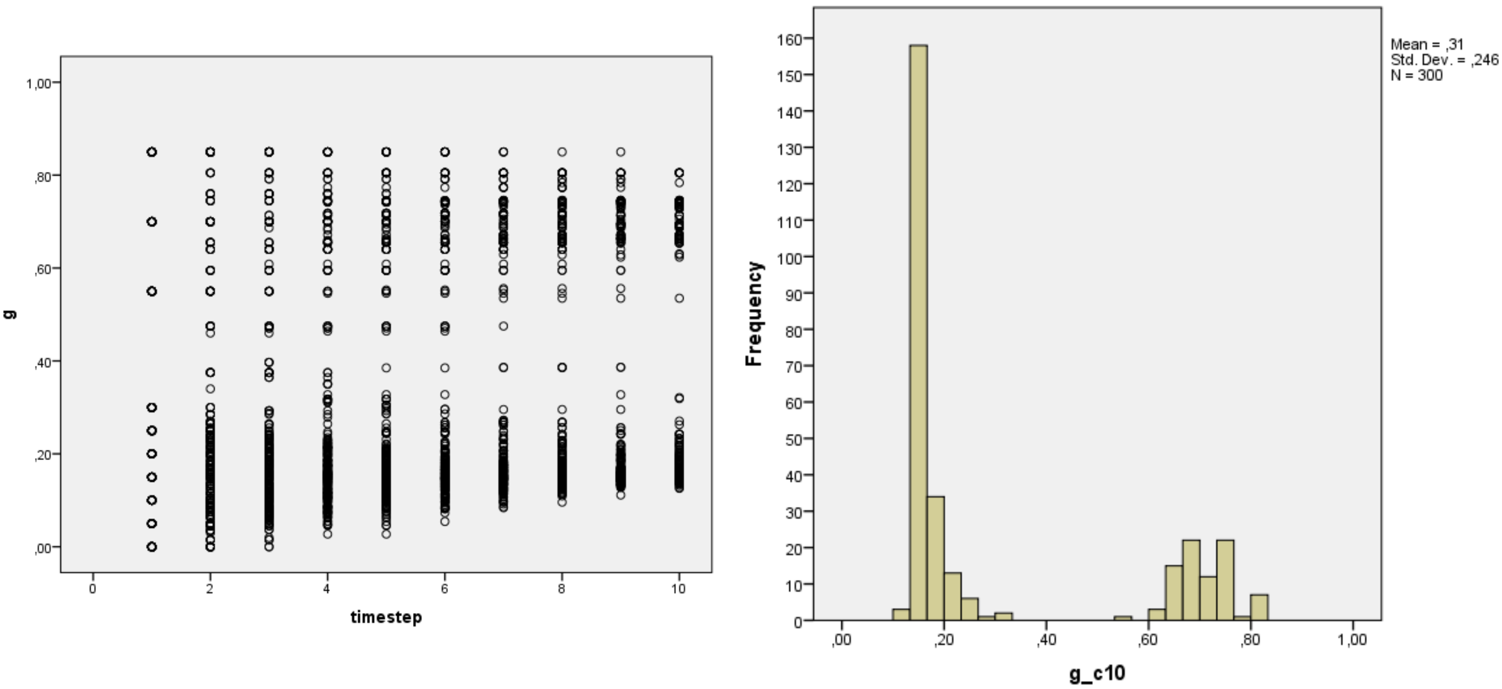


Figure 13: Scatterplot of all datapoints and the histogram of the final distribution for scenario 3: Standard distribution skewed towards low meat attachment

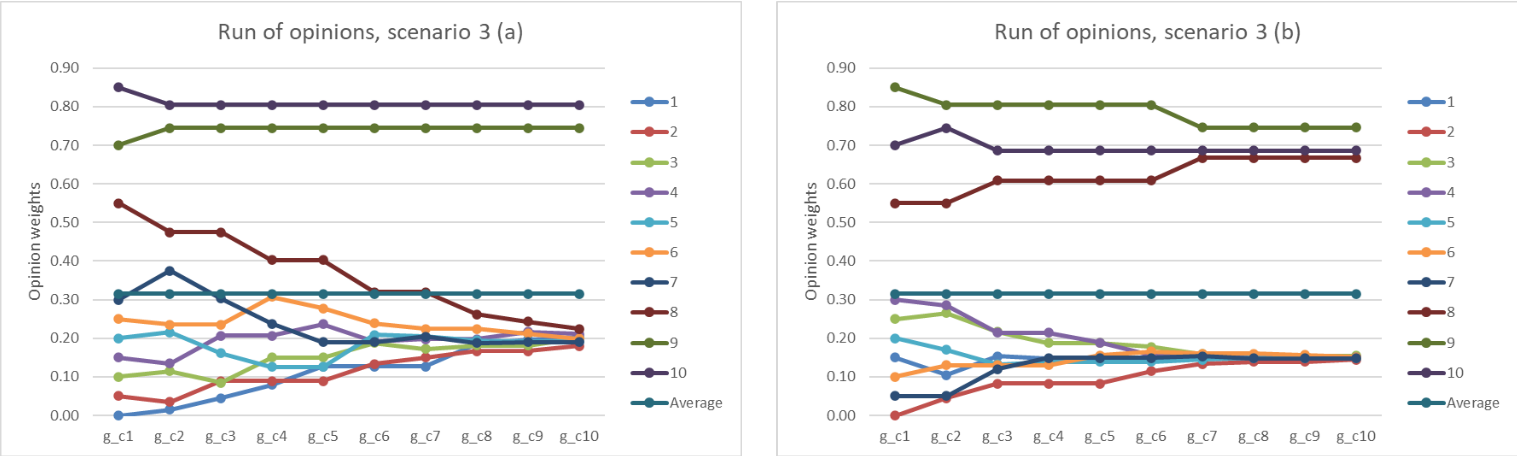


Figure 14: Two examples of a run of scenario 3 (Standard distribution skewed towards low meat attachment).

5.2.4 Standard spread skewed towards high meat attachment

- Scenario 4:
    - Standard threshold d (d = 0.3)
    - Standard convergence parameter μ (μ =0.3)
    - Skewed distribution towards high meat attachment (type 4 distribution)

In figure 15, a scatterplot of all datapoints of scenario 4 and a histogram of the final distribution are illustrated. Both the scatterplot and the histogram show a convergence of the majority opinions and the minority opinion. This results in two polarized positions. The majority seems to converge towards an opinion which indicates a high attachment to meat. Scenario 4 is almost a mirrored version of scenario 3 in this version. As expected by the design of the social influence model. Figure 16, shows two examples of individual runs of scenario 4. Illustrating some of the variation between individual runs.

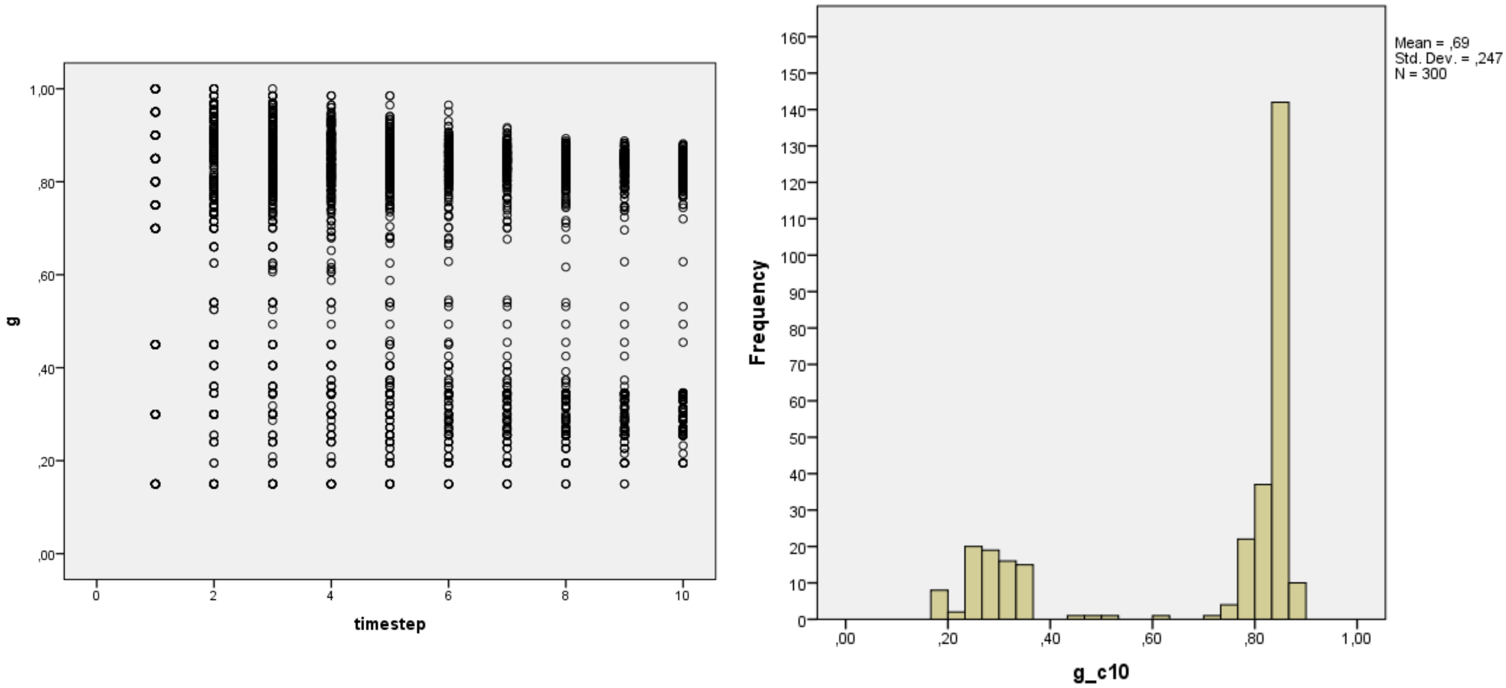
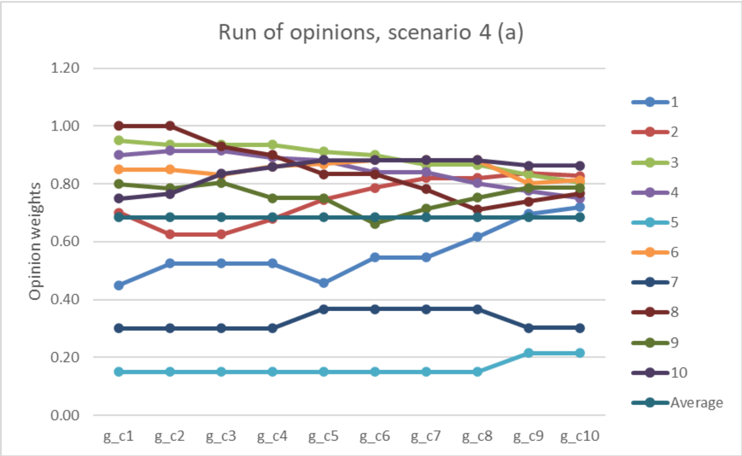


Figure 15: Scatterplot of all datapoints and the histogram of the final distribution for scenario 4: Standard distribution skewed towards high meat attachment



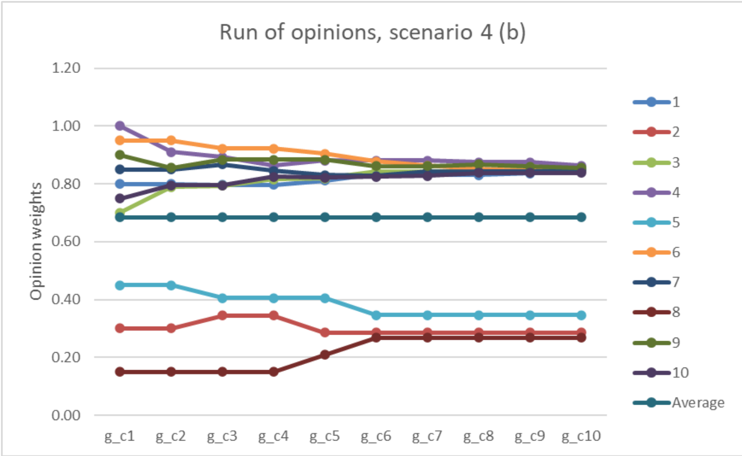


Figure 16: Two examples of a run of scenario 4 (Standard distribution skewed towards high meat attachment).

5.3 Scenarios comparing social influence threshold d

Low social influence thresholds d (Scenario 5, 7, 9, & 11):

- Scenario 5:
  - Low social influence threshold d (d = 0.1)
  - Even distribution (type 1 distribution)
- Scenario 7:
  - Low social influence threshold d (d = 0.1)
  - Polarized distribution (type 2 distribution)
- Scenario 9:
  - Low social influence threshold d (d = 0.1)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 11:
  - Low social influence threshold d (d = 0.1)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High social influence thresholds d (Scenario 6, 8, 10 & 12):

- Scenario 6:
  - High social influence threshold d (d = 0.5)
  - Even distribution (type 1 distribution)
- Scenario 8:
  - High social influence threshold d (d = 0.5)
  - Polarized distribution (type 2 distribution)
- Scenario 10:
  - High social influence threshold d (d = 0.5)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 12:
  - High social influence threshold d (d = 0.5)
  - Skewed distribution towards high meat attachment (type 4 distribution)

Figure 17 and figure 18 on the next page show the scatterplots of the scenarios with a low and high social influence threshold d. When comparing the two figures, it seems scenarios with a high social influence threshold (figure 18), reach a higher rate of consensus at the final distribution, compared to the scenarios with a low social influence threshold (figure 17). Low social influence threshold scenarios, also seem to have more fragmentation compared to the high social influence threshold scenarios.

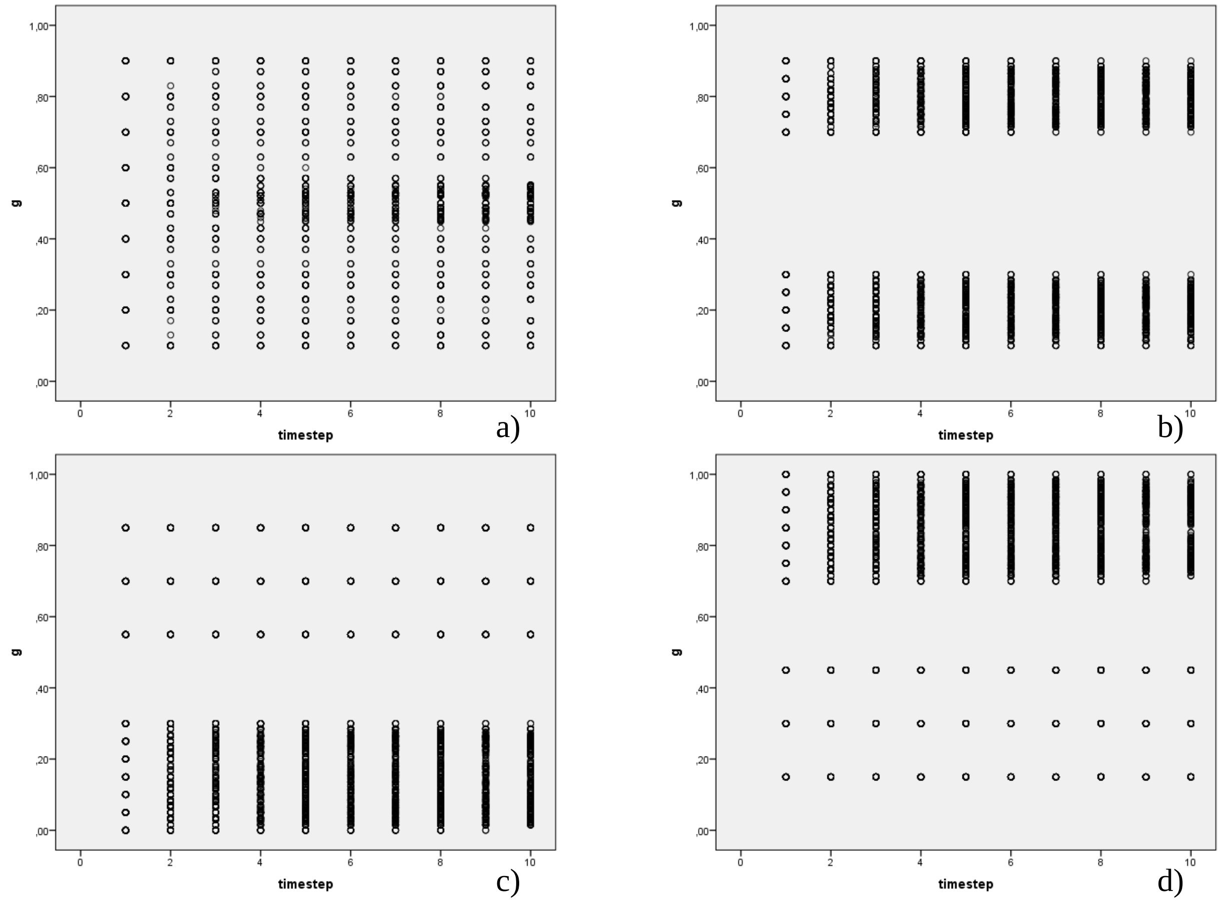


Figure 17: Scatterplots of all datapoints for scenarios with a low social influence threshold d; scenario 5 (a, even distribution), scenario 7 (b, polarized distribution), scenario 9 (c, low meat attachment), and scenario 11 (d, high meat attachment)

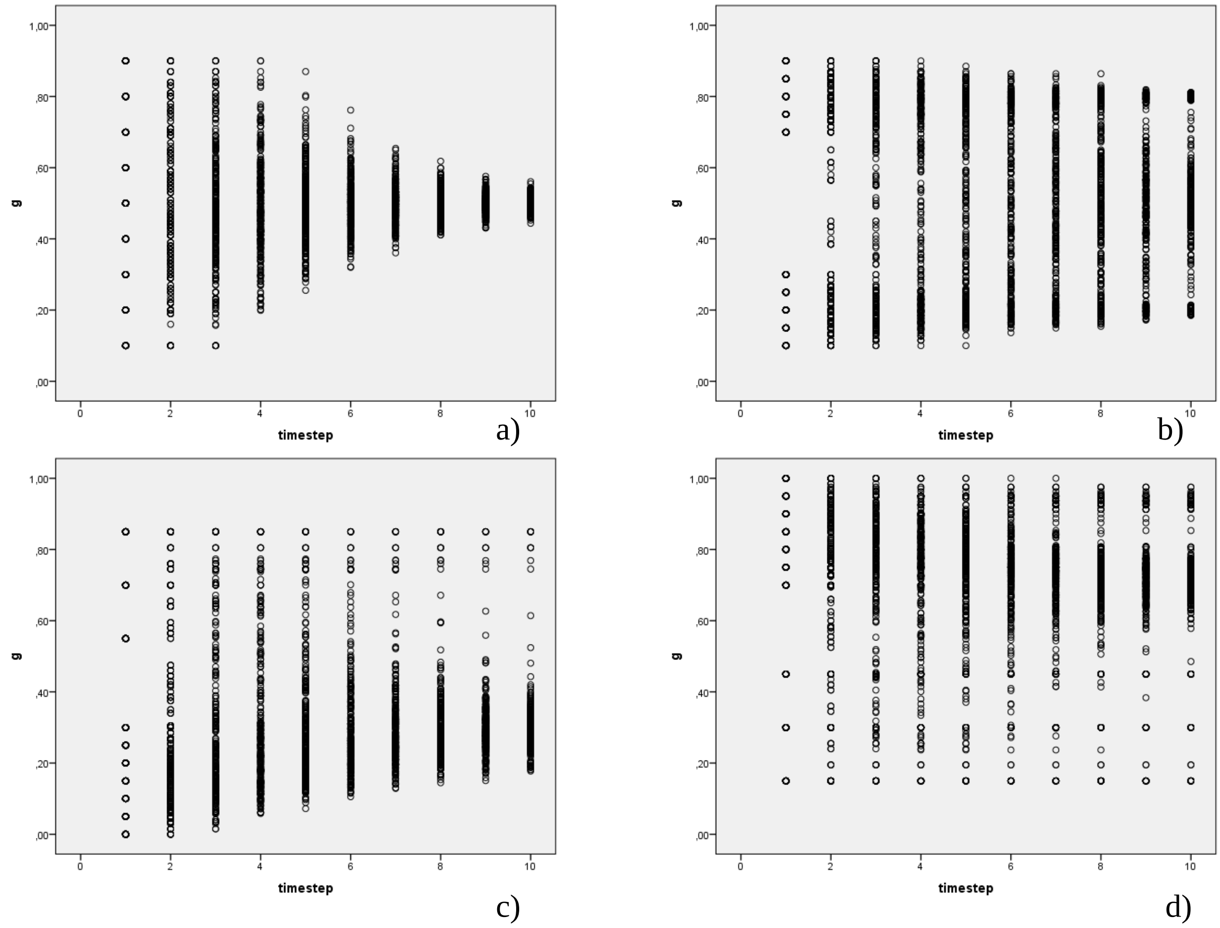


Figure 18: Scatterplots of all datapoints for scenarios with a high social influence threshold d; scenario 6 (a, even distribution), scenario 8 (b, polarized distribution), scenario 10 (c, low meat attachment), and scenario 12(d, high meat attachment)

For low social influence thresholds, there is not a clear convergence of the minority opinions in scenario 9 and 11 (see figure 17c/17d and 19c/19d), in contrast to the standard low and high meat attachment scenarios (scenarios 3 and 4, and figures 13 and 15 respectively). Furthermore, in polarized distribution scenario 7 (see figures 17b and 19b), there is still a polarization in the final distribution. However, within these polarized opinion clusters, the opinions seem to be slightly less closely clustered; When compared to the final distribution of the standard polarized scenario (scenario 2, see figure 11). Similarly, for the even distribution (scenario 5, figures 17a and 19a), there seems to be less convergence towards a consensus around the mean and heavier fragmentation in the final distribution, compared to the standard even distribution (scenario 1, see figure 9).

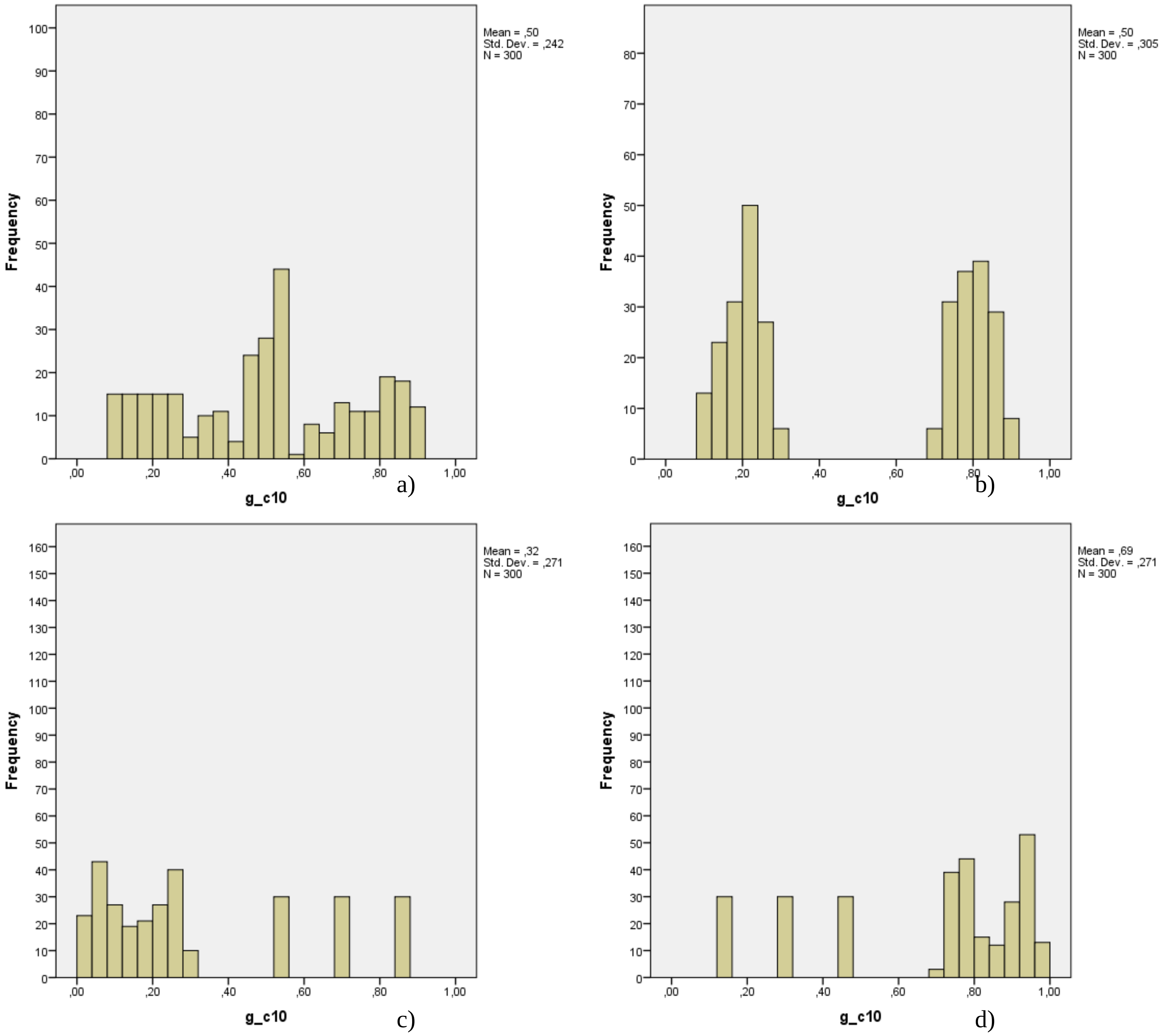


Figure 19: Histograms of the final distributions of scenarios with a low social influence threshold d; 5 (a, even distribution), 7 (b, polarized distribution), 9 (c, low meat attachment distribution), 11 (d, high meat attachment distribution)

However, in the case of high social influence thresholds (figures 18 and 20), it seems as if the effect is opposite. There seems to be a higher consensus in the final distribution around the mean, which is clustered more closely in the even distribution under a high threshold (scenario 6) compared to the standard even distribution (scenario 1). Furthermore, we even see that a very high social threshold can see the beginnings of a break through the polarization in the final distribution of scenario 8. In this scenario the gap between some of the polarized opinions is smaller than the social influence threshold d. The tail ends in scenario 8 are relatively high, suggesting some fragmentation is still left in the final distribution. In the scenarios of low and high meat attachment (scenarios 10 and 12, respectively), there seem to be fewer minority opinions compared to the standard scenarios (scenarios 3 and 4, respectively).

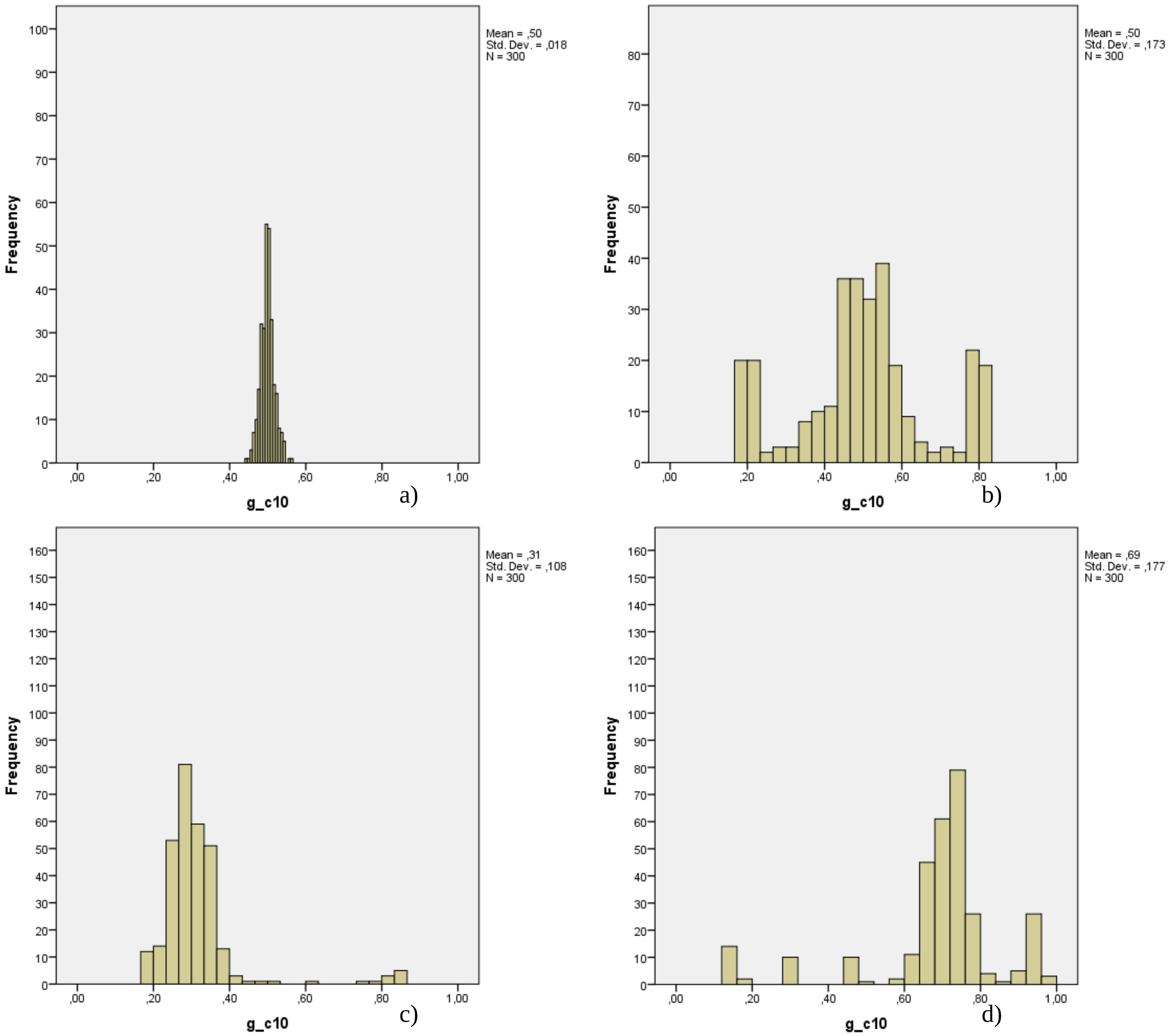


Figure 20: Histograms of the final distributions of scenarios with a high social influence threshold d; 6 (a, even distribution), 8 (b, polarized distribution), 10 (c, low meat attachment distribution), 12 (d, high meat attachment distribution)

To test whether the final distributions of the scenarios are indeed significantly different from each other, Kolmogorov-Smirnov tests can be done. The null-hypothesis is that the final distributions of the scenarios come from the same distribution, i.e., the samples do not have a statistically significantly different distribution. The results of the Kolmogorov-Smirnov tests between scenarios can be found in the tables 1 to 4 below. These tests show that all scenarios starting with the same initial distribution have significantly different final distributions from each other. Thus, confirming that the final distributions in the histograms are all statistically significantly different from each other with a confidence of 95%, since all p-values are lower than 0.05. Thus, indicating changing the social influence threshold d has a significant impact on the final distributions.

Kolmogorov p-values	1	5	6
1 (Standard, model 1)		**0.000**	**0.000**
5 (low d)	**0.000**		**0.000**
6 (high d)	**0.000**	**0.000**	

Table 1: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	7	8
2 (Standard, model 1)		**0.000**	**0.000**
7 (low d)	**0.000**		**0.000**
8 (high d)	**0.000**	**0.000**	

Table 2: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	9	10
3 (Standard, model 1)		**0.000**	**0.000**
9 (low d)	**0.000**		**0.000**
10 (high d)	**0.000**	**0.000**	

Table 3: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	11	12
4 (Standard, model 1)		**0.000**	**0.000**
11 (low d)	**0.000**		**0.000**
12 (high d)	**0.000**	**0.000**	

Table 4: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

5.4 Scenarios comparing convergence parameter μ

Low convergence parameter μ (Scenario 13, 15, 17 & 19):

- Scenario 13:
  - Low convergence parameter μ (μ =0.15)
  - Even distribution (type 1 distribution)
- Scenario 15:
  - Low convergence parameter μ (μ =0.15)
  - Polarized distribution (type 2 distribution)
- Scenario 17:
  - Low convergence parameter μ (μ =0.15)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 19:
  - Low convergence parameter μ (μ =0.15)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High convergence parameter μ (Scenario 14, 16, 18 & 20):

- Scenario 14:
  - High convergence parameter μ (μ =0.45)
  - Even distribution (type 1 distribution)
- Scenario 16:
  - High convergence parameter μ (μ =0.45)
  - Polarized distribution (type 2 distribution)
- Scenario 18:
  - High convergence parameter μ (μ =0.45)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 20:
  - High convergence parameter μ (μ =0.45)
  - Skewed distribution towards high meat attachment (type 4 distribution)

Figures 21 and 22 below, show the scatterplots of all datapoints for the scenarios with either a low or high convergence parameter μ. It seems as if changing convergence parameter μ from the standard value, leads to scatterplots with similar overall trends compared with the standard scenario.

Looking at the scatterplots in figure 21 (scenarios with a low convergence parameter μ), the trends seen in these scenarios seem similar to the trends of the comparable standard scenarios, but perhaps less pronounced.

For the scatterplots for the scenarios with a high convergence parameter μ (figure 22), the plots look rather similar to the scatterplots of the standard scenarios. The trends are similar and a clear difference is difficult to demarcate by only looking at the histograms of the final distribution.

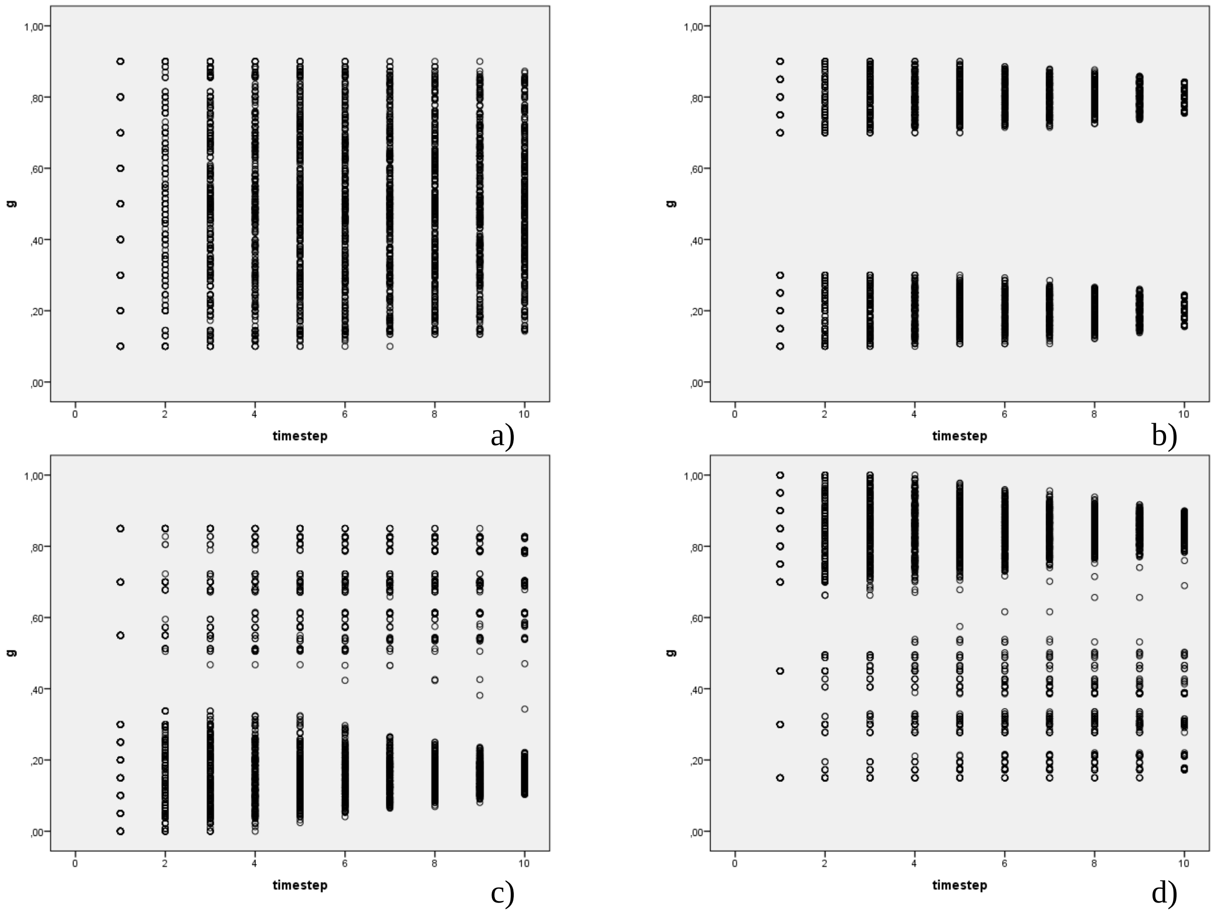


Figure 21: Scatterplots of all datapoints for scenarios with a low convergence parameter μ; scenario 13 (a, even distribution), scenario 15 (b, polarized distribution), scenario 17 (c, low meat attachment), and scenario 19 (d, high meat attachment)

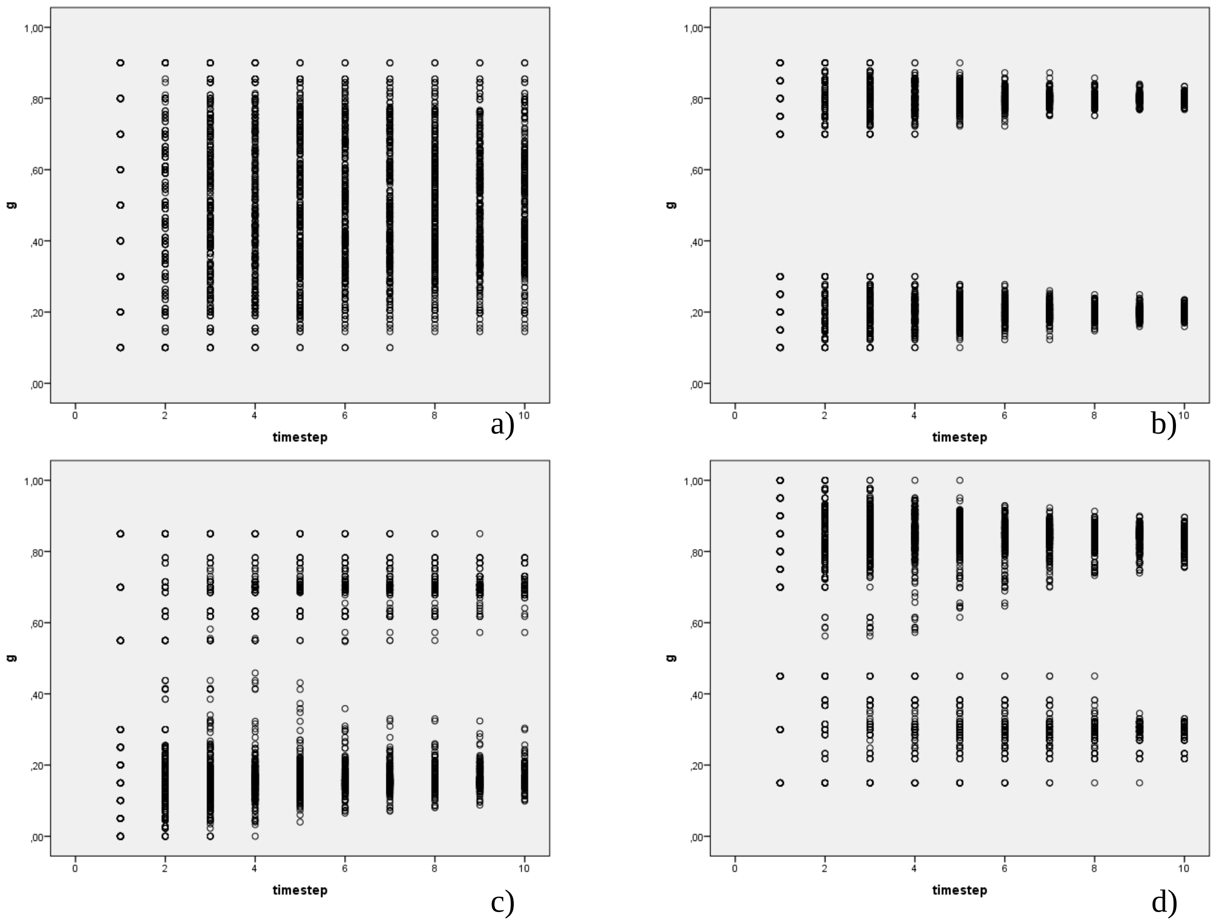


Figure 22: Scatterplots of all datapoints for scenarios with a high convergence parameter μ; scenario 14 (a, even distribution), scenario 16 (b, polarized distribution), scenario 18 (c, low meat attachment), and scenario 20 (d, high meat attachment)

For scenarios with a low convergence parameter μ (figure 23), the trends seen in the histograms of the scenarios seem similar to the trends of the comparable standard scenarios, but less pronounced. In even distribution scenario 13, there is still a convergence towards consensus around the mean compared to the initial distribution. However, compared to the standard even distribution (scenario 1), the consensus seems less pronounced and more spread out and still somewhat fragmented. Comparing polarized distribution scenario 15, with the standard polarized distribution scenario 2, it seems as if observations within the polarization are less heavily clustered, but still polarized. When we look at the low and high meat attachment scenarios (17 and 19, respectively), it seems these scenarios mirror each other fairly well, as is expected from the construction of the simulation model. And therefore, both have a lower convergence for the majority opinion compared to the comparable standard scenarios (3 and 4).

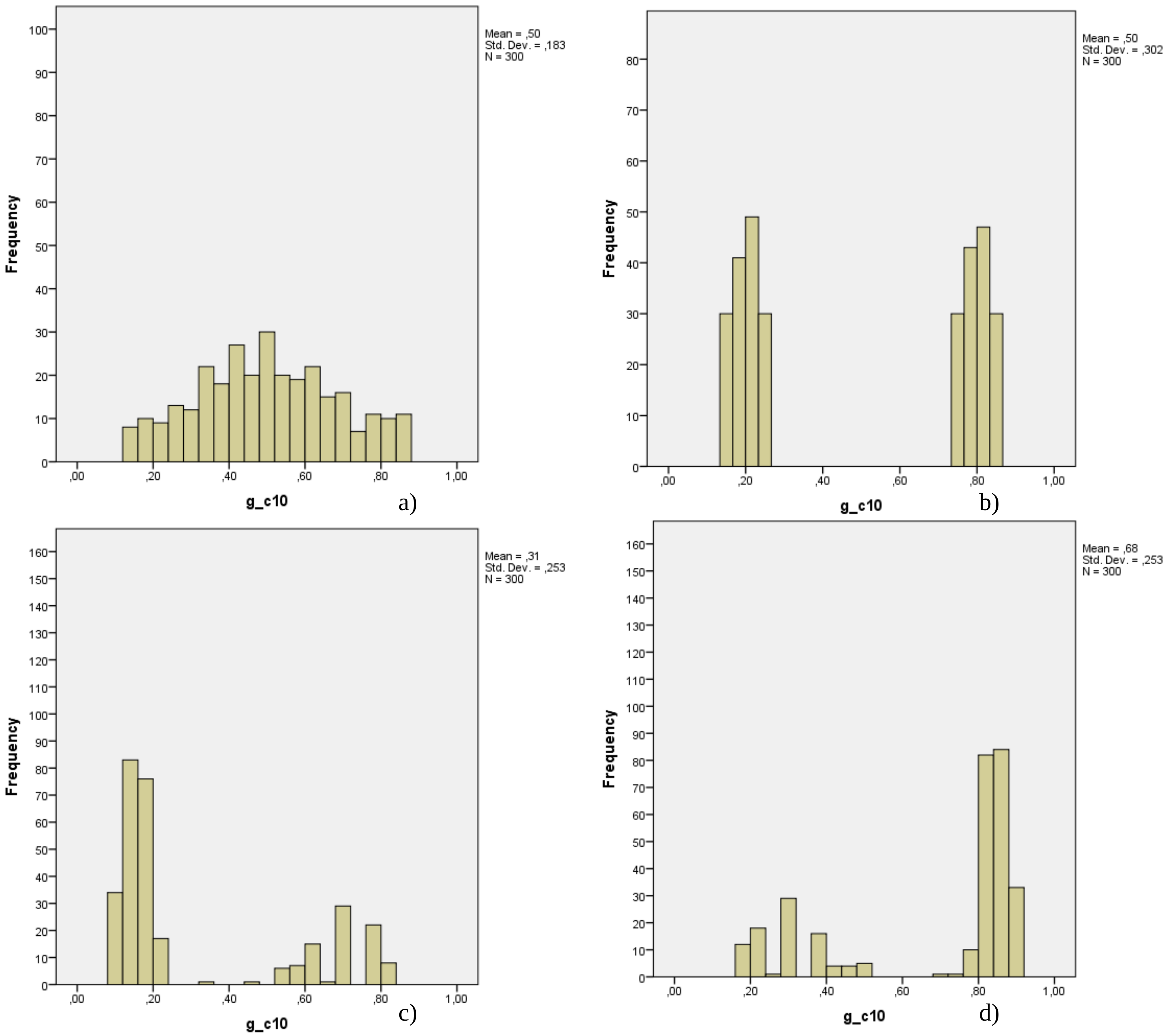


Figure 23: Histograms of the final distributions of the scenarios with a low convergence parameter μ; scenario 13 (a, even distribution), scenario 15 (b, polarized distribution), scenario 17 (c, low meat attachment), and scenario 19 (d, high meat attachment)

Similar to the scatterplots for the scenarios with a high convergence parameter μ, the histograms (see figure 24) also seem to indicate the final distributions are fairly similar to the final distributions of the comparable standard final distributions. A clear difference is difficult to state based on the scatterplots and histograms alone.

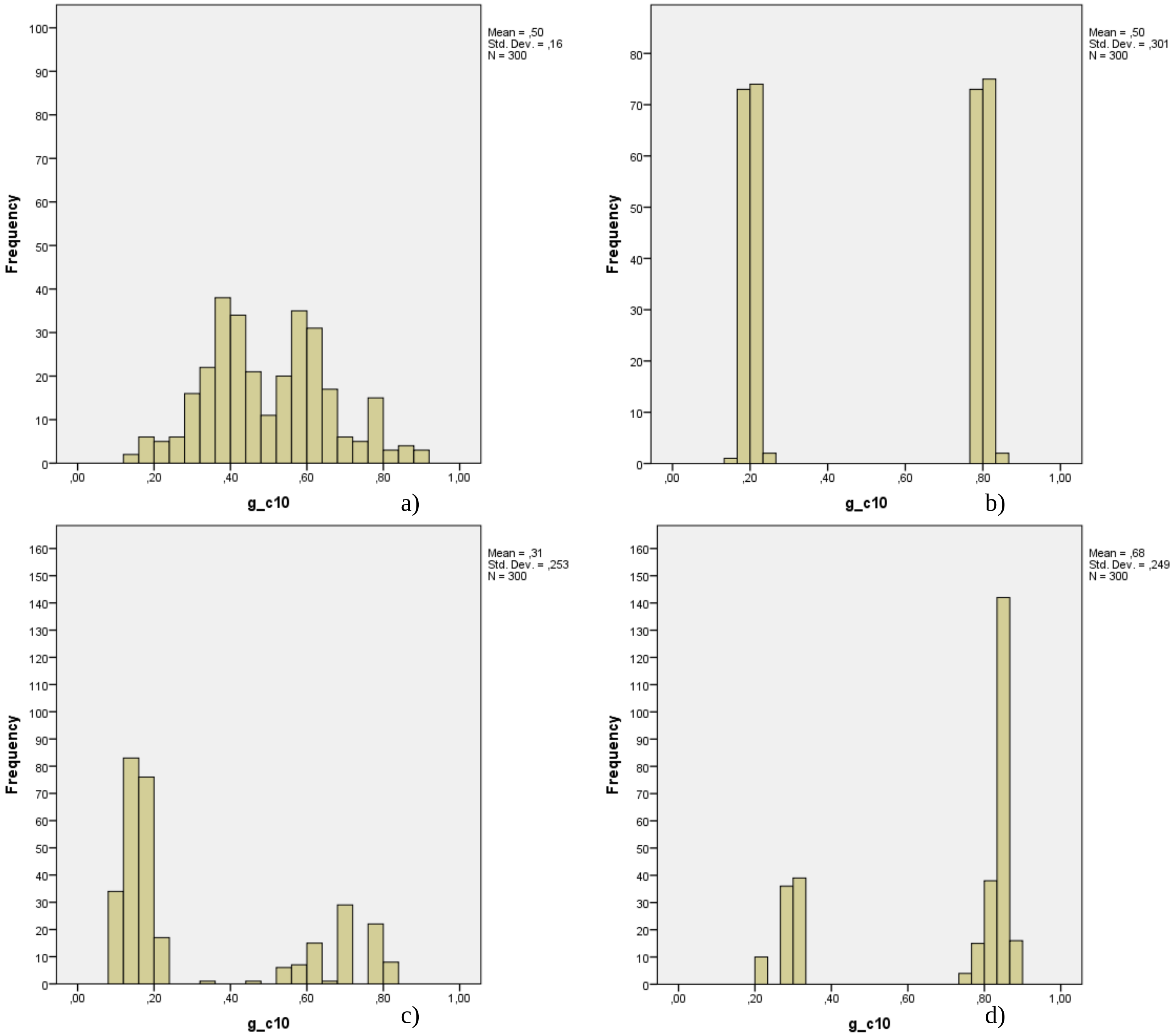


Figure 24: Histograms of the final distributions of the scenarios with a high convergence parameter μ; scenario 14 (a, even distribution), scenario 16 (b, polarized distribution), scenario 18 (c, low meat attachment), and scenario 20 (d, high meat attachment)

To test whether the final distributions of the scenarios are indeed significantly different from each other, Kolmogorov-Smirnov tests can be done. The null-hypothesis is that both samples come from the same distribution, i.e. the samples do not have a statistically significantly different distribution. The results of the Kolmogorov-Smirnov tests between scenarios can be found in the tables 5 to 8 below.

From there, it becomes clear that all scenarios with a low convergence parameter values are all statistically significantly different from the comparable standard scenarios, with a confidence of more than 95%. Thus, it is likely the trends seen in the scatterplots were indeed significantly less pronounced compared to the standard scenarios. Perhaps, the statistical difference for low convergence parameter scenarios is due to a reduction in opportunities of social influence in later timesteps, since agents' opinions move only slightly as a result of social influence. By moving only slightly from their current opinion, instead of a larger step, they might not bridge the gap enough for future encounters to overcome the social influence threshold d. Thus, perhaps resulting in fewer new potential encounters in the next timestep which fall in the sphere with potential for social influence.

Furthermore, none of the Kolmogorov-Smirnov tests comparing the scenarios with a high convergence parameter μ with the comparable standard scenarios, indicated these final distributions could be determined to be statistically different from each other with a confidence of 95%. Which seems to confirm that these final distributions are indeed similar. So, it could be that a higher convergence parameter μ does not bring significant additional possibilities for social influence in future encounters compared to the standard scenarios.

Comparing the scenarios with a low μ to the scenarios with a high μ by doing a Kolmogorov-Smirnov test, indicate this test was significant with a 95% confidence for all types of distributions, except for the even distribution. This is rather unusual, but could be due to the relatively low power of the Kolmogorov-Smirnov test.

Kolmogorov p-values	1	13	14
1 (Standard, model 1)		**0.034**	0.121
13 (low μ)	**0.034**		0.249
14 (high μ)	0.121	0.249	

Table 5: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	15	16
2 (Standard, model 1)		**0.000**	0.847
15 (low μ)	**0.000**		**0.000**
16 (high μ)	0.847	**0.000**	

Table 6: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	17	18
3 (Standard, model 1)		**0.000**	0.292
17 (low μ)	**0.000**		**0.000**
18 (high μ)	0.292	**0.000**	

Table 7: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	19	20
4 (Standard, model 1)		**0.000**	0.249
19 (low μ)	**0.000**		**0.001**
20 (high μ)	0.249	**0.001**	

Table 8: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

6. Results cognitive dissonance model

6.1 General assumptions

For the model of cognitive dissonance, 28 different scenarios were run. All scenarios were run 30 times, where the runs were independent of each other. The parameter values of the standard scenarios of the first model of social influence, were used as the base for the more complex model of cognitive dissonance. Below in figure 26 an overview of the potential values given to the parameters in the scenarios. Figure 27 shows an overview of all scenarios executed for the cognitive dissonance model. Figure 25 shows the initial distributions for each type of distribution. Looking at the Q-Q plots and detrended Q-Q plots, and histograms of the initial and final distributions, showed all data distributions were non-normally distributed and seemed to exhibited unequal variances between scenarios. Therefore, the test done to compare final distributions is the Kolmogorov-Smirnov test, since it does not require data to be normal or the two distributions that are being compared to have equal variances.

	d	μ	P_s	P_l	α
Low	-	-	0.05	0.65	0.05
Standard	0.3	0.3	0.2	0.8	0.1
High	-	-	0.35	0.95	0.15

Figure 25: Range of parameter values for the cognitive dissonance scenarios (model 2)

	Type of distribution	Model	Differing parameter values
Scenario 1	Even distribution (type 1)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 21	Even distribution (type 1)	2	All standard parameter values (P_s = 0.2; P_l = 0.8; α = 0.1)
Scenario 22	Polarized distribution (type 2)	2	All standard parameter values (P_s = 0.2; P_l = 0.8; α = 0.1)
Scenario 23	Low meat attachment distribution (type 3)	2	All standard parameter values (P_s = 0.2; P_l = 0.8; α = 0.1)
Scenario 24	High meat attachment distribution (type 4)	2	All standard parameter values (P_s = 0.2; P_l = 0.8; α = 0.1)
Scenario 25	Even distribution (type 1)	2	Low P_s (P_s=0.05)
Scenario 26	Even distribution (type 1)	2	High P_s (P_s=0.35)
Scenario 27	Polarized distribution (type 2)	2	Low P_s (P_s=0.05)
Scenario 28	Polarized distribution (type 2)	2	High P_s (P_s=0.35)
Scenario 29	Low meat attachment distribution (type 3)	2	Low P_s (P_s=0.05)
Scenario 30	Low meat attachment distribution (type 3)	2	High P_s (P_s=0.35)
Scenario 31	High meat attachment distribution (type 4)	2	Low P_s (P_s=0.05)
Scenario 32	High meat attachment distribution (type 4)	2	High P_s (P_s=0.35)
Scenario 33	Even distribution (type 1)	2	Low P_l (P_l=0.65)
Scenario 34	Even distribution (type 1)	2	High P_l (P_l=0.95)
Scenario 35	Polarized distribution (type 2)	2	Low P_l (P_l=0.65)
Scenario 36	Polarized distribution (type 2)	2	High P_l (P_l=0.95)
Scenario 37	Low meat attachment distribution (type 3)	2	Low P_l (P_l=0.65)
Scenario 38	Low meat attachment distribution (type 3)	2	High P_l (P_l=0.95)
Scenario 39	High meat attachment distribution (type 4)	2	Low P_l (P_l=0.65)
Scenario 40	High meat attachment distribution (type 4)	2	High P_l (P_l=0.95)
Scenario 41	Even distribution (type 1)	2	Low α (α = 0.05)
Scenario 42	Even distribution (type 1)	2	High α (α = 0.15)
Scenario 43	Polarized distribution (type 2)	2	Low α (α = 0.05)
Scenario 44	Polarized distribution (type 2)	2	High α (α = 0.15)
Scenario 45	Low meat attachment distribution (type 3)	2	Low α (α = 0.05)
Scenario 46	Low meat attachment distribution (type 3)	2	High α (α = 0.15)
Scenario 47	High meat attachment distribution (type 4)	2	Low α (α = 0.05)
Scenario 48	High meat attachment distribution (type 4)	2	High α (α = 0.15)

Figure 26: Overview of all scenarios of the cognitive dissonance model

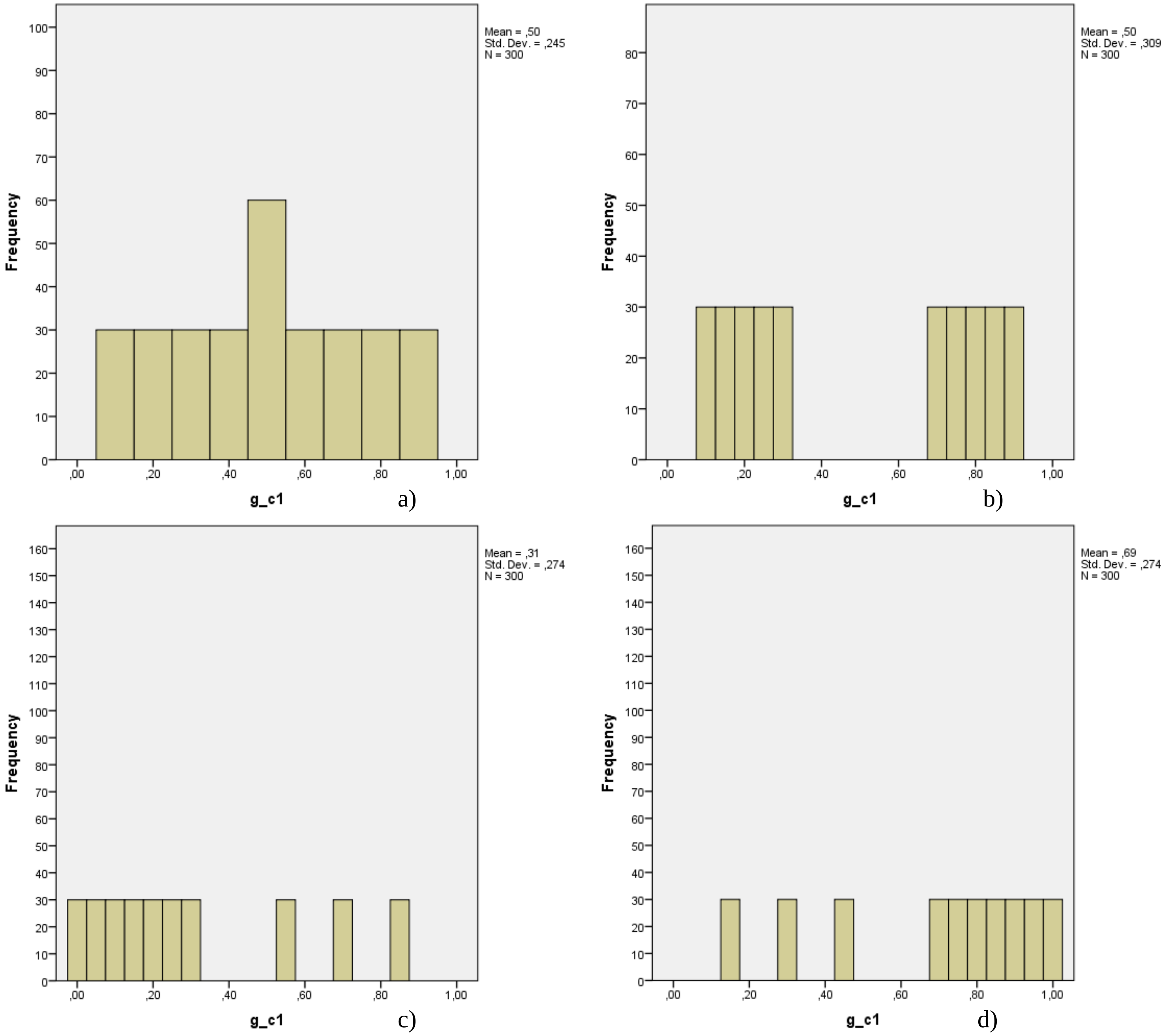


Figure 27: Histograms of the initial distributions: even distribution (a), polarized distribution (b), low meat attachment (c), high meat attachment (d)

6.2 Standard scenarios

6.2.1 Standard even distribution

- Scenario 21:
    - Standard P_s (P_s = 0.2)
    - Standard P_l (P_l =0.8)
    - Standard α (α = 0.1)
    - Even distribution (type 1 distribution)

In figure 28, the scatterplots of all datapoints of scenario 1 (model 1; social influence) and scenario 21 (model 2; cognitive dissonance) can be found side to side. It seems as if scenario 21 has a higher rate of convergence and a higher rate of consensus, compared to scenario 1. Furthermore, the number of outliers seem to be reduced in the final distribution. An example of a run for scenario 21 can be found in figure 30. These previous observations seem to be echoed when comparing the histograms of the final distributions (figure 29). The number of observations around the mean is higher, with fewer opinion observations outside the 0.40-0.60 range. The standard deviation in scenario 1 (0.152) is also higher than the standard deviation in scenario 21 (0.081). The Kolmogorov-Smirnov test, confirms these observations are significantly different. A Kolmogorov-Smirnov test between scenario 1 and scenario 21 results in a p-value of 0.000. Therefore, it can be concluded the final distributions in scenario 1 and 21 are significantly different from each other with a 95% confidence.

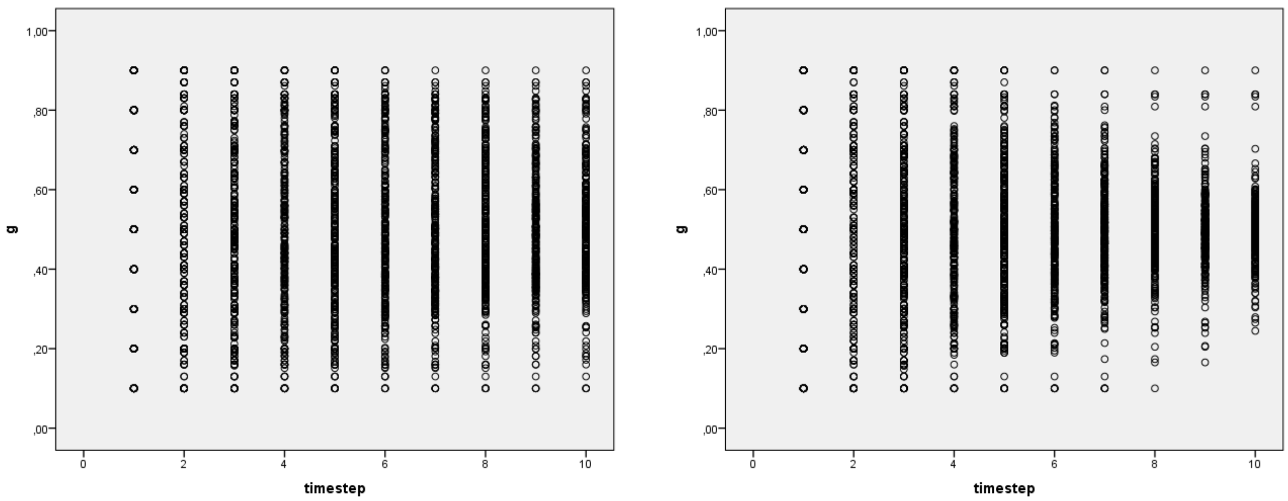


Figure 28: Scatterplots of all datapoints for scenario 1 (left, social influence model) and scenario 21 (right, cognitive dissonance model), Even initial distributions

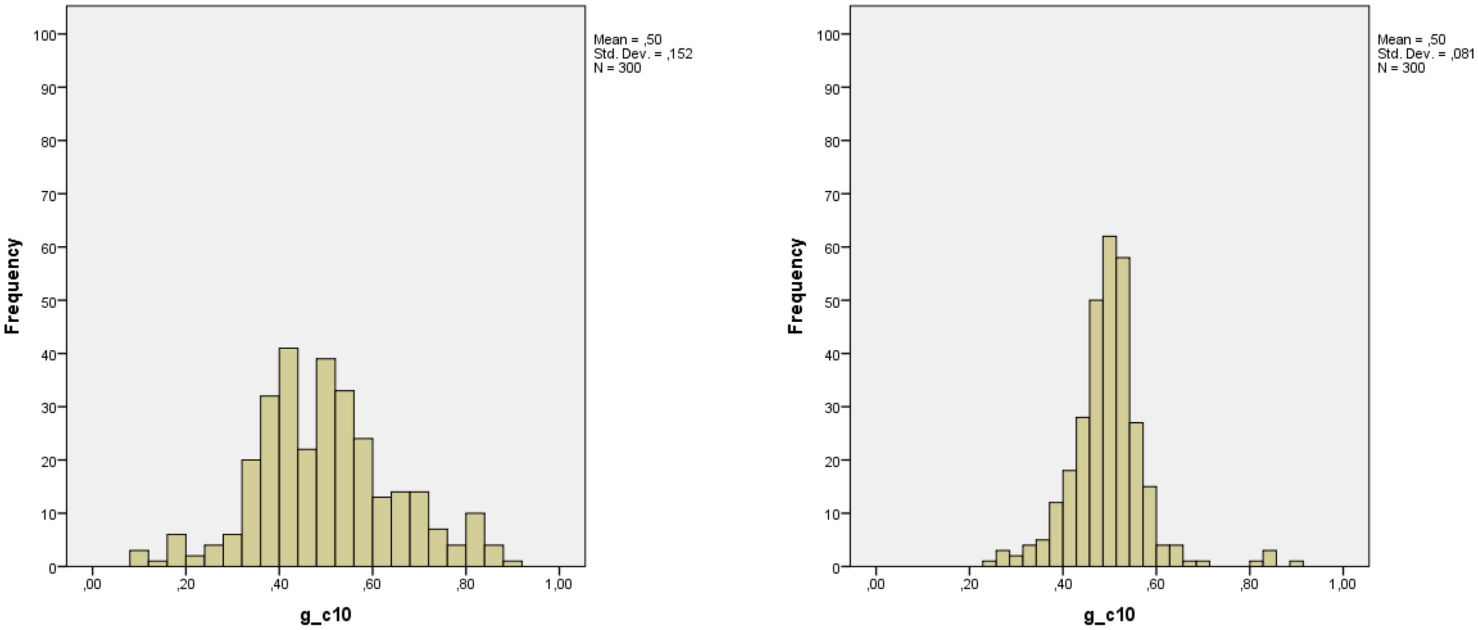


Figure 29: Histograms of final distributions of scenario 1 (left, social influence model) and scenario 21 (right, cognitive dissonance model), Even initial distributions

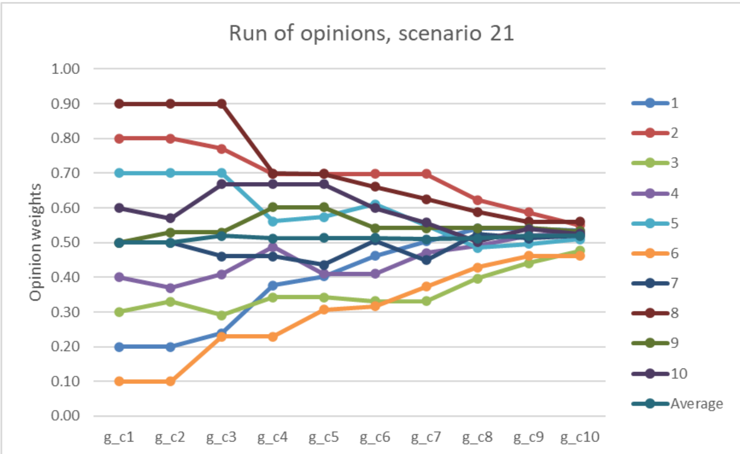


Figure 30: Example of a run of scenario 21: Standard even distribution with cognitive dissonance

6.2.2 Standard Polarized distribution

- Scenario 22:
    - Standard P_s (P_s = 0.2)
    - Standard P_l (P_l =0.8)
    - Standard α (α = 0.1)
    - Polarized distribution (type 2 distribution)

In figure 31, there is a clear difference of a model with and without cognitive dissonance in the case of initially polarized opinions. Introducing cognitive dissonance, seems to help in overcoming polarization of opinions, where each timestep opinions converge closer together. Figure 33, shows an example of an individual run of scenario 22, where around timestep 5 the beginnings of a breakthrough of polarization can be seen. This reduction in polarization can also be clearly seen in the histograms of the final distributions in figure 32. The Kolmogorov-Smirnov test also confirms that these two distributions are statistically significantly different from each other with a p-value of 0.000.

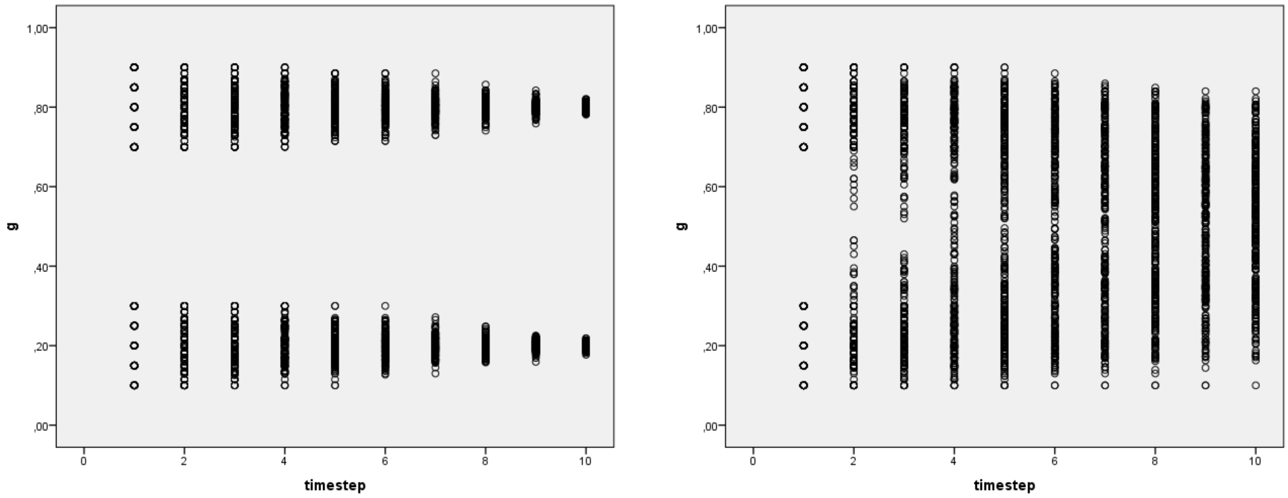


Figure 31: Scatterplots of all datapoints for scenario 2 (left, social influence model) and scenario 22 (right, cognitive dissonance model), Polarized initial distributions

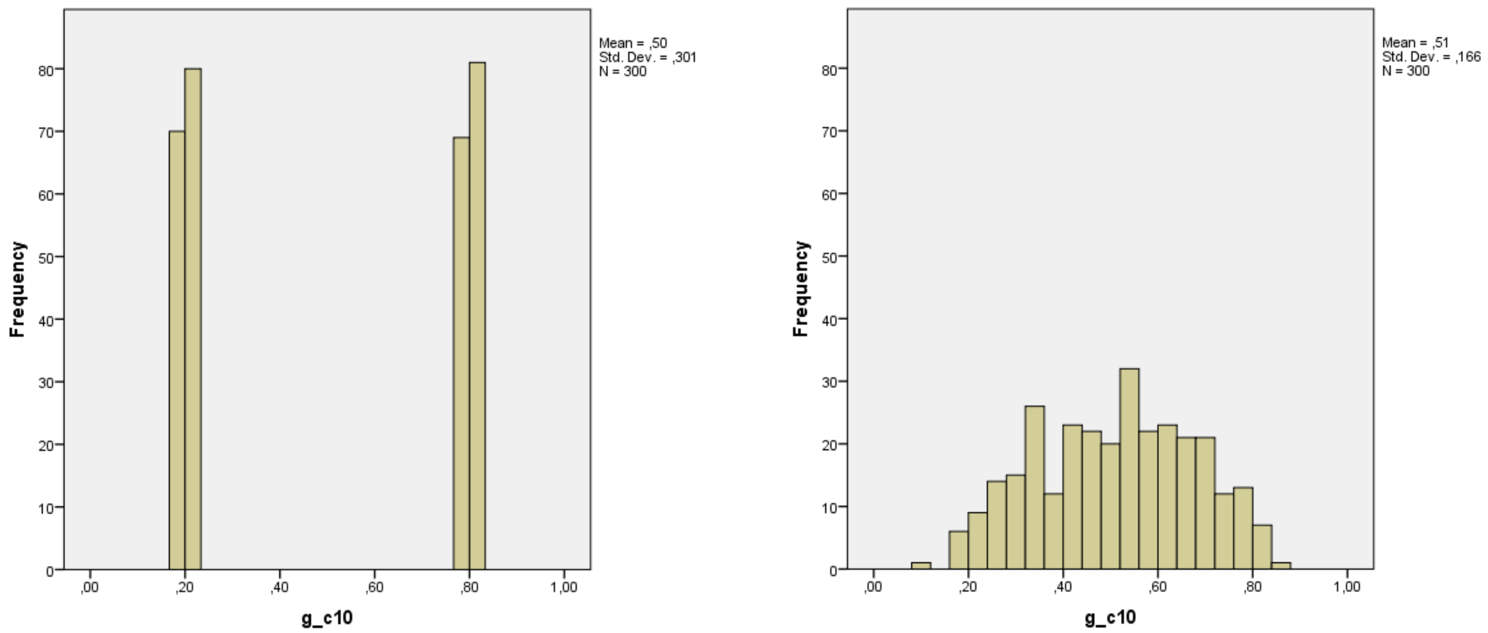


Figure 32: Histograms of final distributions of scenario 2 (left, social influence model) and scenario 22 (right, cognitive dissonance model), Polarized initial distributions

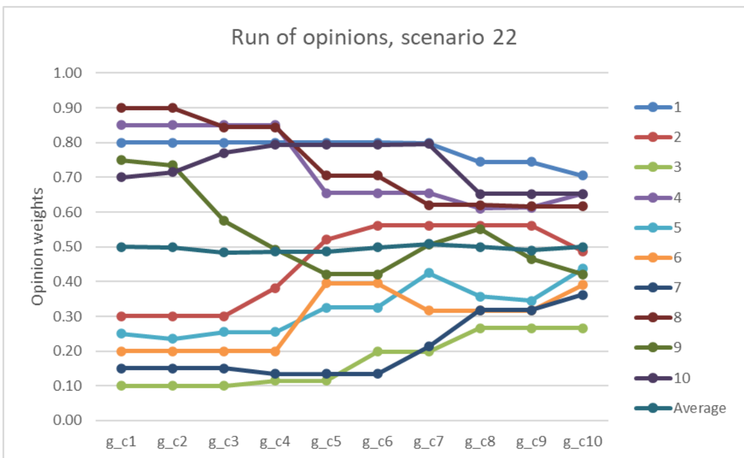


Figure 33: Example of a run of scenario 22: Polarized distribution with cognitive dissonance

6.2.3 Standard spread skewed towards low meat attachment

- Scenario 23:
  - Standard P_s (P_s = 0.2)
  - Standard P_l (P_l =0.8)
  - Standard α (α = 0.1)
  - Skewed distribution towards low meat attachment (type 3 distribution)

Figure 34 and 35, show that compared to the social influence model, adding cognitive dissonance for skewed initial distributions, seems to reduce the distinction between the majority and minority opinion (scenario 3 compared to scenario 23). The final distribution seems to converge around the mean, in between the majority and minority opinion of the initial distribution and also in between the majority and minority opinion of scenario 3. Figure 36 shows an example of an individual run of scenario 23. The clustering of the majority and the minority opinion does not seem to happen under a model with cognitive dissonance. The Kolmogorov-Smirnov test to compare distributions between scenarios, confirms the two final distributions of scenario 3 and scenario 23 are statistically significantly different from each other with a p-value of 0.000.

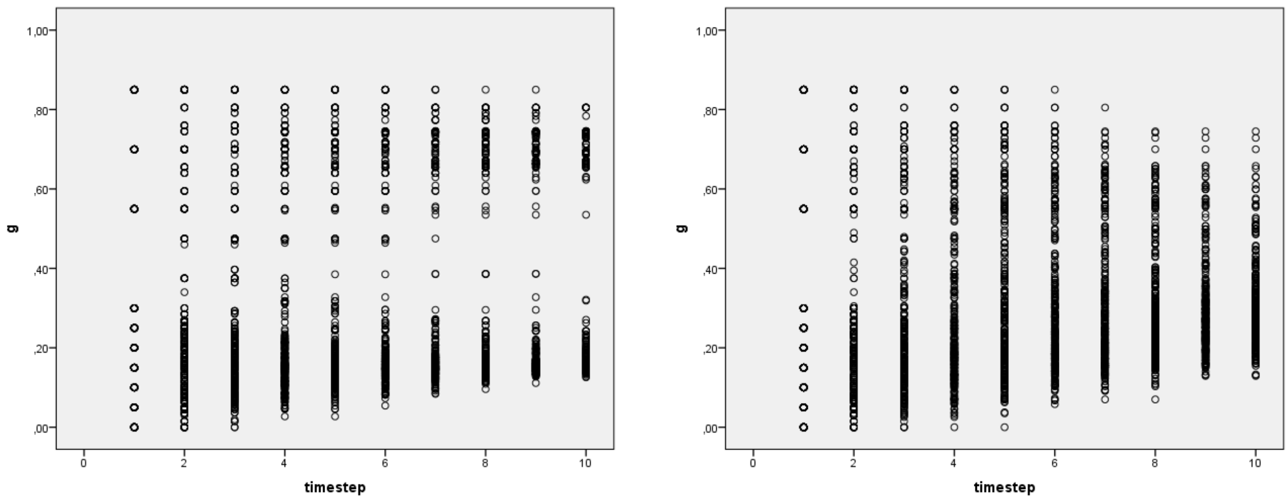


Figure 34: Scatterplots of all datapoints for scenario 3 (left, social influence model) and scenario 23 (right, cognitive dissonance model), Initial distributions skewed towards low meat attachment.

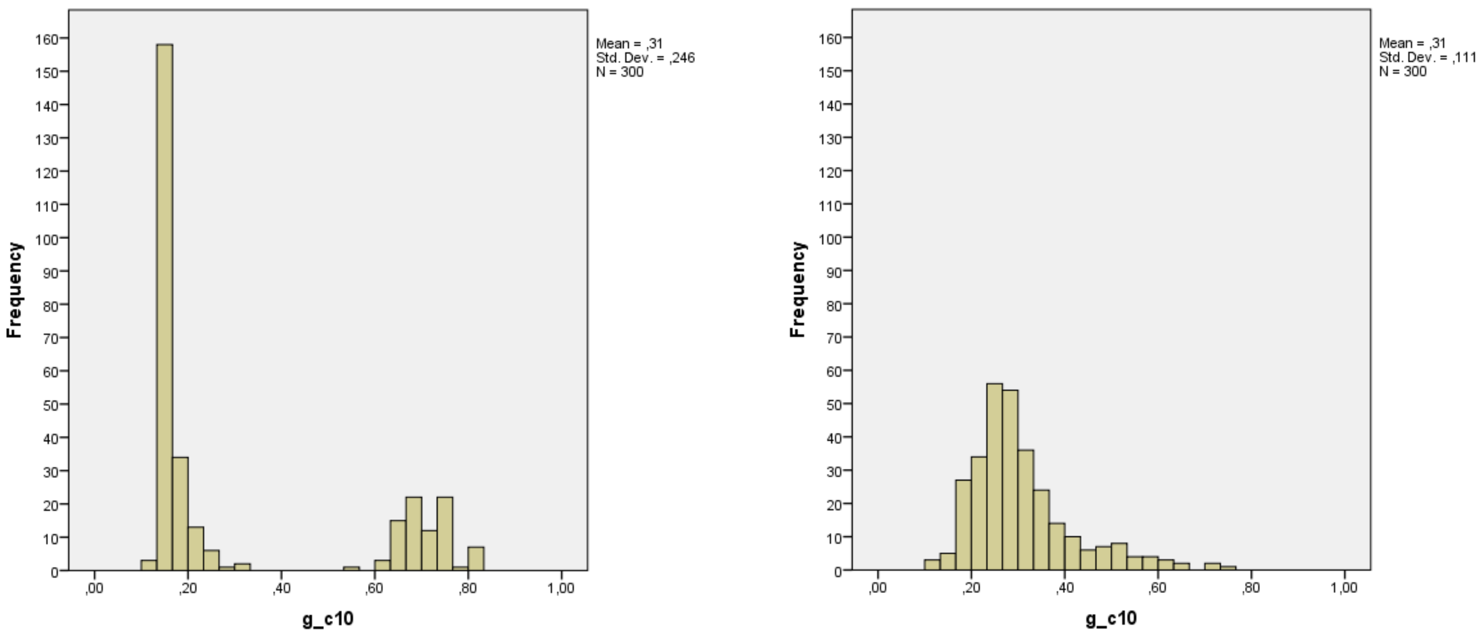


Figure 35: Histograms of the final distributions of scenario 3 (left, social influence model) and scenario 23 (right, cognitive dissonance model), Initial distributions skewed towards low meat attachment.

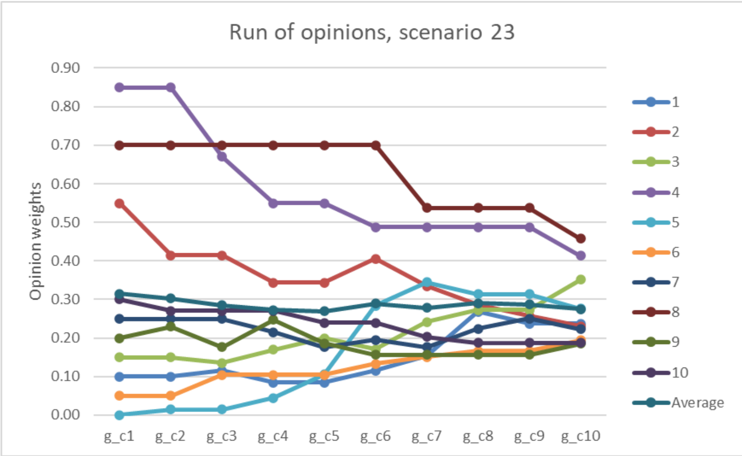


Figure 36: Example of a run of scenario 23: Low meat attachment distribution with cognitive dissonance.

6.2.4 Standard spread skewed towards high meat attachment

- Scenario 24:
  - Standard P_s ($P_s = 0.2$)
  - Standard P_l ($P_l = 0.8$)
  - Standard α (α = 0.1)
  - Skewed distribution towards high meat attachment (type 4 distribution)

In figures 37 and 38, similar effects can be seen as in scenario 23 (standard low meat attachment distribution with cognitive dissonance), but mirrored. There is a reduction in the distinction between the majority and minority opinion, which seem to slowly converge towards the mean. Instead of resulting in a polarized majority and minority opinion consensus. In figure 39, the example run of scenario 24, agents holding the minority opinions have moved closer towards the majority opinion. The p-value of the Kolmogorov-Smirnov test is 0.000, thus confirming the final distribution of scenario 4 is significantly different from the final distribution of scenario 24.

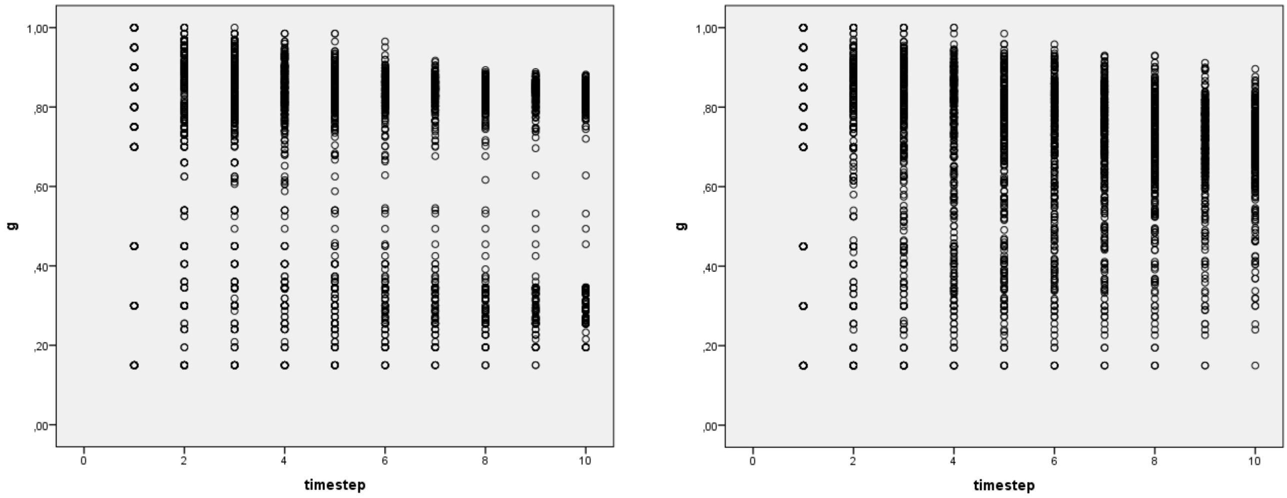


Figure 37: Scatterplots of all datapoints for scenario 4 (left, social influence model) and scenario 24 (right, cognitive dissonance model), Initial distributions skewed towards high meat attachment.

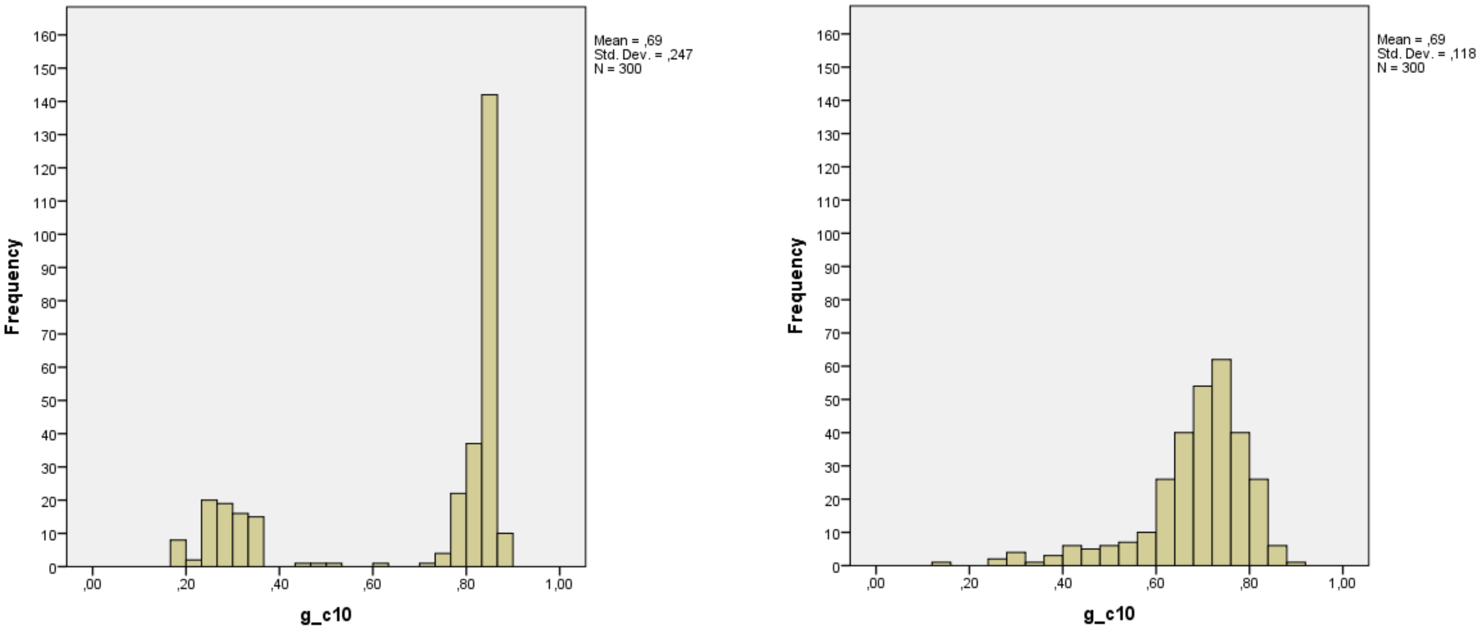


Figure 38: Histograms of the final distributions of scenario 4 (left, social influence model) and scenario 24 (right, cognitive dissonance model), Initial distributions skewed towards high meat attachment.

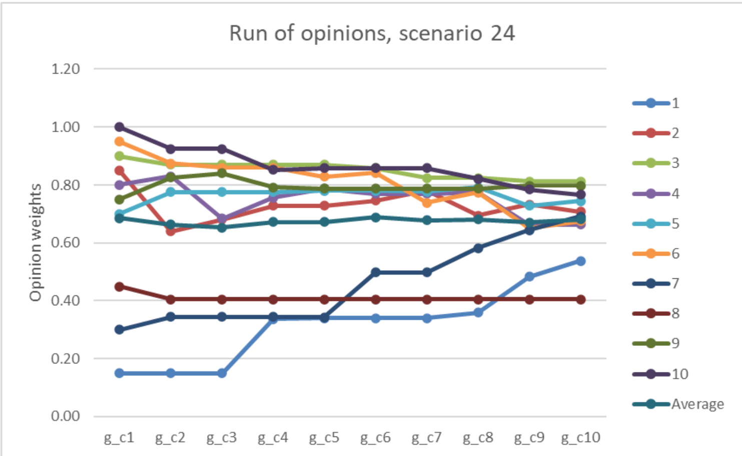


Figure 39: Example of a run of scenario 24: High meat attachment distribution with cognitive dissonance.

6.3 Scenarios comparing the likelihood of applying moral disengagement strategies P_s

Low P_s (Scenario 25, 27, 29 & 31):

- Scenario 25:
  - Low P_s (P_s = 0.05)
  - Even distribution (type 1 distribution)
- Scenario 27:
  - Low P_s (P_s = 0.05)
  - Polarized distribution (type 2 distribution)
- Scenario 29:
  - Low P_s (P_s = 0.05)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 31:
  - Low P_s (P_s = 0.05)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High P_s (Scenario 26, 28, 30 & 32):

- Scenario 26:
  - High P_s (P_s = 0.35)
  - Even distribution (type 1 distribution)
- Scenario 28:
  - High P_s (P_s = 0.35)
  - Polarized distribution (type 2 distribution)
- Scenario 30:
  - High P_s (P_s = 0.35)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 32:
  - High P_s (P_s = 0.35)
  - Skewed distribution towards high meat attachment (type 4 distribution)

A low P_s indicates that in only 5% of the meetings, where opinion differences are small an agent will apply moral disengagement strategies and disregard social influence. A high P_s indicates that during an encounter with small opinion differences there is a possibility of 35% of applying moral disengagement strategies and disregarding social influence. The lower P_s, the likelier it is that social influence takes place for each agent when encountering small opinion differences. In the scatterplots of figure 40 (low P_s scenarios) and figure 41 (high P_s scenarios), it is difficult to see a clear distinction between the comparable scatterplots of figure 40 and 41. This distinction is also difficult to spot when comparing them to the comparable standard scenarios of the cognitive dissonance model (scenario 21-24). The same trends as in the standard cognitive dissonance model scenarios seem to be happening regardless of whether P_s is adjusted.

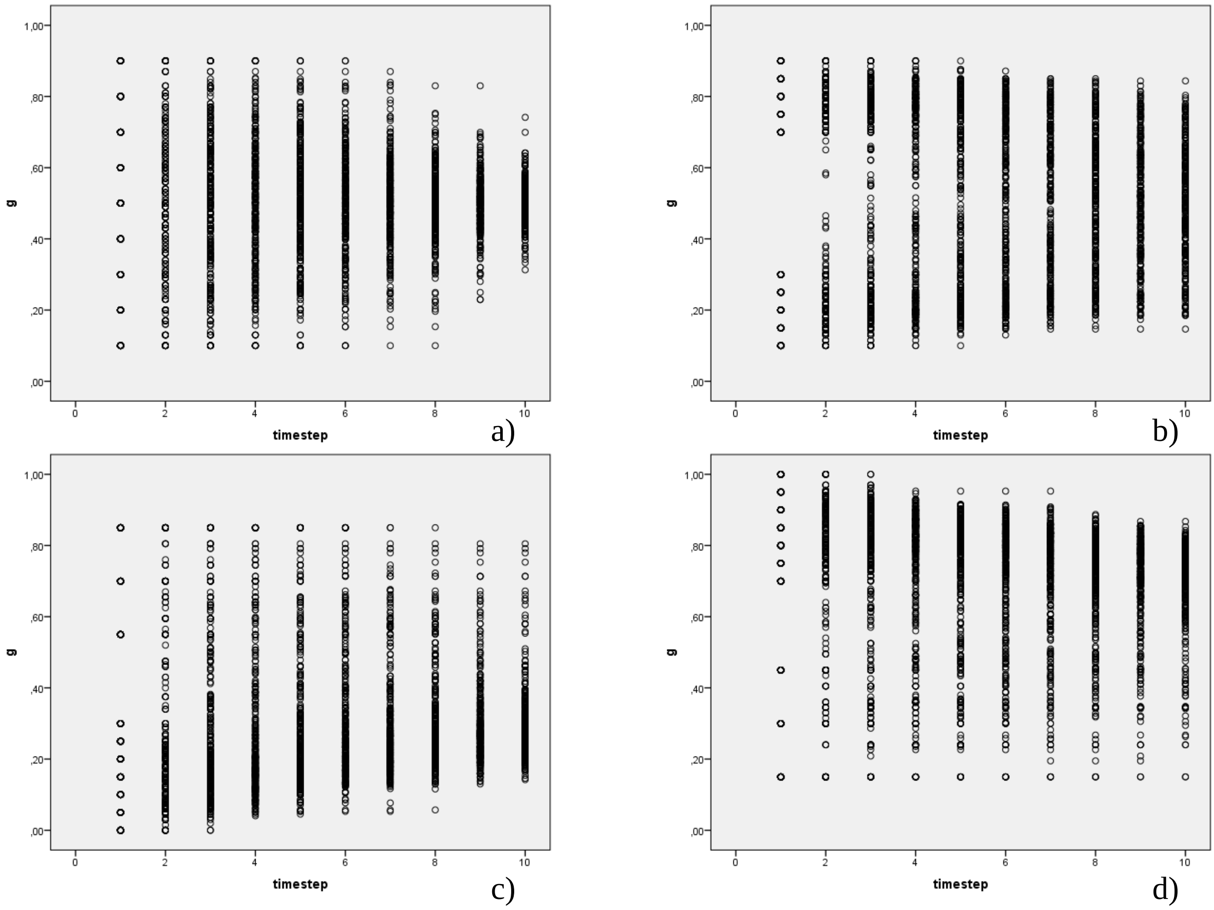


Figure 40: Scatterplots of all datapoints for scenarios with a low P_S; scenario 25 (a, even distribution), scenario 27 (b, polarized distribution), scenario 29 (c, low meat attachment), and scenario 31 (d, high meat attachment)

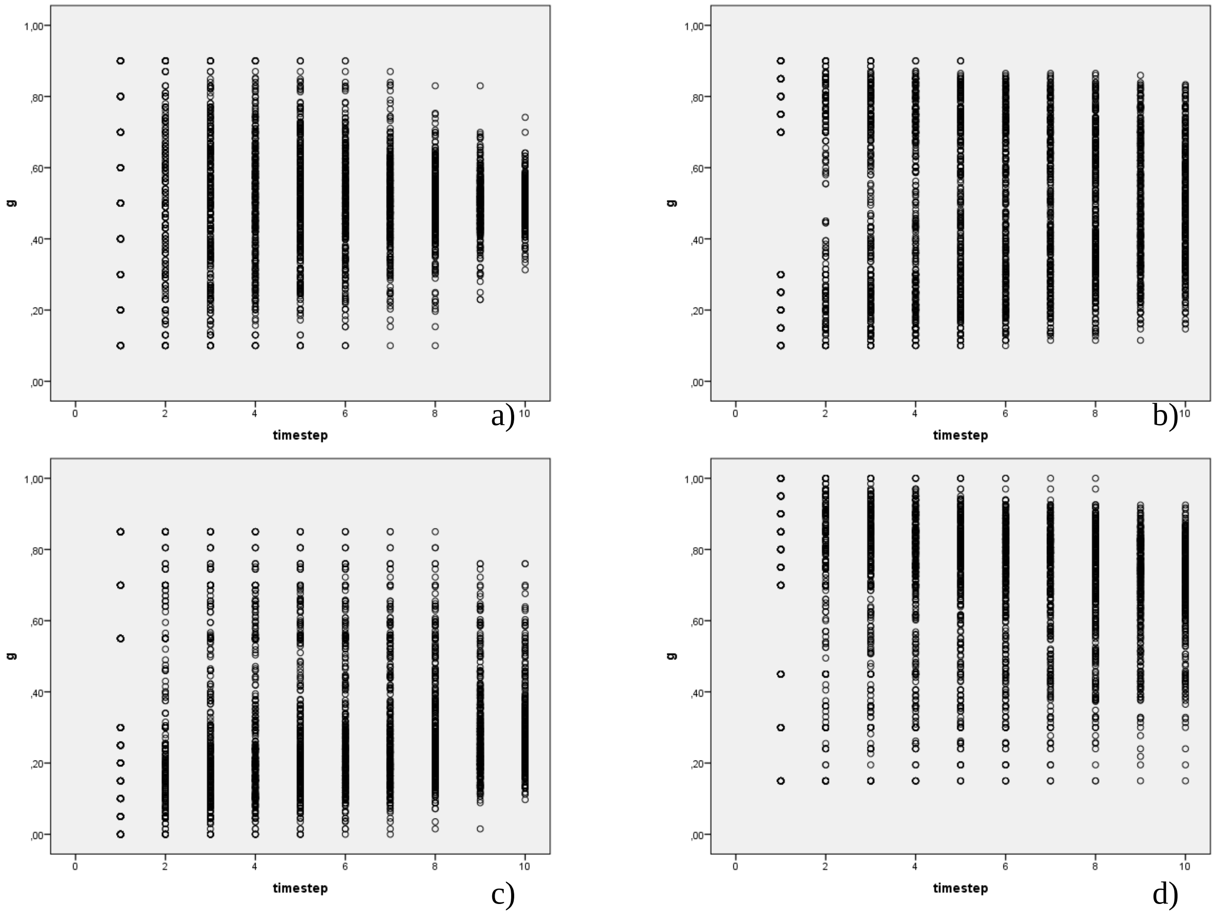


Figure 41: Scatterplots of all datapoints for scenarios with a high P_S; scenario 26 (a, even distribution), scenario 28 (b, polarized distribution), scenario 30 (c, low meat attachment), and scenario 32 (d, high meat attachment)

Looking at the histograms for scenarios with a low P_s in figure 42, and comparing them to comparable standard cognitive dissonance scenarios, the final distributions still seem fairly similar. However, they do still look somewhat different compared to the standard scenarios of the first model with solely social influence.

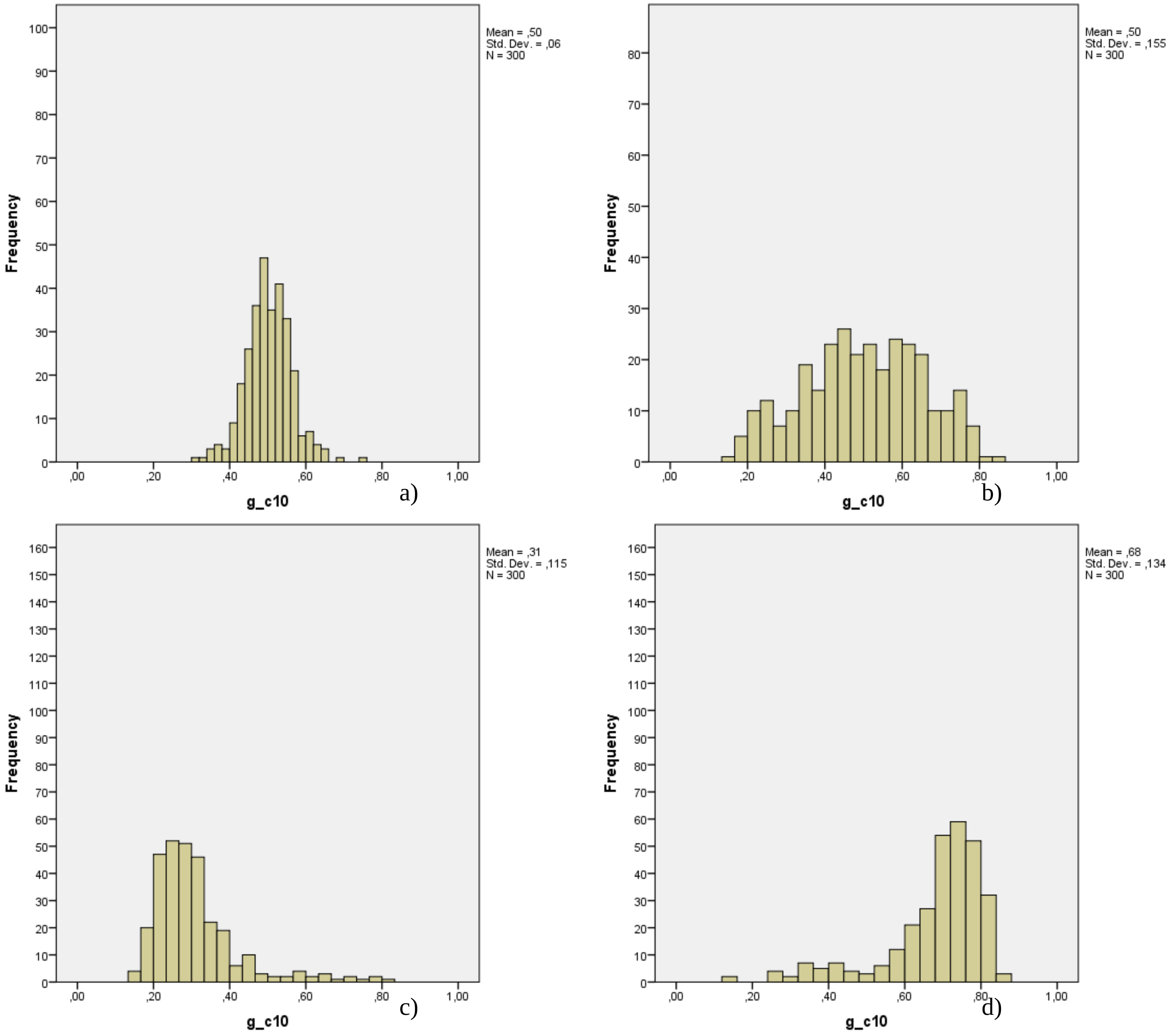


Figure 42: Histograms of the final distributions of scenarios with a low P_s; 25 (a, even distribution), 27 (b, polarized distribution), 29 (c, low meat attachment distribution), 31 (d, high meat attachment distribution)

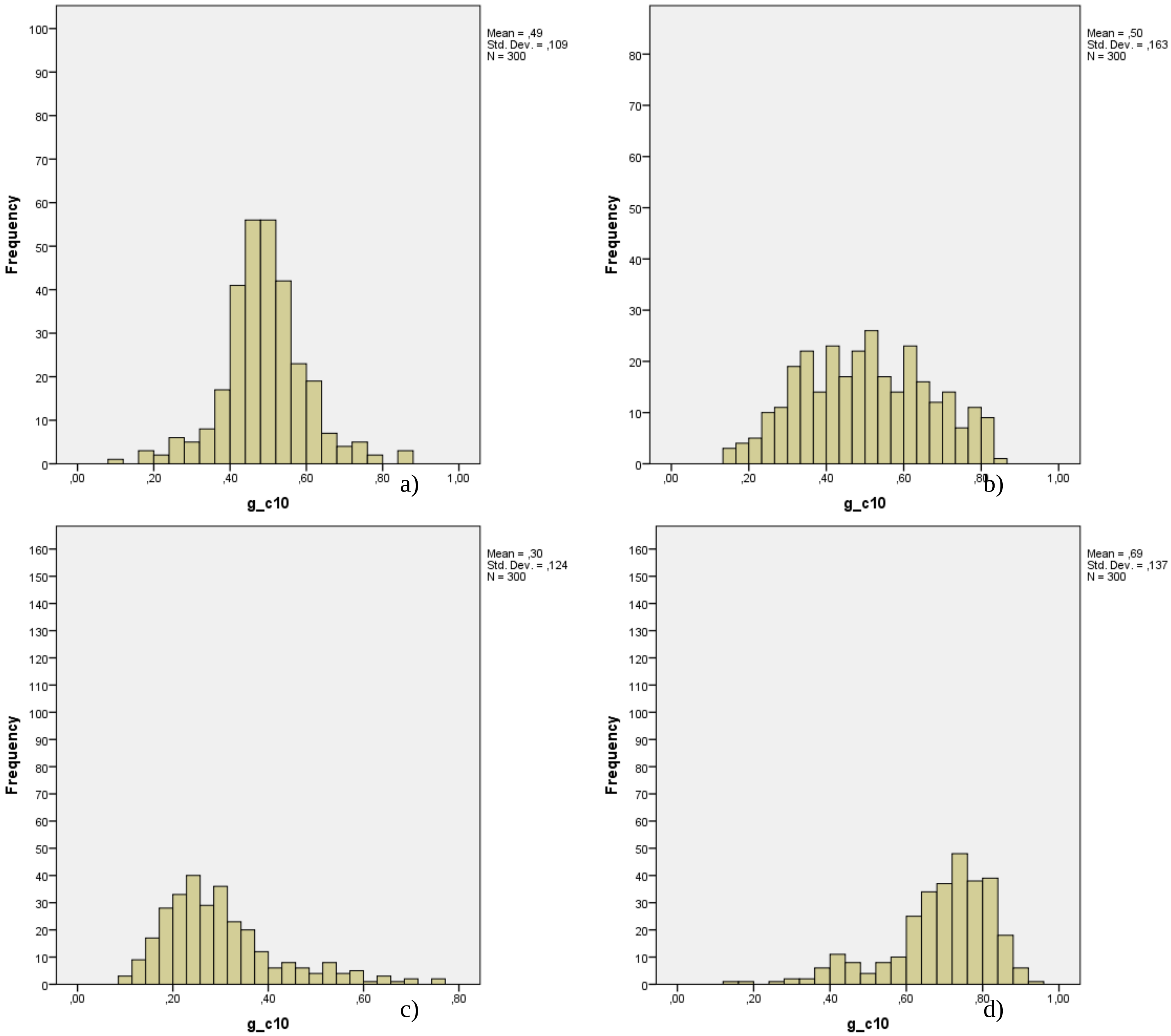


Figure 43: Histograms of the final distributions of scenarios with a high P_s; 26 (a, even distribution), 28 (b, polarized distribution), 30 (c, low meat attachment distribution), 32 (d, high meat attachment distribution)

Comparing the final distribution of even scenario 25 with scenario 26 (figure 42a and figure 43a, respectively), it seems as if a relatively low value for P_s does lead to a different final distribution compared to a relatively high value for P_s. A Kolmogorov-Smirnov test comparing these two final distributions, confirms this with a p-value of 0.000 (see table 9). The histogram of scenario 26 (high P_s) is also statistically significantly different from standard scenario 21 (standard cognitive dissonance scenario for even distributions).

The histograms for polarized scenarios 27 and 29 (figure 41b and 43b), seem rather similar to each other and standard polarized scenario 22. This is also reflected by the Kolmogorov-Smirnov p-values, which all indicate these polarized scenarios do not have a statistically significantly different final distribution (table 10).

Tables 9 to 12, show similar findings for all types of distributions. The scenarios executed with the model of cognitive dissonance, all lead to significantly different final distributions compared to the standard models of the previous model with 95% confidence, since all p-values are lower than 0.05. Furthermore, comparing the scenarios with a low P_s to the standard scenarios of this model show these scenarios do not lead statistically significantly different final distributions. Comparing low P_s scenarios with the comparable high P_s scenarios show, that the final distributions of these scenarios are significantly different from each other, except for the case of initially polarized scenarios (scenario 27 and 28, see table 10). When contrasting high P_s scenarios with the comparable standard scenarios of the cognitive dissonance model, we see a statistically significant difference in final distributions for the even scenarios and the scenarios skewed towards high meat attachment, but not for the polarized scenarios and the scenarios skewed towards low meat attachment.

Kolmogorov p-values	1	21	25	26
1 (Standard, model 1)		**0.000**	**0.000**	**0.034**
21 (Standard model 2)	**0.000**		0.292	**0.006**
25 (Low P_s)	**0.000**	0.292		**0.000**
26 (High P_s)	**0.034**	**0.006**	**0.000**	

Table 9: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	22	27	28
2 (Standard, model 1)		**0.000**	**0.000**	**0.000**
22 (Standard model 2)	**0.000**		0.584	0.341
27 (Low P_s)	**0.000**	0.584		0.721
28 (High P_s)	**0.000**	0.341	0.721	

Table 10: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	23	29	30
3 (Standard, model 1)		**0.000**	**0.000**	**0.000**
23 (Standard model 2)	**0.000**		0.941	0.100
29 (Low P_s)	**0.000**	0.941		**0.027**
30 (High P_s)	**0.000**	0.100	**0.027**	

Table 11: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	24	31	32
4 (Standard, model 1)		**0.000**	**0.000**	**0.000**
24 (Standard model 2)	**0.000**		0.518	**0.016**
31 (Low P_s)	**0.000**	0.518		**0.034**
32 (High P_s)	**0.000**	**0.016**	**0.034**	

Table 12: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

6.4 Scenarios comparing likelihood of applying moral disengagement strategies P_l

Low P_l (Scenario 33, 35, 37 & 39):

- Scenario 33:
  - Low P_l (P_l =0.65)
  - Even distribution (type 1 distribution)
- Scenario 35:
  - Low P_l (P_l =0.65)
  - Polarized distribution (type 2 distribution)
- Scenario 37:
  - Low P_l (P_l =0.65)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 39:
  - Low P_l (P_l =0.65)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High P_l (Scenario 34, 36, 38 & 40)

- Scenario 34:
  - High P_l (P_l =0.95)
  - Even distribution (type 1 distribution)
- Scenario 36:
  - High P_l (P_l =0.95)
  - Polarized distribution (type 2 distribution)
- Scenario 38:
  - High P_l (P_l =0.95)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 40:
  - High P_l (P_l =0.95)
  - Skewed distribution towards high meat attachment (type 4 distribution)

A low P_l indicates that only in 65% of first-time encounters with large opinion differences, agents apply moral disengagement strategies and disregard social influence. This means that agents are relatively open to social influence, even if opinion differences are large. This simulates scenarios where the effort of employing moral disengagement strategies is high, and people are more likely to adjust their beliefs. As we can see in the scatterplots of figure 44, such a relatively low likelihood of applying moral disengagement strategies seems to lead to a relative consensus around the mean regardless of the initial distribution. For the polarized scenario (scenario 36), this leads to a final distribution without two polarized opinion clusters. Similarly, in the scenarios which started skewed towards either low or high meat attachment, the majority and minority opinion seem to have converged in the final distribution.

In contrast, a high P_l indicates that in 95% of the first-time encounters with large opinion differences, moral disengagement strategies are employed and no social influence takes place. In later encounters this likelihood can be reduced due to the power of P_l being influenced by the number of previous encounters with large opinion differences. For these scenarios with a high likelihood of applying moral disengagement strategies, where the opinion difference is larger than the social influence threshold d (high P_l), there is considerably less convergence compared to the scenarios with a low P_l. As well as compared to the comparable standard cognitive dissonance scenarios (scenarios 21-24).

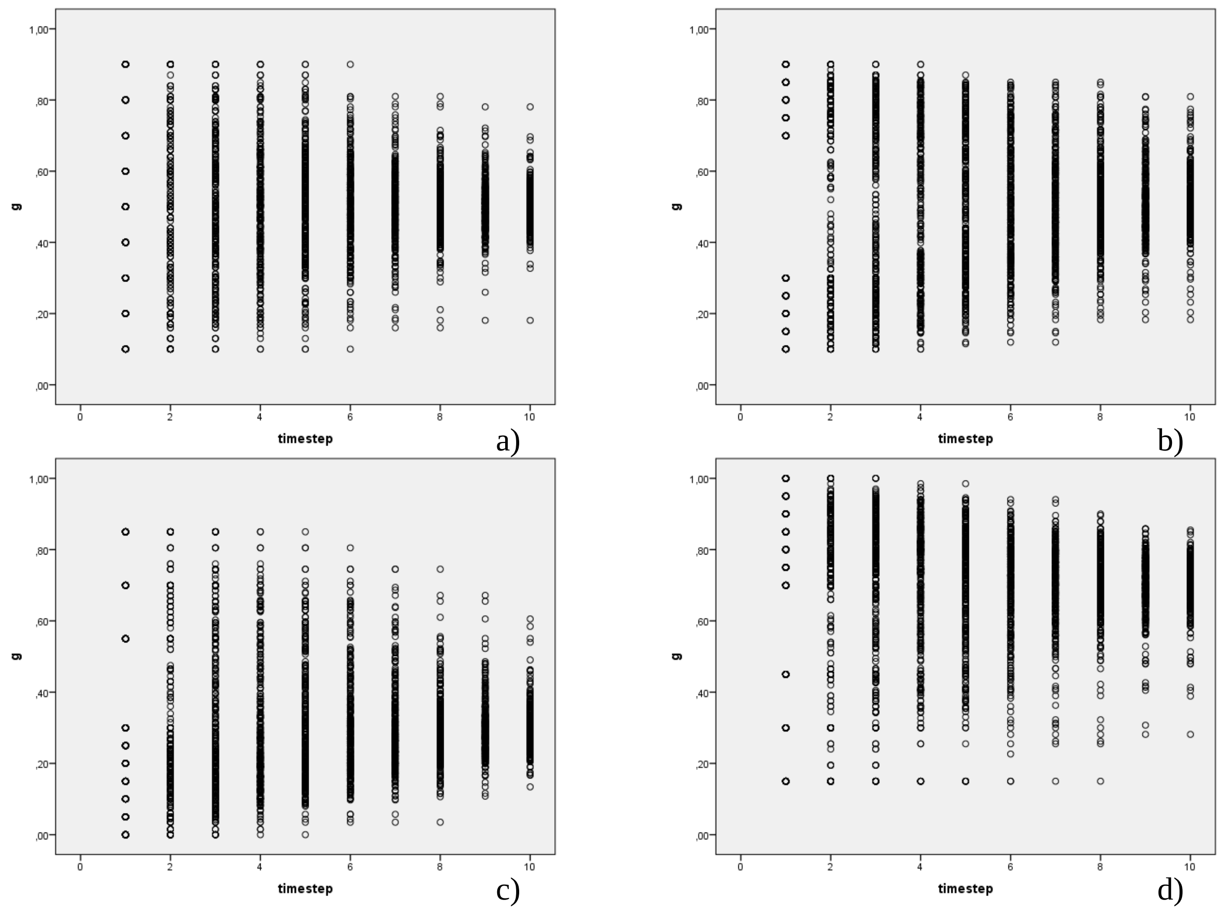


Figure 44: Scatterplots of all datapoints for scenarios with a low P_I; scenario 33 (a, even distribution), scenario 35 (b, polarized distribution), scenario 37 (c, low meat attachment), and scenario 39 (d, high meat attachment)

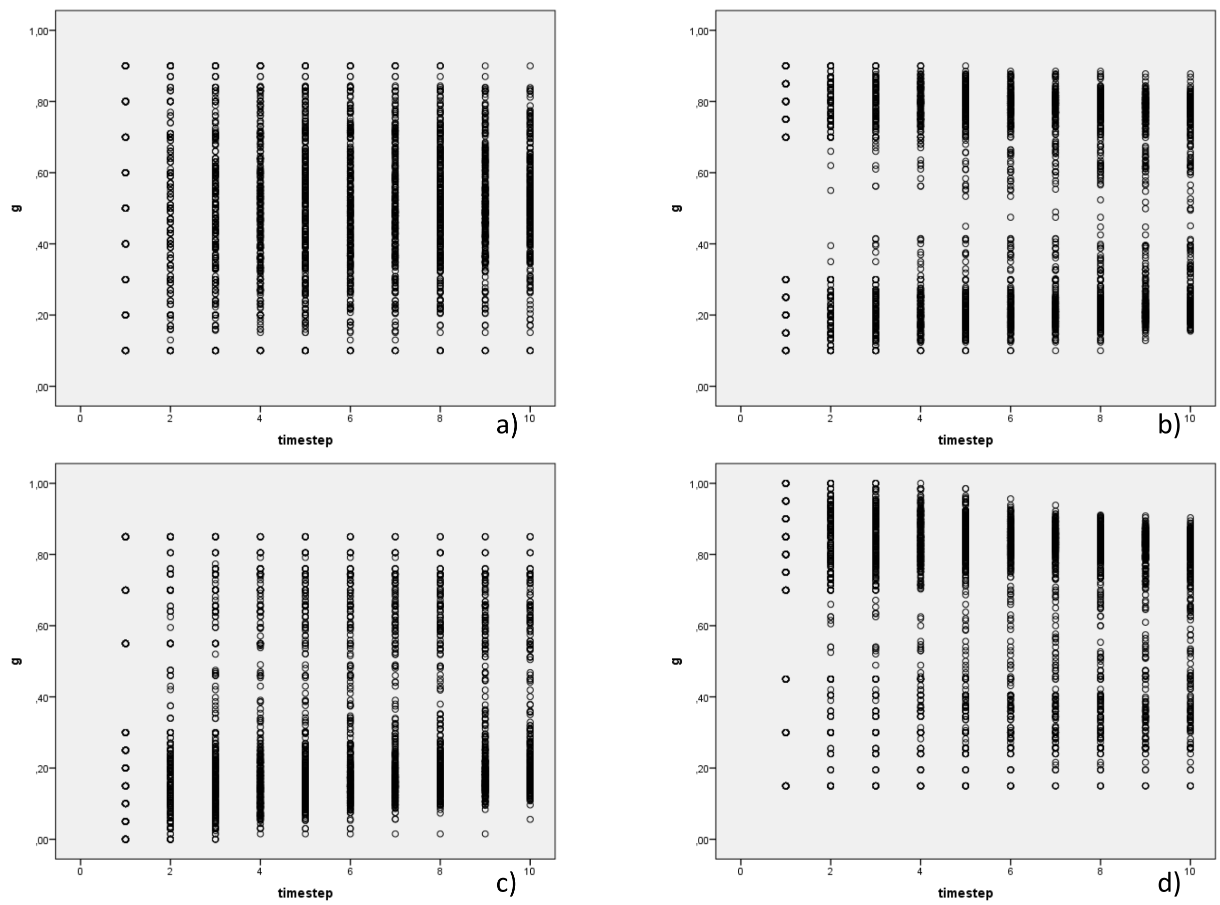


Figure 45: Scatterplots of all datapoints for scenarios with a high P_I; scenario 34 (a, even distribution), scenario 36 (b, polarized distribution), scenario 38 (c, low meat attachment), and scenario 40 (d, high meat attachment)

The histograms below in figure 46, show the high rate of consensus for scenarios with a low P_l. This also shows in the relatively lower standard deviations compared to figure 47, which shows the histograms for the scenarios with a high P_l. The standard deviations for these scenarios with a low P_l are also lower compared to the standard scenarios of the model 1 of social influence. The consensus of polarized scenario 35 (figure 46b) is especially striking, when comparing it to its original distribution. Similarly, for scenario 37 and 39 where the initial distribution was heavily skewed (towards low and high meat attachment respectively), the minority opinion seems to have virtually disappeared (see figure 46c and 46d).

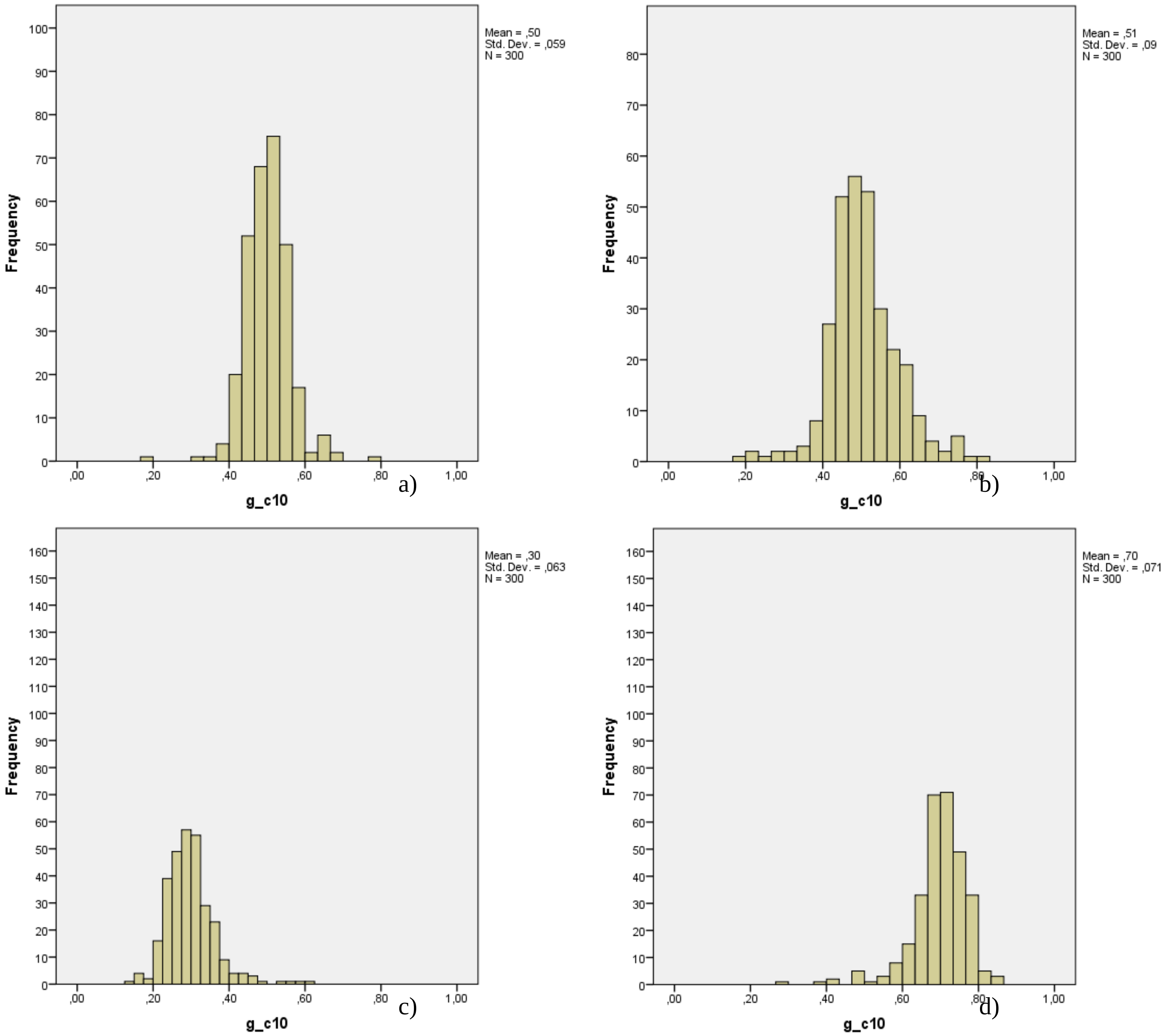


Figure 46: Histograms of the final distributions of scenarios with a low P_l; 33 (a, even distribution), 35 (b, polarized distribution), 37 (c, low meat attachment distribution), 39 (d, high meat attachment distribution)

The histograms of figure 47, representing the scenarios with a high P_l, show a starkly different picture compared to figure 46, which shows scenarios with a low P_l. Compared to those scenarios, the effect of only a slight impact of cognitive dissonance seems very small. However, even with a very high likelihood of applying moral disengagement strategies, there seems to be the inklings and beginnings of a starting consensus in all final distributions that started with some form of polarization or skewedness of opinions (scenarios 28, 30 and 32). Especially compared to the standard scenarios of the social influence model. This seems to indicate that even a small probability of cognitive dissonance occurring has an impact on overcoming or breaking through polarization in this simulation model.

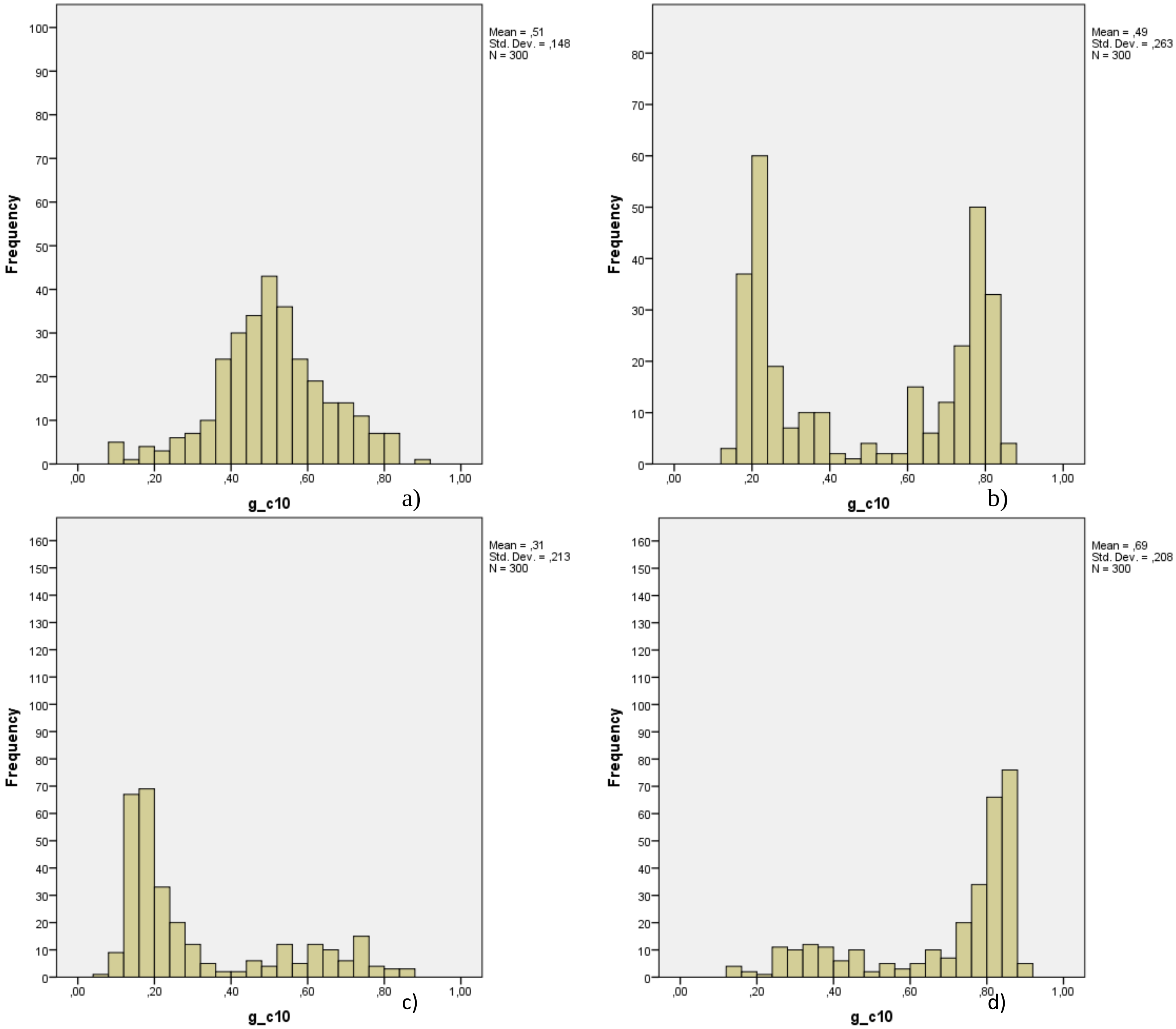


Figure 47: Histograms of the final distributions of scenarios with a high P_l; 34 (a, even distribution), 36 (b, polarized distribution), 38 (c, low meat attachment distribution), 40 (d, high meat attachment distribution)

When the final distributions of the scenarios are compared with each other by doing Kolmogorov-Smirnov tests, they result in the p-values of tables 13 to 16. These tests show that except for scenario 34 (even distribution with a high P_I), all scenarios result in a significantly different final distribution compared to the first model which only implemented social influence. This shows that in cases where the initial distribution has some form of polarization or big opinion gap which is larger than the determined social influence threshold, introducing cognitive dissonance in the model for large opinion differences leads to a significantly different final distribution within this simulation model.

Furthermore, the tables show that for type 2, 3 and 4 initial distributions, all scenarios from the same initial distribution are all significantly different from each other as well. This suggests that P_I is a very important parameter within this simulation model, which influences the final distribution strongly. For the even distribution scenarios, it turns out that the standard even cognitive dissonance scenario (scenario 21) and the scenario with a low P_I (scenario 33) are not significantly different from each other in the final distribution. Scenario 34 (even distribution with a high P_I) does have a significantly different final distribution compared with scenario 21 and 33. But is not significantly different to the standard scenario of model 1 (scenario 1). This indicates that for the even distribution, when there is no polarization present to such a degree that social influence cannot overcome it by itself, a very high P_I simulates similar to the first model of social influence for the given number of encounters.

Kolmogorov p-values	1	21	33	34
1 (Standard, model 1)		**0.000**	**0.000**	0.121
21 (Standard model 2)	**0.000**		0.249	**0.000**
33 (Low P_I)	**0.000**	0.249		**0.000**
34 (High P_I)	0.121	**0.000**	**0.000**	

Table 13: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	22	35	36
2 (Standard, model 1)		**0.000**	**0.000**	**0.000**
22 (Standard model 2)	**0.000**		**0.000**	**0.000**
35 (Low P_I)	**0.000**	**0.000**		**0.000**
36 (High P_I)	**0.000**	**0.000**	**0.000**	

Table 14: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	23	37	38
3 (Standard, model 1)		**0.000**	**0.000**	**0.000**
23 (Standard model 2)	**0.000**		**0.006**	**0.000**
37 (Low P_I)	**0.000**	**0.006**		**0.000**
38 (High P_I)	**0.000**	**0.000**	**0.000**	

Table 15: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	24	39	40
4 (Standard, model 1)		**0.000**	**0.000**	**0.000**
24 (Standard model 2)	**0.000**		**0.034**	**0.000**
39 (Low P_I)	**0.000**	**0.034**		**0.000**
40 (High P_I)	**0.000**	**0.000**	**0.000**	

Table 16: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

6.5 Scenarios comparing influence of repeated exposure α

Low α (Scenario 41, 43, 45 & 47):

- Scenario 41:
  - Low α (α = 0.05)
  - Even distribution (type 1 distribution)
- Scenario 43:
  - Low α (α = 0.05)
  - Polarized distribution (type 2 distribution)
- Scenario 45:
  - Low α (α = 0.05)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 47:
  - Low α (α = 0.05)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High α (Scenario 42, 44, 46 & 48):

- Scenario 42:
  - High α (α = 0.15)
  - Even distribution (type 1 distribution)
- Scenario 44:
  - High α (α = 0.15)
  - Polarized distribution (type 2 distribution)
- Scenario 46:
  - High α (α = 0.15)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 48:
  - High α (α = 0.15)
  - Skewed distribution towards high meat attachment (type 4 distribution)

The α parameter, indicates the effect of repeated exposure to large opinion difference on P_I. P_I is the likelihood of applying moral disengagement strategies when encountering large opinion differences for the first time. As alpha increases, previous exposure to large opinion differences, reduces the likelihood of applying moral disengagement strategies when encountering large opinion differences in the next encounter. Therefore, the effect of α is most prominent in distributions where agents encounter large opinion differences more frequently (aka polarized distributions). Furthermore, α also has a higher impact on opinions in the extremities, since fewer opinions encountered fall within threshold d, for those opinions. The impact of α also increases in later timesteps, as it is more likely agents have previously encountered large opinion differences. However, looking at the scatterplots in figure 48 and 49, the impact of α, seems to be limited for the chosen values. Discernable differences between the scatterplots of similar distributions with a low and high α, seem to be negligible.

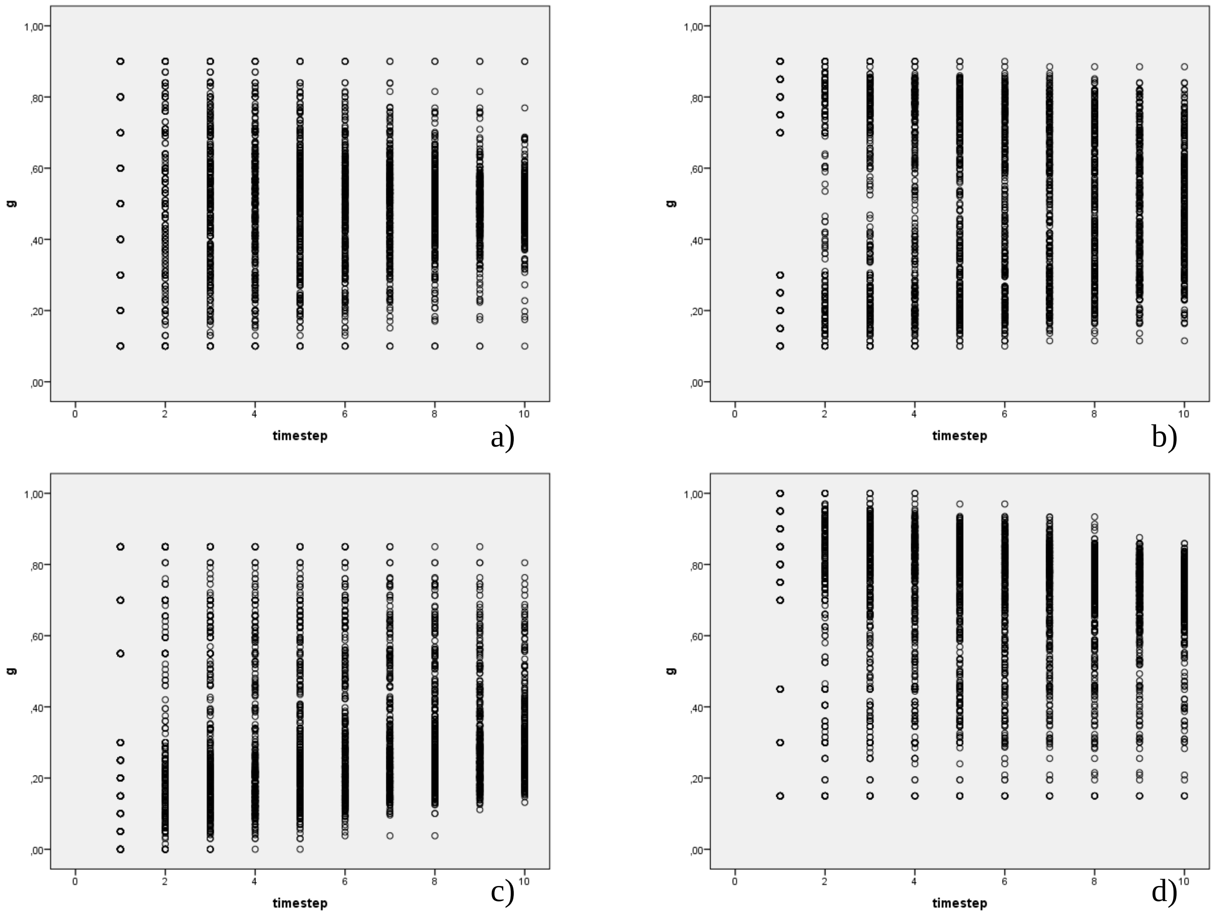


Figure 48: Scatterplots of all datapoints for scenarios with a low α; scenario 41 (a, even distribution), scenario 43 (b, polarized distribution), scenario 45 (c, low meat attachment), and scenario 47 (d, high meat attachment)

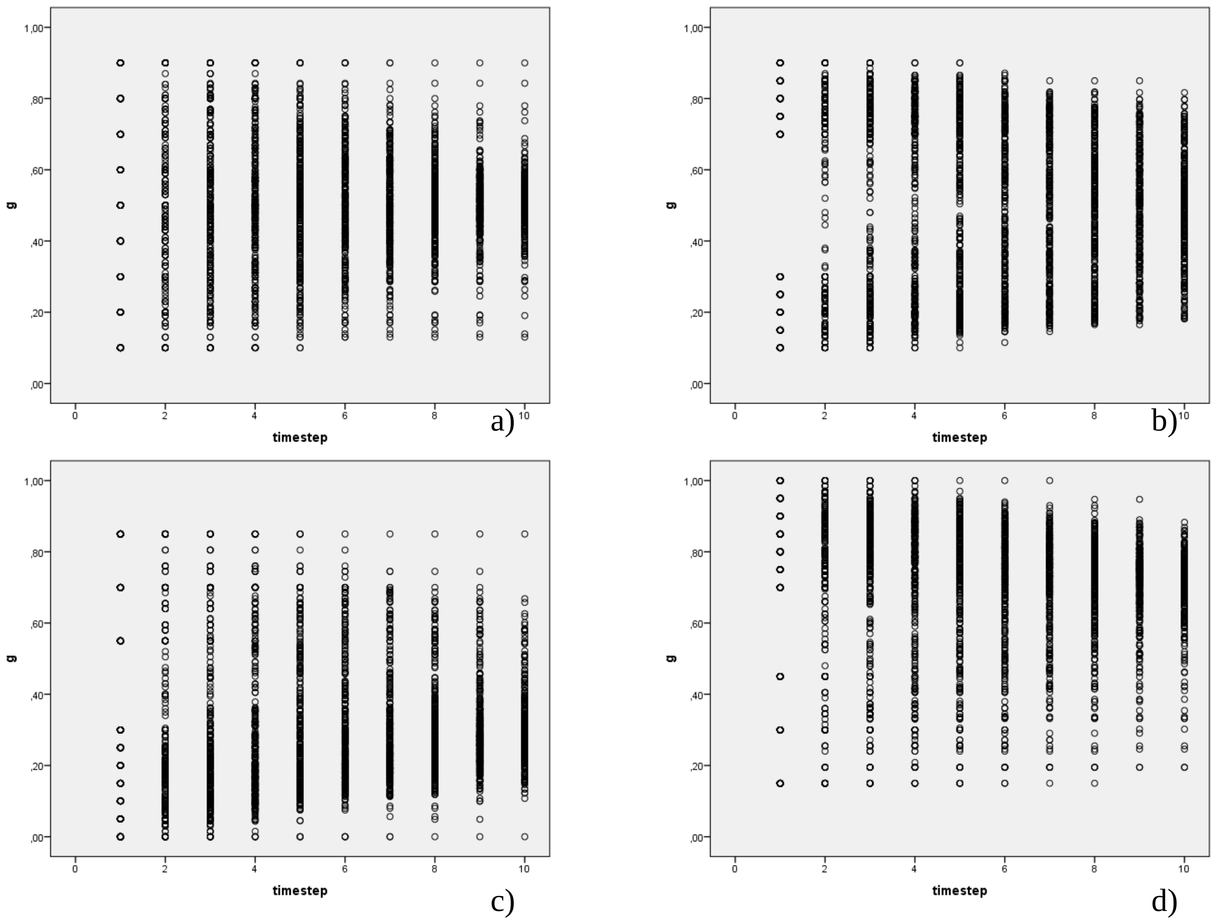


Figure 49: Scatterplots of all datapoints for scenarios with a high α; scenario 42 (a, even distribution), scenario 44 (b, polarized distribution), scenario 46 (c, low meat attachment), and scenario 48 (d, high meat attachment)

The histograms in figures 50 and 51, similarly do not show a very discernible difference in the final distributions. It seems as if the scenarios with a high α, seem to be slightly clustered more around the mean for the even and polarized distributions (scenarios 42 and 44), compared to similar scenarios with a low α (scenarios 41 and 43). The standard deviation seems to differ slightly for the polarized and skewed distributions; however, the difference seems to be slight. Testing for significantly different final distributions between all these scenarios with Kolmogorov-Smirnov tests, shows that there is no statistical difference between the final distributions of any of the comparable scenarios presented in figure 50 and 51 (see tables 17-20).

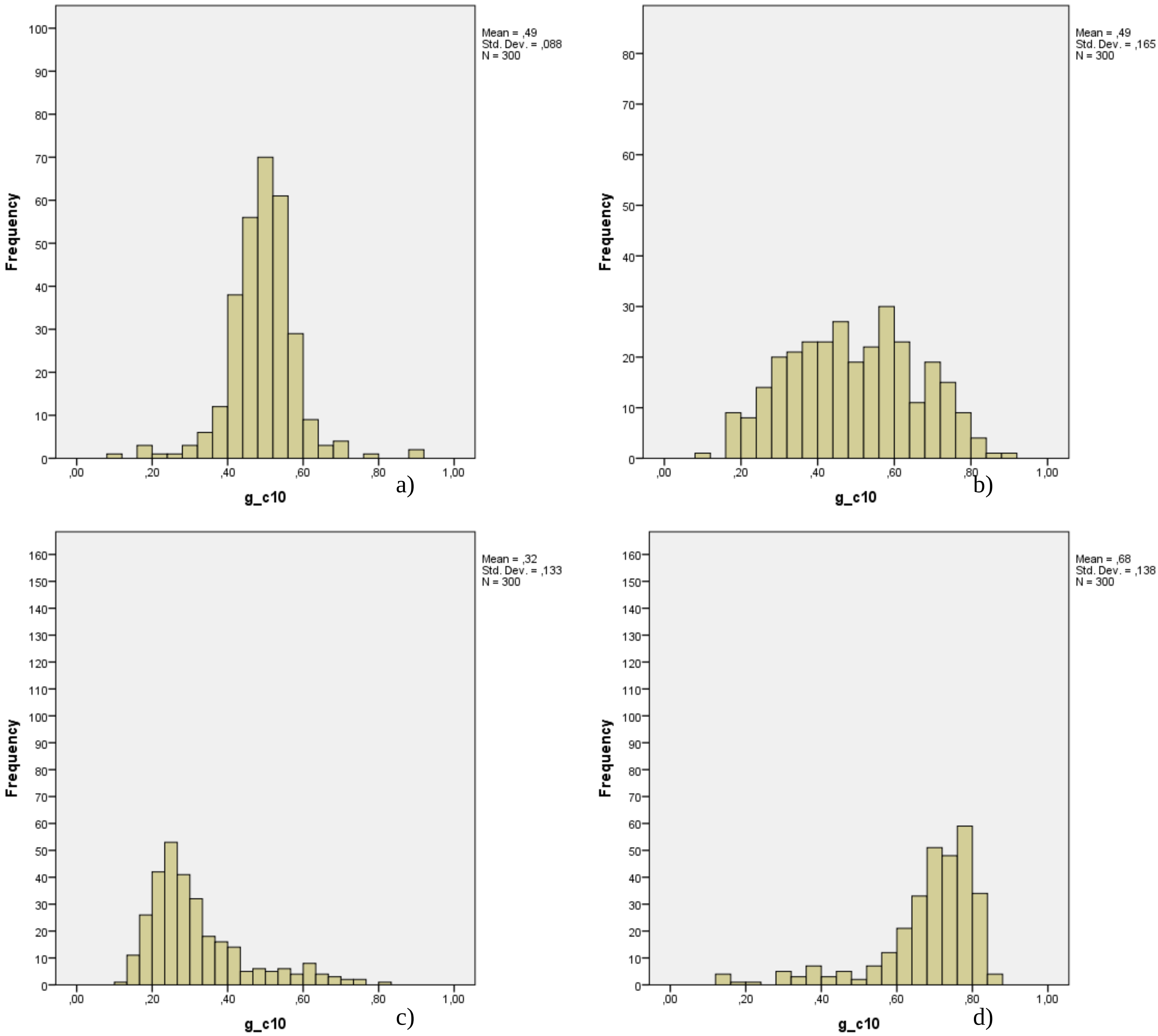


Figure 50: Histograms of the final distributions of scenarios with a low α; 41 (a, even distribution), 43 (b, polarized distribution), 45 (c, low meat attachment distribution), 47 (d, high meat attachment distribution)

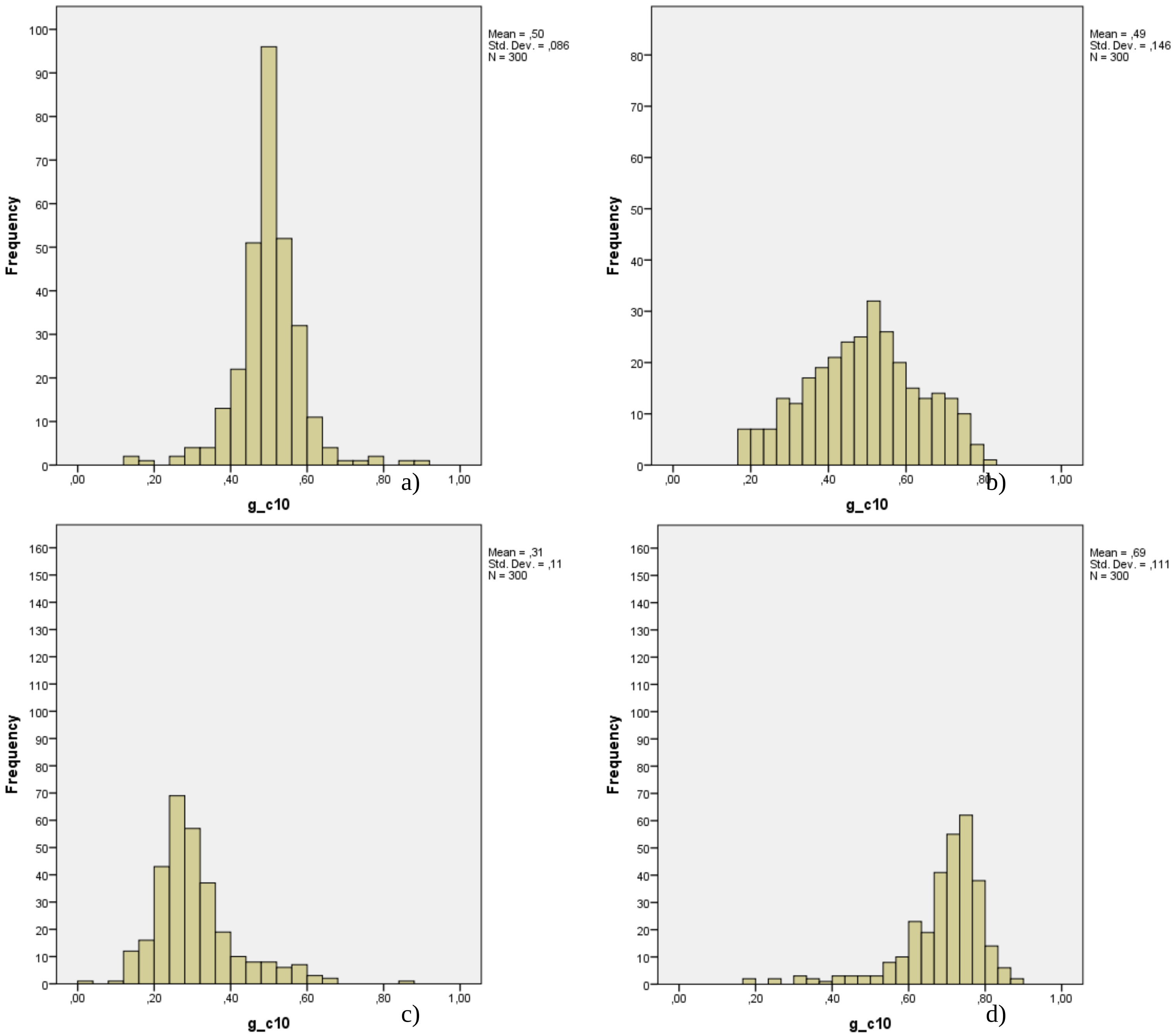


Figure 51: Histograms of the final distributions of scenarios with a high α; 42 (a, even distribution), 44 (b, polarized distribution), 46 (c, low meat attachment distribution), 48 (d, high meat attachment distribution)

The Kolmogorov-Smirnov tests between these scenarios, reveal that the final distributions under the scenarios with differing α, are not significantly different from each other or the standard cognitive dissonance scenarios (see tables 17-20). The scenarios final distributions are significantly different from the standard scenarios of model 1, similarly to most other cognitive dissonance scenarios. Due to the potentially overshadowing effect of α, the values assigned to α were kept fairly low (from 0.05 - 0.15) as to not overshadow the effect of the main cognitive dissonance effect. These tests seem to confirm that α's values did not overtake the effect of P_I. However, further simulation analysis could test the sensitivity of α at higher values.

Kolmogorov p-values	1	21	41	42
1 (Standard, model 1)		**0.000**	**0.000**	**0.000**
21 (Standard model 2)	**0.000**		0.721	0.249
41 (low α)	**0.000**	0.721		0.249
42 (high α)	**0.000**	0.249	0.249	

Table 17: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	22	43	44
2 (Standard, model 1)		**0.000**	**0.000**	**0.000**
22 (Standard model 2)	**0.000**		0.454	0.053
43 (low α)	**0.000**	0.454		0.395
44 (high α)	**0.000**	0.053	0.395	

Table 18: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	23	45	46
3 (Standard, model 1)		**0.000**	**0.000**	**0.000**
23 (Standard model 2)	**0.000**		0.787	0.721
45 (low α)	**0.000**	0.787		0.341
46 (high α)	**0.000**	0.721	0.341	

Table 19: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	24	47	48
4 (Standard, model 1)		**0.000**	**0.000**	**0.000**
24 (Standard model 2)	**0.000**		0.210	0.454
47 (low α)	**0.000**	0.210		0.121
48 (high α)	**0.000**	0.454	0.121	

Table 20: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

7. Results idealism and cognitive dissonance model

7.1 General assumptions

For the third model, which adds the concept of idealism to the second model of cognitive dissonance, 12 different scenarios were run. All scenarios were run 30 times. Below in figure 52 is an overview of the potential values given to the parameters in the different scenarios. Figure 53, gives an overview of all scenarios for the idealism model. Figure 54, is an overview of the types of initial distributions. Looking at the Q-Q plots and detrended Q-Q plots, and histograms of the initial and final distributions, showed all data distributions were non-normally distributed and seemed to exhibited unequal variances between scenarios. Therefore, the test done to compare final distributions is the Kolmogorov-Smirnov test, since it does not require data to be normal or the two distributions that are being compared to have equal variances.

	d	μ	Ps	Pl	α	I
Low	-	-	-	-	-	0.1
Standard	0.3	0.3	0.2	0.8	0.1	0.25
High	-	-	-	-	-	0.4

Figure 52: Range of parameter values for the idealism scenarios (model 3)

	Type of distribution	Model	Differing parameter values
Scenario 1	Even distribution (type 1)	1	All standard parameter values (d = 0.3; μ = 0.3)
Scenario 21	Even distribution (type 1)	2	All standard parameter values (P_s = 0.2; P_l = 0.8; α = 0.1)
Scenario 49	Even distribution (type 1)	3	All standard parameter values (ι = 0.25)
Scenario 50	Polarized distribution (type 2)	3	All standard parameter values (ι = 0.25)
Scenario 51	Low meat attachment distribution (type 3)	3	All standard parameter values (ι = 0.25)
Scenario 52	High meat attachment distribution (type 4)	3	All standard parameter values (ι = 0.25)
Scenario 53	Even distribution (type 1)	3	Low ι (ι =0.1)
Scenario 54	Even distribution (type 1)	3	High ι (ι =0.4)
Scenario 55	Polarized distribution (type 2)	3	Low ι (ι =0.1)
Scenario 56	Polarized distribution (type 2)	3	High ι (ι =0.4)
Scenario 57	Low meat attachment distribution (type 3)	3	Low ι (ι =0.1)
Scenario 58	Low meat attachment distribution (type 3)	3	High ι (ι =0.4)
Scenario 59	High meat attachment distribution (type 4)	3	Low ι (ι =0.1)*Omitted, since it is equal to scenario 24
Scenario 60	High meat attachment distribution (type 4)	3	High ι (ι =0.4)

Figure 53: Overview of all the idealism model scenarios.

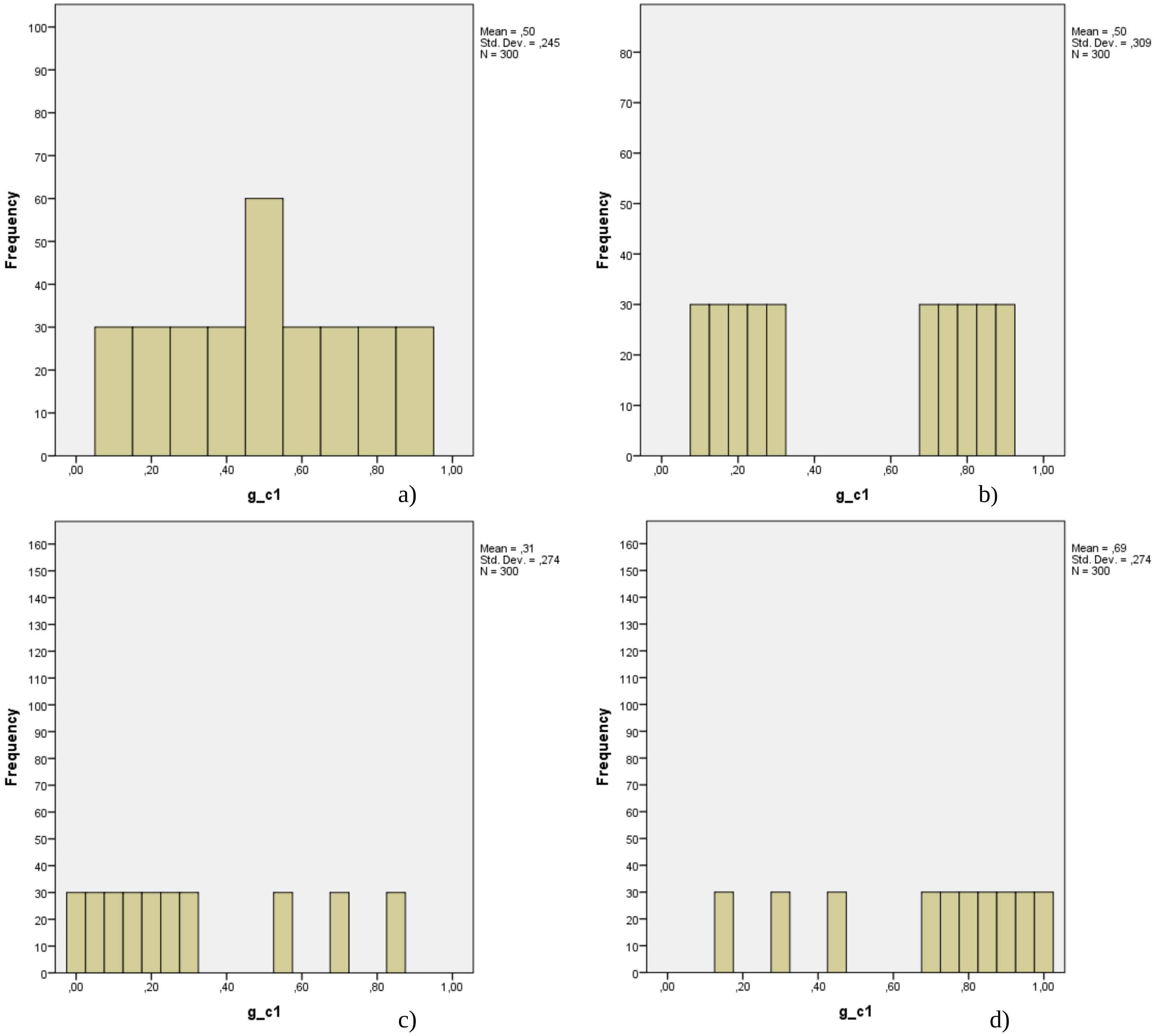


Figure 54: Histograms of the initial distributions: even distribution (a), polarized distribution (b), low meat attachment (c), high meat attachment (d)

7.2 Standard scenarios

7.2.1 Standard even distribution

- Scenario 49:
  - Standard ι (ι =0.25)
  - Even distribution (type 1 distribution)

In figure 55 and 56, the scatterplots of all datapoints and histograms of the final distributions of scenarios 1, 21, and 49 can be found. Compared to the scatterplots of scenario 1 and 21, we see that the final distribution in scenario 49 is more heavily skewed towards low meat attachment. There are fewer agents in the final distribution remaining with strong opinions towards high meat attachment. Introducing idealism into the model for an even distribution, seems to reduce the mean in the final distribution. The mean in scenario 49 was 0.43 for the final distribution, compared to the initial distribution mean of 0.5 (see figure 56). Comparing the final distribution of scenario 49 with the final distributions of scenario 1 and 21, the Kolmogorov-Smirnov tests return that the final distribution of scenario 49 is significantly different from them (p-values 0.000 and 0.000 respectively). An example of a run from scenario 49, can be found in figure 57. For scenario 49, agents reaching an opinion weight below or equal to 0.25, do not adjust their opinions anymore when encountering non-idealists. An example of this in figure 57, is agent 10, who initially starts with an opinion weight of 0.30, but is only influenced by other idealists after changing their opinion below the idealism threshold ι.

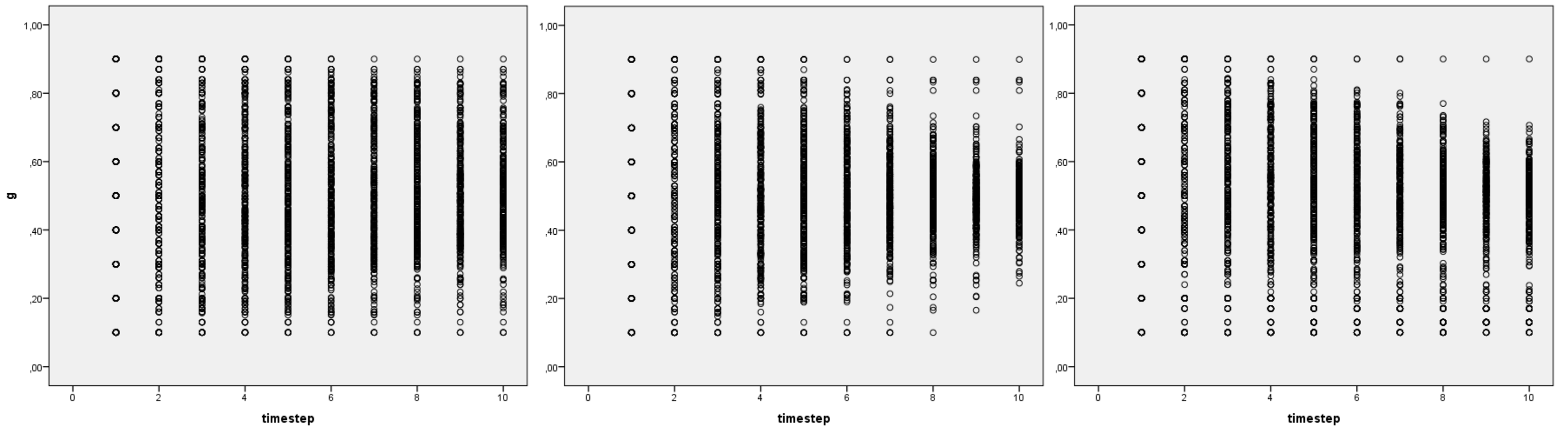


Figure 55: Scatterplots of all datapoints for scenario 1 (left, social influence model), scenario 21 (middle, cognitive dissonance model), and scenario 49 (right, idealism model). Even initial distributions

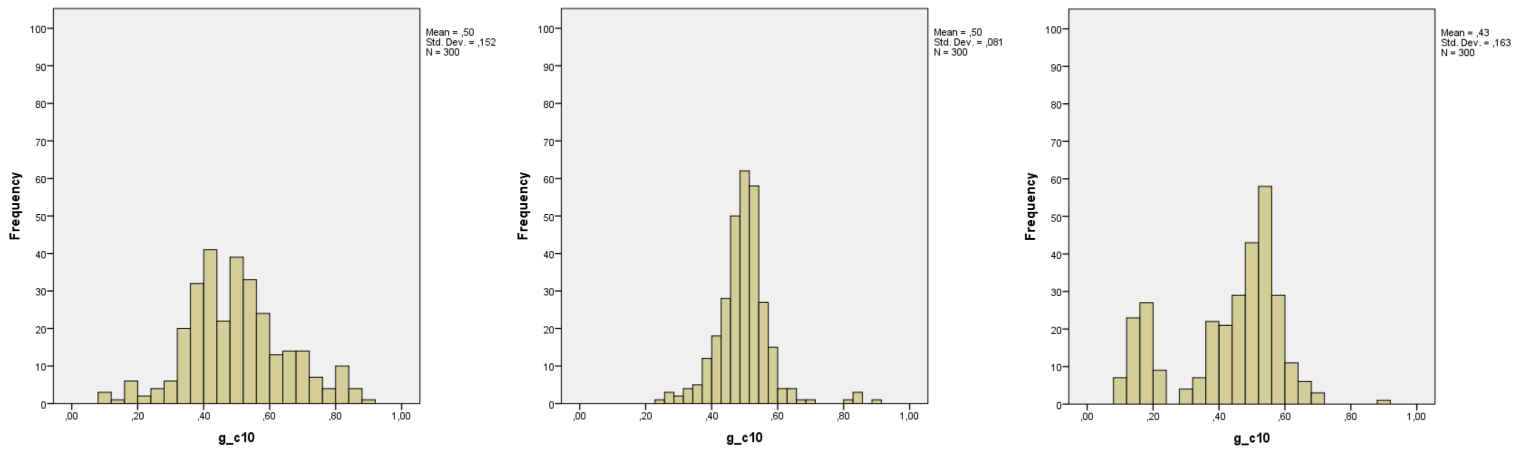


Figure 56: Histograms of final distributions of scenario 1 (left, social influence model) scenario 21 (middle, cognitive dissonance model), and scenario 49 (right, idealism model). Standard even distribution scenarios

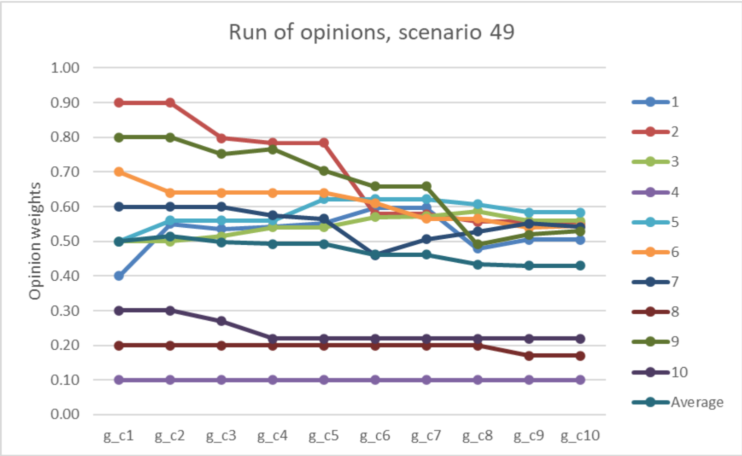


Figure 57: Example of a run of scenario 49. Even distribution under the idealism model

7.2.2 Standard Polarized distribution

- Scenario 50:
  - Standard ι (ι =0.25)
  - Polarized distribution (type 2 distribution)

In the scatterplots and histograms of figure 58 and 59, the standard scenarios starting with a polarized distribution are depicted. The first model of social influence resulted in two clusters of polarized opinions in scenario 2. The second model of cognitive dissonance overcame this polarization and a higher rate of consensus was reached in scenario 22. It seems that for the idealism model, the gap between the polarized clusters seems smaller compared to the first model final distribution. However, there seems to be less consensus compared to cognitive dissonance scenario 22, likely due to the fact that the idealists are not trying to bridge the gap anymore. It would be interesting to see if given more encounters opinions would reach consensus again. For the timesteps given, the non-idealists seem to be slowly creeping towards the idealist threshold. This pattern can also be seen in an example of a run of scenario 50 in figure 60. The mean in the initial distribution for scenario 50 is 0.50, while the mean for the final distribution is 0.41 as can be seen in figure 59.

Comparing the final distribution of scenario 50 with the final distributions of standard scenarios 2 and 22, scenario 50 turns out to be statistically significantly different from both with the p-values 0.000 and 0.000 respectively.

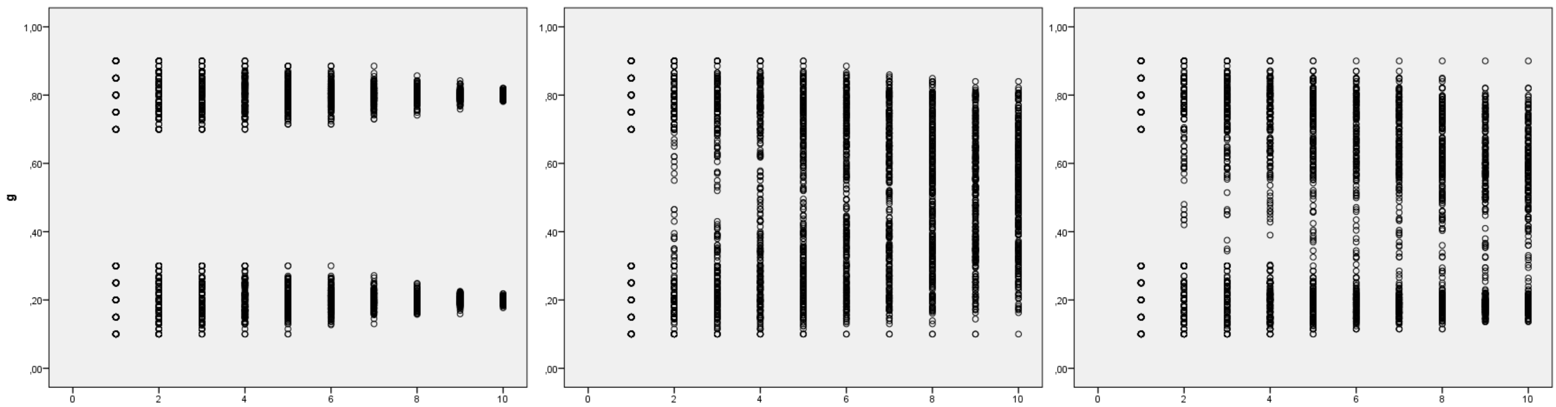


Figure 58: Scatterplots of all datapoints for scenario 2 (left, social influence model), scenario 22 (middle, cognitive dissonance model), and scenario 50 (right, idealism model). Polarized initial distributions

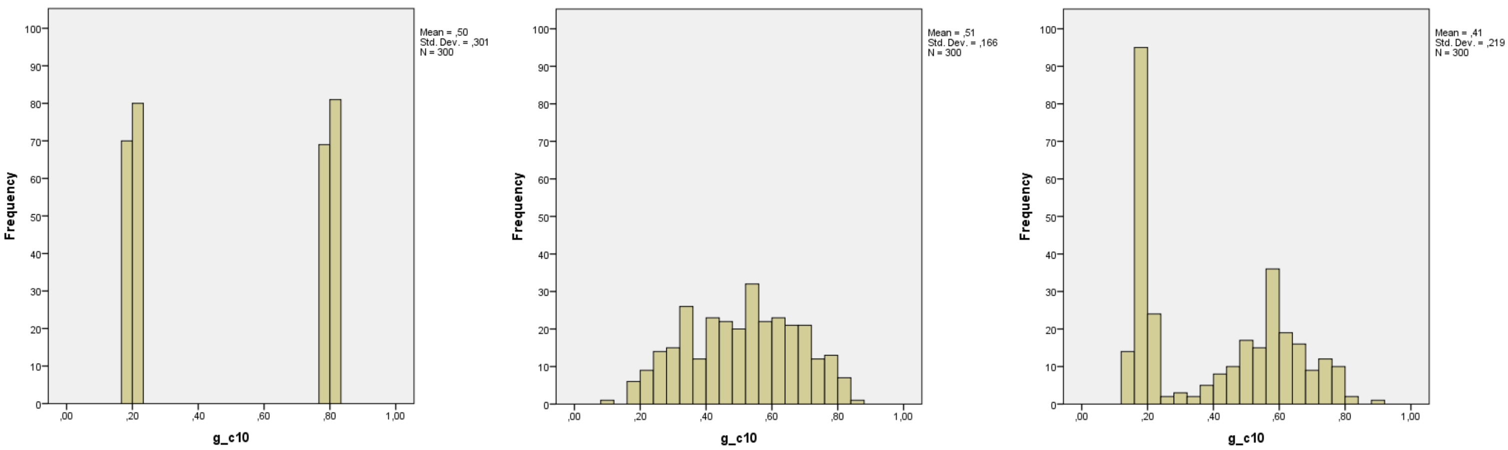


Figure 59: Histograms of final distributions of scenario 2 (left, social influence model) scenario 22 (middle, cognitive dissonance model), and scenario 50 (right, idealism model). Polarized initial distributions

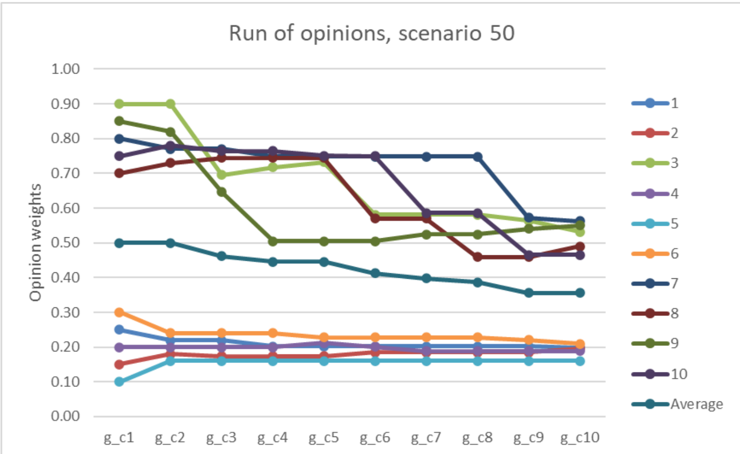


Figure 60: Example of a run of scenario 50, standard polarized distribution under idealism.

7.2.3 Standard spread skewed towards low meat attachment

- Scenario 51:
  - Standard ι (ι =0.25)
  - Skewed distribution towards low meat attachment (type 3 distribution)

In the scatterplots and the histograms of figure 61 and 62, the difference between scenario 23 and 51 seems to be that in scenario 23 the minority and majority opinion move towards each other. In scenario 51 the minority opinion still moves towards the majority opinion. However, most of the majority opinions are idealists and thus do not move towards the minority opinion anymore. This is also the case in the example run of scenario 51 illustrated in figure 63. The initial distribution mean for scenario 51 was 0.3, the final distribution mean was 0.23 (see figure 62). Both Kolmogorov-Smirnov tests to compare the final distribution of scenario 51 with the final distribution of the standard scenarios of the first and second model returned both p-values to be 0.000 (scenario 3 and 23). Thus, it can be concluded that the standard scenario of the third model indeed does lead to significantly different final distributions when starting with a type 3 initial distribution.

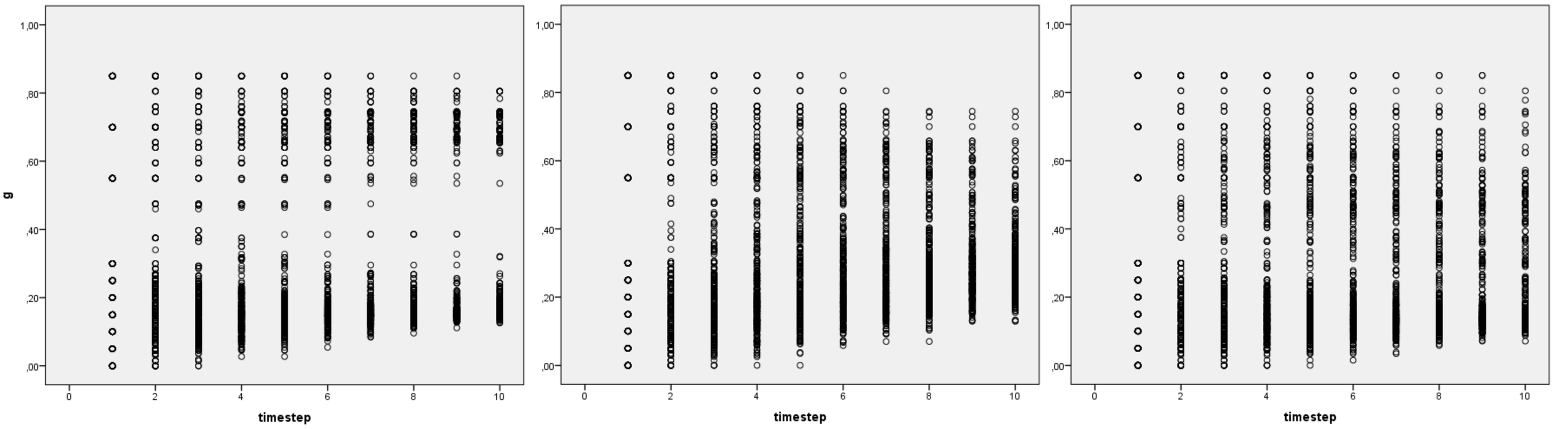


Figure 61: Scatterplots of all datapoints for scenario 3 (left, social influence model), scenario 23 (middle, cognitive dissonance model), and scenario 51 (right, idealism model). Initial distributions skewed towards low meat attachment

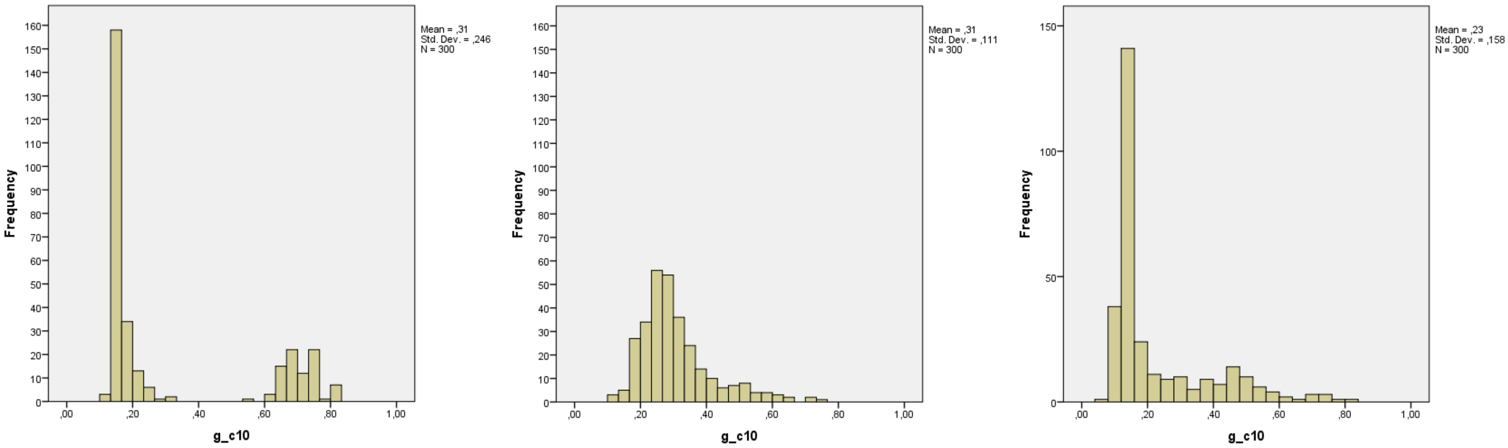


Figure 62: Histograms of final distributions of scenario 3 (left, social influence model) scenario 23 (middle, cognitive dissonance model), and scenario 51 (right, idealism model). Initial distributions skewed towards low meat attachment

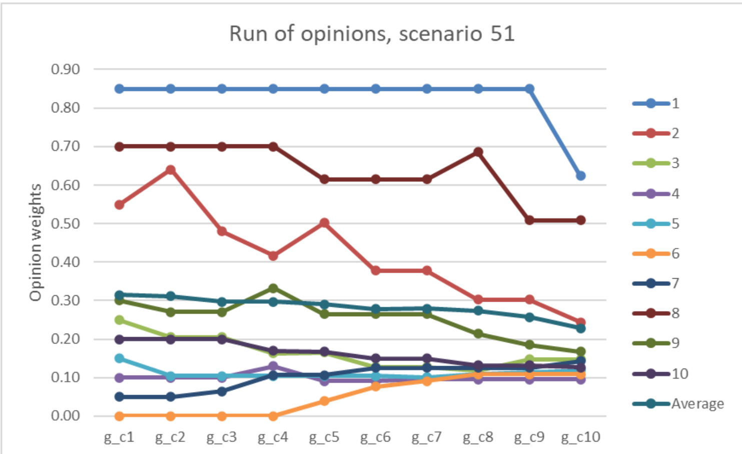


Figure 63: Example of a run of scenario 51, Low meat attachment distribution under the idealism model

7.2.4 Standard spread skewed towards high meat attachment

- Scenario 52:
  - Standard ι (ι =0.25)
  - Skewed distribution towards high meat attachment (type 4 distribution)

In figure 64 and 65, the scatterplots and histograms of scenario 4, 24 and 52 are compared. The scatterplots and histograms of scenario 53 and scenario 24 are fairly similar. The main difference is that the agents with the one opinion under idealism threshold ι stay with their opinion, since there are no other idealists to be influenced by. The mean in the initial distribution was 0.70, while the mean in the final distribution was 0.64, as can be seen in figure 65.

The final distribution of scenario 52 is significantly different from the final distribution in scenario 4, with a p-value of 0.000 for the Kolmogorov-Smirnov test. However, the Kolmogorov-Smirnov test could not prove that the final distribution of scenario 52 is statistically significantly different from the final distribution of scenario 24 with a 95% confidence (p-value 0.100). This might be due to the low number of idealists in this scenario combined with the relatively low power of the Kolmogorov-Smirnov test, since the difference seems quite clear in the histogram of figure 65. See figure 66 for an example of an individual run of scenario 52.

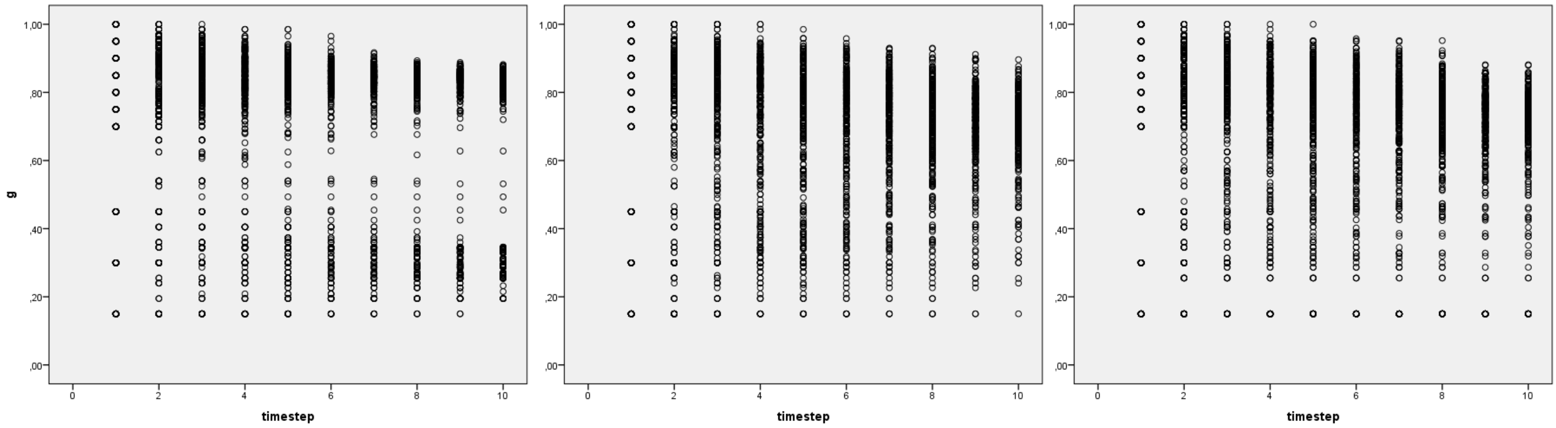


Figure 64: Scatterplots of all datapoints for scenario 4 (left, social influence model), scenario 24 (middle, cognitive dissonance model), and scenario 52 (right, idealism model). Initial distributions skewed towards high meat attachment

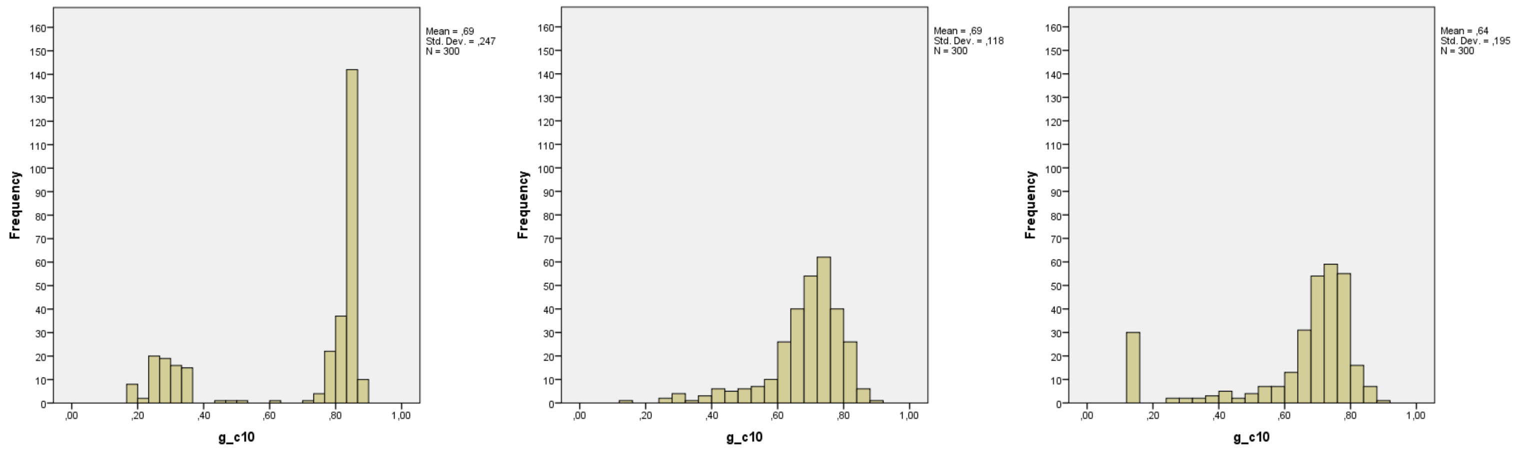


Figure 65: Histograms of final distributions of scenario 4 (left, social influence model) scenario 24 (middle, cognitive dissonance model), and scenario 52 (right, idealism model). Initial distributions skewed towards high meat attachment

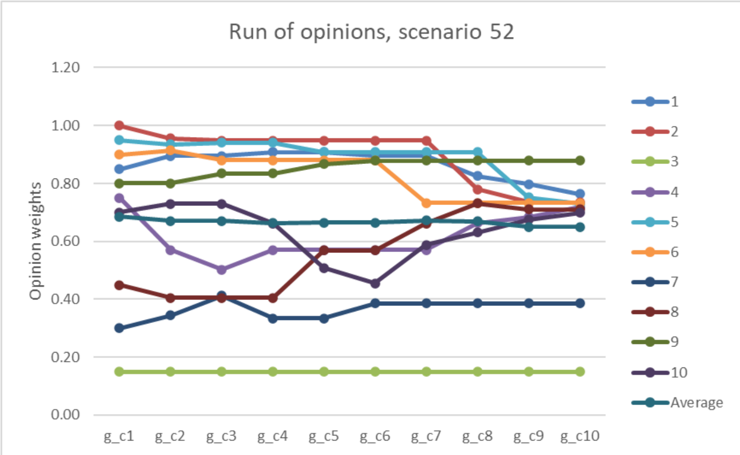


Figure 66: Example of a run of scenario 52, High meat attachment distribution under the idealism model.

7.3 Scenarios comparing idealism thresholds ι

Low ι (Scenario 53, 55, 57, 59):

- Scenario 53:
  - Low ι (ι =0.1)
  - Even distribution (type 1 distribution)
- Scenario 55:
  - Low ι (ι =0.1)
  - Polarized distribution (type 2 distribution)
- Scenario 57:
  - Low ι (ι =0.1)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 59:
  - Low ι (ι =0.1)
  - Skewed distribution towards high meat attachment (type 4 distribution)

High ι (Scenario 54, 56, 58, 60):

- Scenario 54:
  - High ι (ι =0.4)
  - Even distribution (type 1 distribution)
- Scenario 56:
  - High ι (ι =0.4)
  - Polarized distribution (type 2 distribution)
- Scenario 58:
  - High ι (ι =0.4)
  - Skewed distribution towards low meat attachment (type 3 distribution)
- Scenario 60:
  - High ι (ι =0.4)
  - Skewed distribution towards high meat attachment (type 4 distribution)

The ι parameter represents the threshold for idealism. Whenever an agent holds an opinion below the idealism threshold, they will only allow themselves to be potentially influenced by other idealists under the idealism threshold. Therefore, in the scenarios with a very low ι, there are relatively few idealists in each run, which are possibly more likely to have large opinion differences with other agents depending on the type of distribution. Scenarios 53 and 55 only start with one idealist in the initial distribution. Scenario 57 starts with three idealists in the initial distribution. Scenario 59, the high meat attachment distribution and low ι, does not start with any idealists and is therefore similar to standard cognitive dissonance scenario 24 and can be omitted from the Kolmogorov-Smirnov tests. Therefore, looking at the scatterplots in figure 67, the scatterplot for scenario 59 will look fairly similar to the standard scenario of the cognitive dissonance model. The scenarios with only one idealist (scenarios 53 and 55 in the initial distribution, seem to result in a final distribution similar to the standard cognitive dissonance scenarios (scenarios 21 and 22).

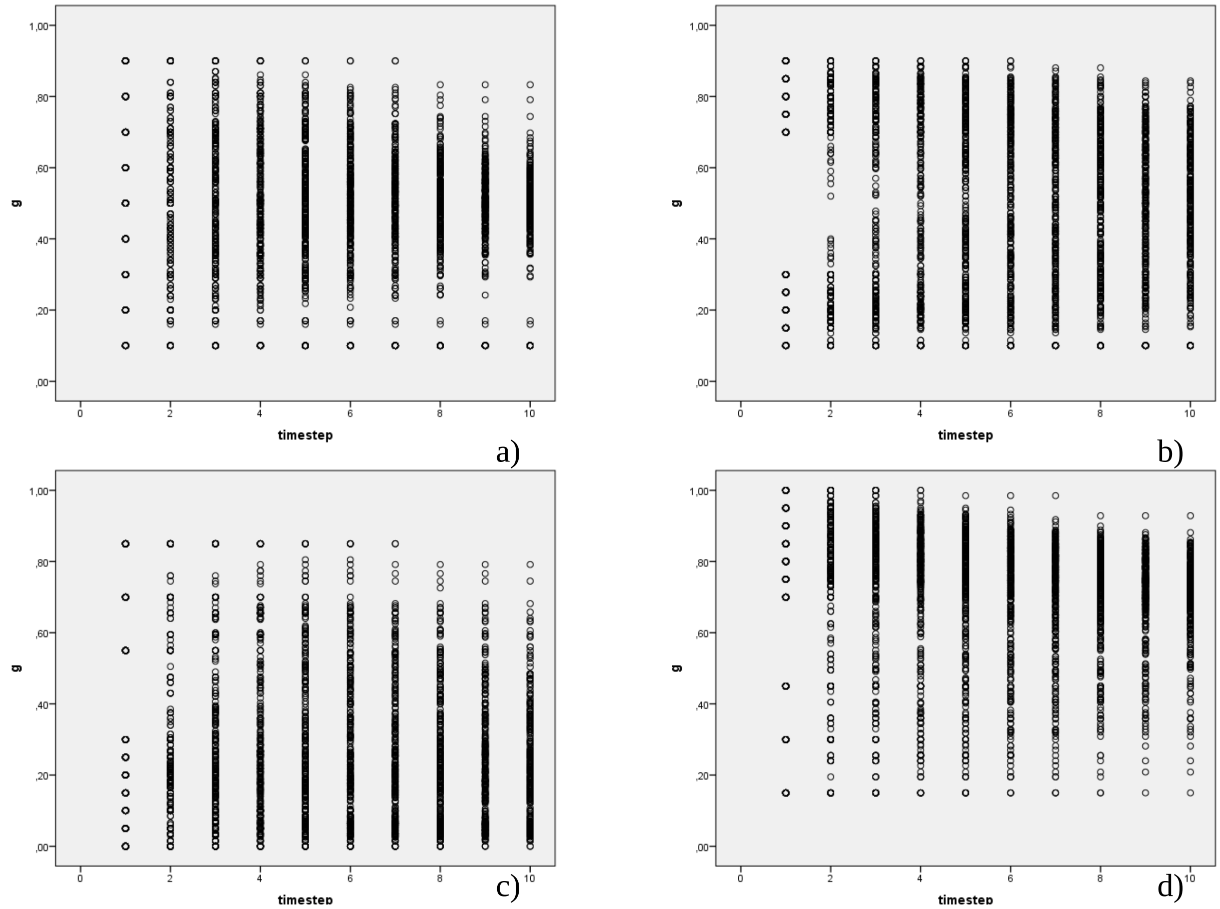


Figure 67: Scatterplots of all datapoints for scenarios with a *low* ι; scenario 53 (a, even distribution), scenario 55 (b, polarized distribution), scenario 57 (c, low meat attachment), and scenario 59 (d, high meat attachment)

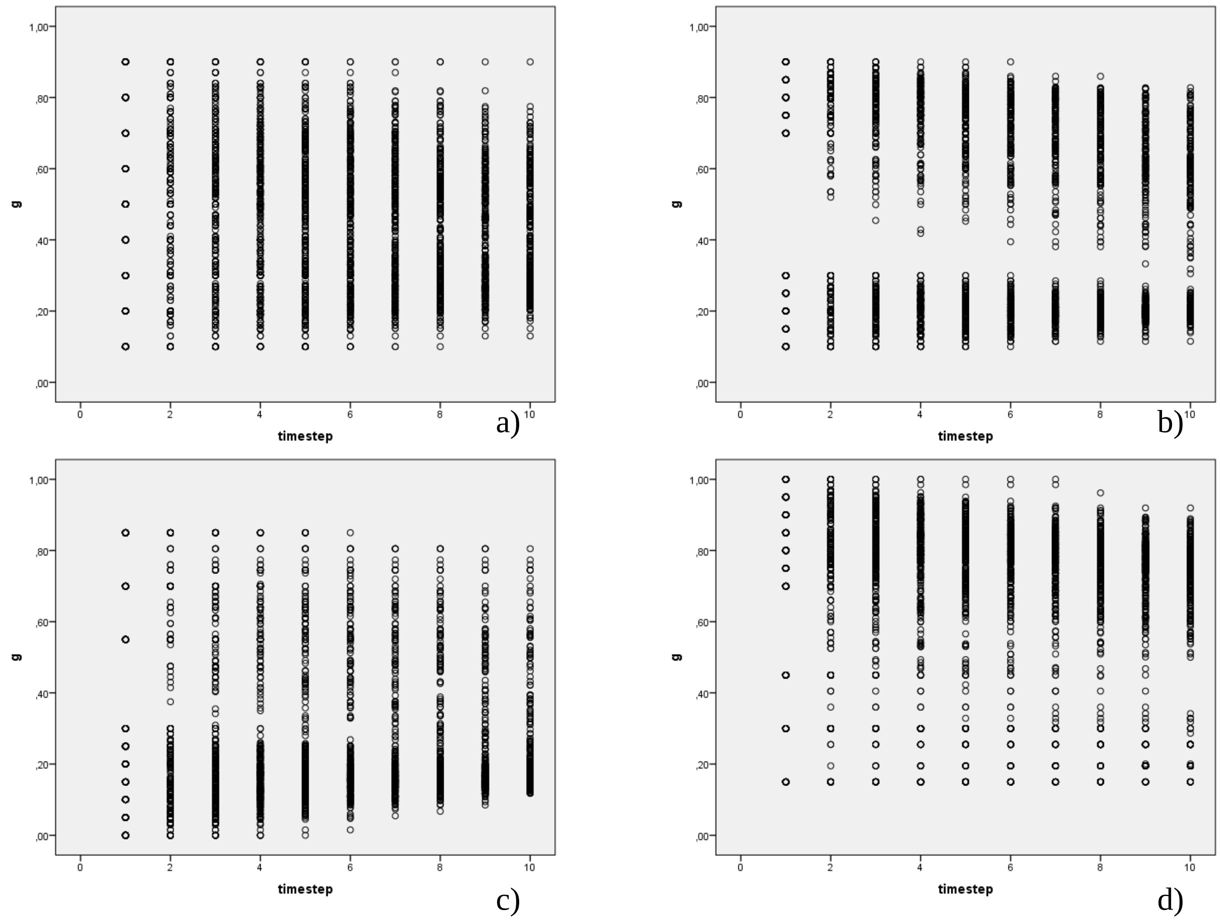


Figure 68: Scatterplots of all datapoints for scenarios with a high ι; scenario 54 (a, even distribution), scenario 56 (b, polarized distribution), scenario 58 (c, low meat attachment), and scenario 60 (d, high meat attachment)

Looking at the histograms for the scenarios 53 and 55 (figure 69a and 69b), the distributions look fairly similar to the histograms of the standard cognitive dissonance scenarios (scenarios 21 and 22), with the exception of one bar on the left side of the histogram which represents the idealists. The corresponding Kolmogorov-Smirnov tests comparing scenario 21 with scenario 53, was not significant with p-value 0.081. The Kolmogorov-Smirnov tests comparing scenario 22 with scenario 55, was not significant with p-value 0.066. For scenario 57, the final distribution (see figure 69c) does indeed look somewhat different compared to the final distribution of scenario 23. This is confirmed by the p-value (0.000) of the corresponding Kolmogorov-Smirnov test.

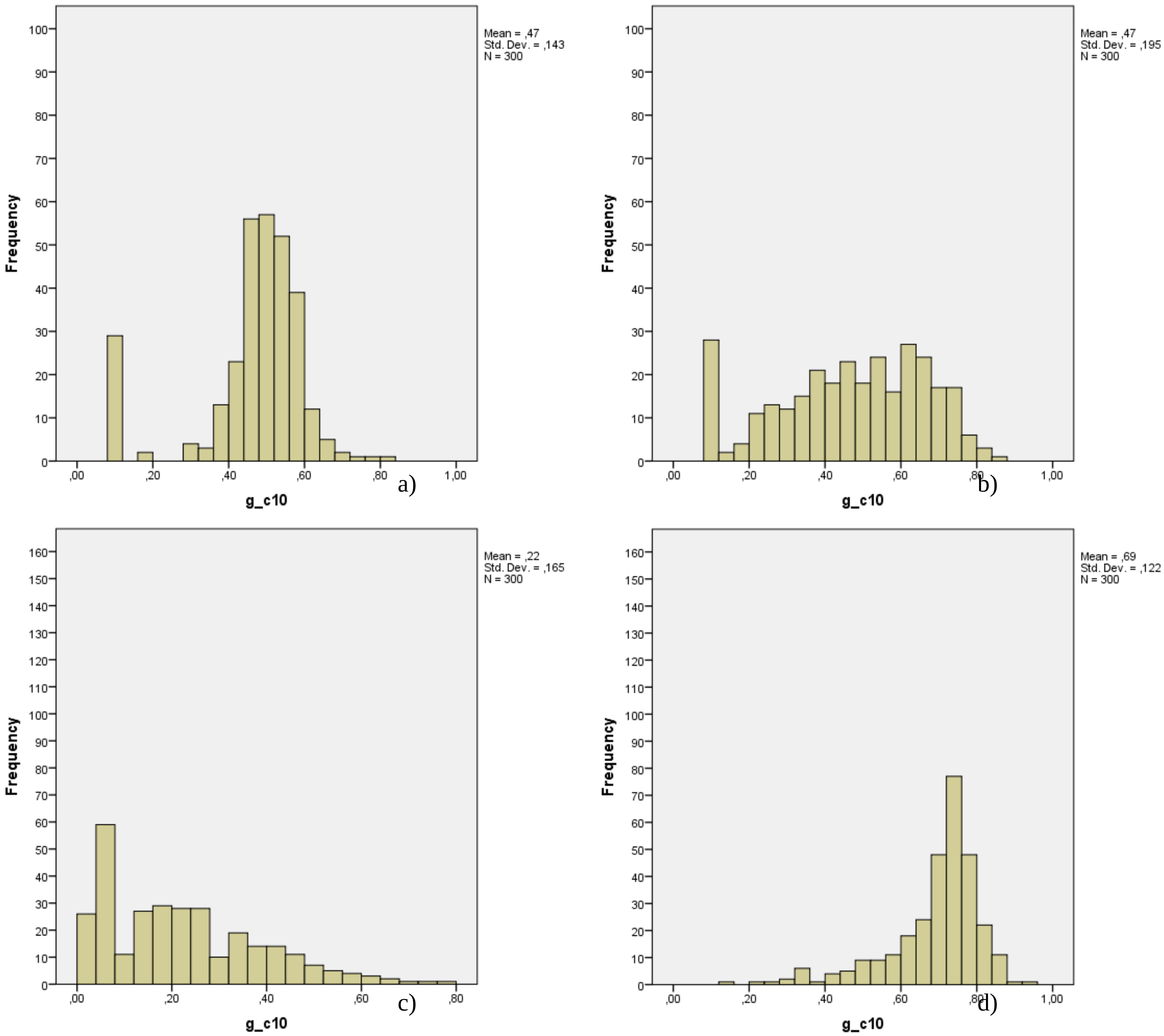


Figure 69: Histograms of the final distributions of scenarios with a low ι; 53 (a, even distribution), 55 (b, polarized distribution), 57 (c, low meat attachment distribution), 59 (d, high meat attachment distribution)

The histograms for the scenarios with a high idealism threshold ι in figure 70, definitely seem more skewed towards a lower meat attachment compared to the standard scenarios for the model of cognitive dissonance. This is also confirmed by the Kolmogorov-Smirnov tests comparing the final distributions of the standard scenarios of the model of cognitive dissonance with the comparable scenario with a high ι, which all returned a p-value of 0.000 (see tables 21 to 24).

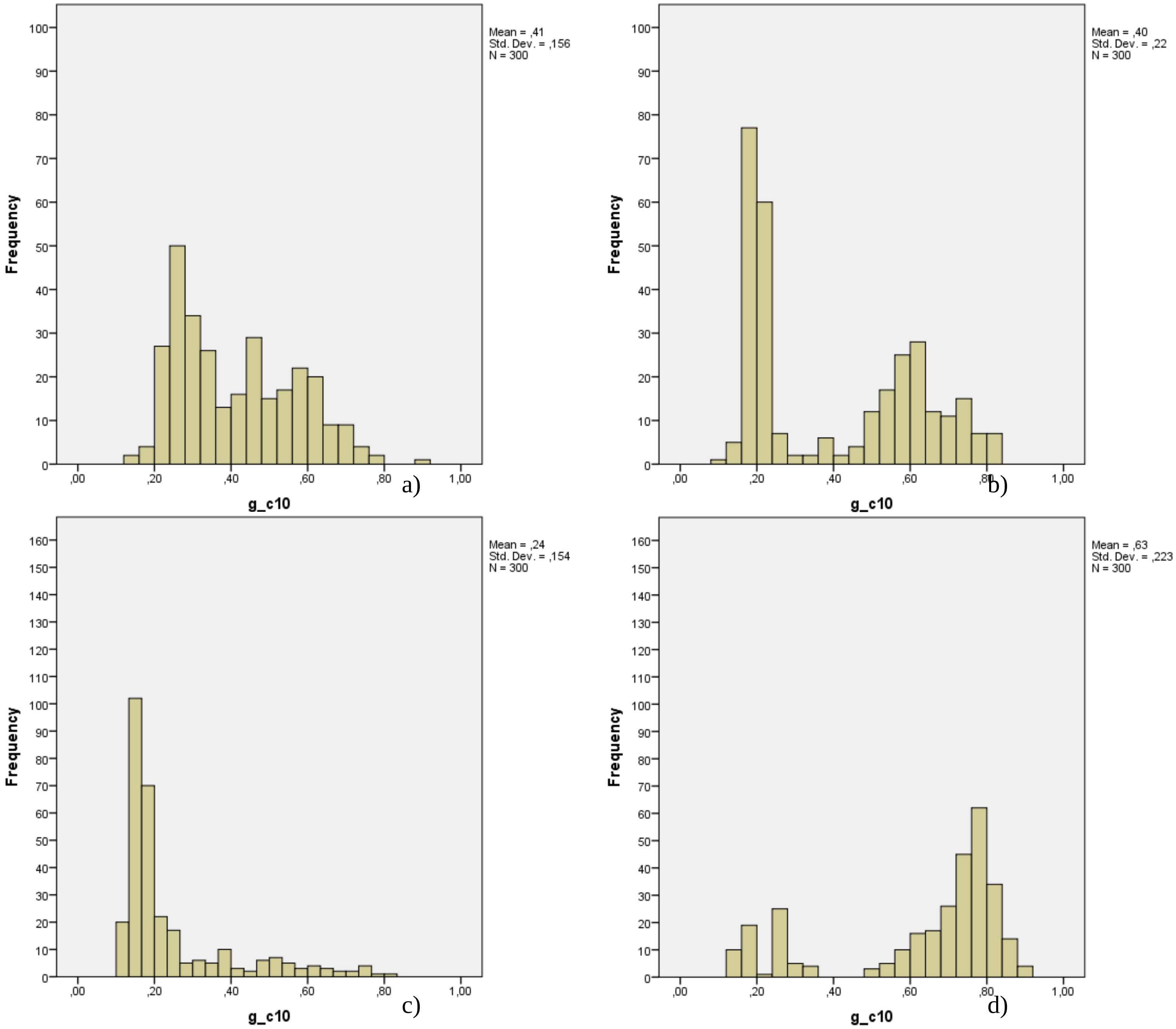


Figure 70: Histograms of the final distributions of scenarios with a high ι; 54 (a, even distribution), 56 (b, polarized distribution), 58 (c, low meat attachment distribution), 60 (d, high meat attachment distribution)

Looking at the results of the executed Kolmogorov-Smirnov tests in tables 21 to 24, it shows that the scenarios with high idealism thresholds ι have significantly different final distributions from their comparable standard idealism scenarios. For the even distribution, polarized distribution and low meat attachment distribution, these tests were significant with p-values 0.000, 0.000 and 0.000 respectively. For the high meat attachment distribution, the test was significant as well with p-value 0.013. As previously mentioned, all tests with the comparable standard scenarios of the cognitive dissonance model (scenarios 21, 22, 23 and 24) were significant for the scenarios with standard and high ι. For the low ι scenarios, it was only significant for the low meat attachment distribution, which had multiple idealists in the initial distribution.

Kolmogorov p-values	1	21	49	53	54
1 (Standard, model 1)		**0.000**	**0.000**	**0.001**	**0.000**
21 (Standard model 2)	**0.000**		**0.000**	0.081	**0.000**
49 (Standard model 3)	**0.000**	**0.000**		**0.000**	**0.000**
53 (low ι)	**0.001**	0.081	**0.000**		**0.000**
54 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	

Table 21: P-values of the Kolmogorov-Smirnov tests for the even distributions (type 1)

Kolmogorov p-values	2	22	50	55	56
2 (Standard, model 1)		**0.000**	**0.000**	**0.000**	**0.000**
22 (Standard model 2)	**0.000**		**0.000**	0.066	**0.000**
50 (Standard model 3)	**0.000**	**0.000**		**0.000**	**0.000**
55 (low ι)	**0.000**	0.066	**0.000**		**0.000**
56 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	

Table 22: P-values of the Kolmogorov-Smirnov tests for the polarized distributions (type 2)

Kolmogorov p-values	3	23	51	57	58
3 (Standard, model 1)		**0.000**	**0.000**	**0.000**	**0.000**
23 (Standard model 2)	**0.000**		**0.000**	**0.000**	**0.000**
51 (Standard model 3)	**0.000**	**0.000**		**0.000**	**0.000**
57 (low ι)	**0.000**	**0.000**	**0.000**		**0.000**
58 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	

Table 23: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards low meat attachment (type 3)

Kolmogorov p-values	4	24	52	60
4 (Standard, model 1)		**0.000**	**0.000**	**0.000**
24 (Standard model 2)	**0.000**		0.100	**0.000**
52 (Standard model 3)	**0.000**	0.100		**0.013**
60 (high ι)	**0.000**	**0.000**	**0.013**	

Table 24: P-values of the Kolmogorov-Smirnov tests for the distributions skewed towards high meat attachment (type 4)

8. Final overview of the Kolmogorov-Smirnov comparison tests

In order to see the impact of different models and different parameter values on the final opinion distributions, two sample Kolmogorov-Smirnov tests were executed. The null hypothesis of the Kolmogorov-Smirnov test is that the compared samples are from the same distribution. Thus, if the null hypothesis can be rejected, the two final distributions that were compared are significantly different from each other. To get an idea of how the final distributions are different from each other, one can look at the histograms of the final distributions of each scenario.

Table 25, shows an overview of all the p-values of the Kolmogorov-Smirnov tests comparing the even distribution scenarios with each other. Table 26, shows an overview of all the p-values of the Kolmogorov-Smirnov tests comparing polarized distribution scenarios with each other. Table 27, shows an overview of all the p-values of the Kolmogorov-Smirnov tests comparing scenarios with distributions skewed towards low meat attachment with each other. Table 28, shows an overview of all the p-values of the Kolmogorov-Smirnov tests comparing scenarios with distributions skewed towards high meat attachment with each other.

For the model of social influence, the scenarios investigating different values of social influence threshold d, were significantly different from each other. Suggesting social influence threshold d is a parameter with an important influence on the final distribution. The main influence of d when comparing the histograms of the final distributions, seems to be that the parameter value of d determines the degree of fragmentation and polarization within the final distribution. The multiple scenarios investigating convergence parameter μ values, did not lead significantly different final distributions, when μ had a high parameter value. It did lead to significantly different final distributions when μ was low (see table 25 to 28). The main influence of μ seemed to be related to the rate of convergence, when looking at the scatterplots of these scenarios. The difference between low, standard and high μ values in each scenario were also slightly smaller compared to the differences of social influence threshold d. These steps were deemed seemed more appropriate due to the restriction of $\mu<0.5$. Furthermore, conclusions from comparisons between scenarios that investigate different parameters have to be carefully made, as they differ in parameter value d and parameter value μ simultaneously.

From the Kolmogorov-Smirnov tests, it became clear that the cognitive dissonance model results in significantly different final distributions compared to the standard social influence scenario. Thus, showing that adding cognitive dissonance to the model, significantly changes the final distribution of opinions (see table 25 to 28). The only exception to this is scenario 34, which is an even distribution scenario with a high value for parameter P_I. A high parameter value of P_I, brings the model of cognitive dissonance closer to the model of social influence, since for a parameter value of 1, social influence will never take place when the difference in opinions is larger than social influence threshold d. This might indicate that when the initial distribution does not lead to some form of polarization in the social influence model, a high P_I does not have enough impact to significantly alter the final distribution. From the Kolmogorov-Smirnov tests and comparisons of histograms of the final distributions, it seems as if P_I's influence results in a breakthrough of polarization or fragmentation of opinions. The lower P_I, the faster this breakthrough of polarization and consensus around the mean seems to happen. In contrast different values of P_s, do not lead to different final distributions with comparable scenarios in all cases. Scenarios comparing different values of α, were not significantly different from each other. Thus, for the values of α chosen for this model, there was on significant difference in the final distribution. The values chosen for α were chosen between 0.05 and 0.15, due to the increasing nature of α on 1 + αN (and thus decreasing effect on $P_l^{1+\alpha N}$). Therefore, this cognitive dissonance model suggests that cognitive dissonance will homogenize beliefs on the importance of meat around the mean if given enough encounters and the current parameter values. Introducing cognitive dissonance leads to significantly different distributions of opinions surrounding the importance of meat compared to the social influence model. Especially, when there is fragmentation or polarization in opinions that cannot be overcome by social influence by itself.

Furthermore, the cognitive final distributions were also significantly different from the non-standard influence scenarios' final distributions in all, but two cases. However, the comparison between those scenarios is tenuous, as they differ not only based on the cognitive dissonance scenario, but also use different values for parameter d and μ. Similarly comparing cognitive dissonance scenarios that investigate different parameter values has to be done carefully, as they differ in at least two parameter values simultaneously.

The idealism model was also significantly different in its final distributions compared to the standard scenarios of the social influence model. However, when compared to the cognitive dissonance model, the idealism model was significantly different from every comparable standard cognitive dissonance model scenario when the initial distribution contained more than one idealist, regardless the initial distribution type. When the initial distribution contained only one idealist, the equivalent standard cognitive dissonance scenario did not have a significantly different distribution compared with the idealism model. This seems to suggest that at least two individuals need to be idealists within the initial distribution in order to end up with a significantly different final distribution for the given amount of timesteps compared to an equivalent cognitive dissonance scenario. These tests combined with the histograms of the final distributions seem to suggest that a few idealists in the initial distribution of opinions surrounding the importance of meat, can reduce the mean of the final distribution. Thus, suggesting a lower attachment to meat overall, when both cognitive and idealists are present in the model.

Kolmogorov p-values	1	5	6	13	14	21	25	26	33	34	41	42	49	53	54
1 (Standard, model 1)		**0.000**	**0.000**	**0.034**	0.121	**0.000**	**0.000**	**0.034**	**0.000**	0.121	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**
5 (low d)	**0.000**		**0.000**	**0.010**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
6 (high d)	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
13 (low μ)	**0.034**	**0.010**	**0.000**		0.249	**0.000**	**0.000**	**0.000**	**0.000**	**0.016**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
14 (high μ)	0.121	**0.000**	**0.000**	0.249		**0.000**	**0.000**	**0.000**	**0.000**	**0.007**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
21 (Standard model 2)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		0.292	**0.006**	0.249	**0.000**	0.721	0.249	**0.000**	0.081	**0.000**
25 (Low P_s)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.292		**0.000**	0.249	**0.000**	0.100	0.787	**0.000**	**0.007**	**0.000**
26 (High P_s)	**0.034**	**0.000**	**0.000**	**0.000**	**0.000**	**0.006**	**0.000**		**0.000**	**0.007**	0.100	**0.001**	**0.000**	0.100	**0.000**
33 (Low P_l)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.249	0.249	**0.000**		**0.000**	0.066	0.518	**0.000**	**0.002**	**0.000**
34 (High P_l)	0.121	**0.000**	**0.000**	**0.016**	**0.007**	**0.000**	**0.000**	**0.007**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
41 (low α)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.721	0.100	0.100	0.066	**0.000**		0.249	**0.000**	0.100	**0.000**
42 (high α)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.249	0.787	**0.001**	0.518	**0.000**	0.249		**0.000**	**0.034**	**0.000**
49 (Standard model 3)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**

Table 25: Overview of all the p-values of the Kolmogorov-Smirnov tests comparing even distribution scenarios

Kolmogorov p-values	2	7	8	15	16	22	27	28	35	36	43	44	50	55	56
2 (Standard, model 1)		**0.000**	**0.000**	**0.000**	0.847	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
7 (low d)	**0.000**		**0.000**	**0.034**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
8 (high d)	**0.000**	**0.000**		**0.000**	**0.000**	**0.004**	**0.021**	**0.021**	**0.000**	**0.000**	**0.010**	**0.016**	**0.000**	**0.001**	**0.000**
15 (low μ)	**0.000**	**0.034**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
16 (high μ)	0.847	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
22 (Standard model 2)	**0.000**	**0.000**	**0.004**	**0.000**	**0.000**		0.584	0.341	**0.000**	**0.000**	0.454	0.053	**0.000**	0.066	**0.000**
27 (Low P_s)	**0.000**	**0.000**	**0.021**	**0.000**	**0.000**	0.584		0.721	**0.000**	**0.000**	0.518	0.249	**0.000**	0.066	**0.000**
28 (High P_s)	**0.000**	**0.000**	**0.021**	**0.000**	**0.000**	0.341	0.721		**0.000**	**0.000**	0.941	0.249	**0.000**	**0.034**	**0.000**
35 (Low P_l)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
36 (High P_l)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
43 (low α)	**0.000**	**0.000**	**0.010**	**0.000**	**0.000**	0.454	0.518	0.941	**0.000**	**0.000**		0.395	**0.000**	0.121	**0.000**
44 (high α)	**0.000**	**0.000**	**0.016**	**0.000**	**0.000**	0.053	0.249	0.249	**0.000**	**0.000**	0.395		**0.000**	**0.034**	**0.000**
50 (Standard model 3)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**
55 (low ι)	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	0.066	0.066	**0.034**	**0.000**	**0.000**	0.121	**0.034**	**0.000**		**0.000**
56 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Table 26: Overview of all the p-values of the Kolmogorov-Smirnov tests comparing polarized distribution scenarios

Kolmogorov p-values	3	9	10	17	18	23	29	30	37	38	45	46	51	57	58
3 (Standard, model 1)		**0.000**	**0.000**	**0.000**	0.292	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
9 (low d)	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
10 (high d)	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.210	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
17 (low μ)	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
18 (high μ)	0.292	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
23 (Standard model 2)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		0.941	0.100	**0.006**	**0.000**	0.787	0.721	**0.000**	**0.000**	**0.000**
29 (Low P_s)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.941		**0.027**	**0.004**	**0.000**	0.341	0.721	**0.000**	**0.000**	**0.000**
30 (High P_s)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.100	**0.027**		**0.000**	**0.000**	0.518	**0.042**	**0.000**	**0.000**	**0.000**
37 (Low P_l)	**0.000**	**0.000**	0.210	**0.000**	**0.000**	**0.006**	**0.004**	**0.000**		**0.000**	**0.000**	**0.021**	**0.000**	**0.000**	**0.000**
38 (High P_l)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
45 (low α)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.787	0.341	0.518	**0.000**	**0.000**		0.341	**0.000**	**0.000**	**0.000**
46 (high α)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	0.721	0.721	**0.042**	**0.021**	**0.000**	0.341		**0.000**	**0.000**	**0.000**
51 (Standard model 3)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**
57 (low ι)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**
58 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	

Table 27: Overview of all the p-values of the Kolmogorov-Smirnov tests comparing scenarios with distributions skewed towards low meat attachment

Kolmogorov p-values	4	11	12	19	20	24	31	32	39	40	47	48	52	60
4 (Standard, model 1)		**0.000**	**0.000**	**0.000**	0.249	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
11 (low d)	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
12 (high d)	**0.000**	**0.000**		**0.000**	**0.000**	0.053	**0.042**	**0.010**	**0.007**	**0.000**	**0.013**	**0.042**	**0.042**	**0.000**
19 (low μ)	**0.000**	**0.000**	**0.000**		**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
20 (high μ)	0.249	**0.000**	**0.000**	**0.001**		**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**
24 (Standard model 2)	**0.000**	**0.000**	0.053	**0.000**	**0.000**		0.518	**0.016**	**0.034**	**0.000**	0.210	0.454	0.100	**0.000**
31 (Low P_s)	**0.000**	**0.000**	**0.042**	**0.000**	**0.000**	0.518		**0.034**	**0.002**	**0.000**	0.900	0.341	0.147	**0.000**
32 (High P_s)	**0.000**	**0.000**	**0.010**	**0.000**	**0.000**	**0.016**	**0.034**		**0.000**	**0.000**	0.100	**0.002**	**0.006**	**0.000**
39 (Low P_l)	**0.000**	**0.000**	**0.007**	**0.000**	**0.000**	**0.034**	**0.002**	**0.000**		**0.000**	**0.000**	**0.010**	**0.001**	**0.000**
40 (High P_l)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		**0.000**	**0.000**	**0.000**	**0.000**
47 (low α)	**0.000**	**0.000**	**0.013**	**0.000**	**0.000**	0.210	0.900	0.100	**0.000**	**0.000**		0.121	0.210	**0.000**
48 (high α)	**0.000**	**0.000**	**0.042**	**0.000**	**0.000**	0.454	0.341	**0.002**	**0.010**	**0.000**	0.121		0.081	**0.000**
52 (Standard model 3)	**0.000**	**0.000**	**0.042**	**0.000**	**0.000**	0.100	0.147	**0.006**	**0.001**	**0.000**	0.210	0.081		**0.013**
60 (high ι)	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.013**	

Table 28: Overview of all the p-values of the Kolmogorov-Smirnov tests comparing scenarios with distributions skewed towards high meat attachment

9. Conclusion

Reducing the current consumption of meat is one of the ways suggested by the FAO to create more sustainable diets (Burlingame & Dernini, 2011). However, as the consumption of food and in particular meat is a highly social and cultural behavior, changing food practices is known to be a challenge (Perry & Grace, 2015; Sanchez-Sabate & Sabaté, 2019). Often some form of social mechanism, for instance social influence, is necessary to facilitate a reduction in meat consumption. One social concept that is described as both a barrier and a driver in order to change behavior surrounding meat consumption is the concept of cognitive dissonance. In this thesis defined as "*the feelings of unease and discomfort when behavior and perceptions of self-identity are misaligned, often instigated by being presented new information or different beliefs through social connections*". This discomfort as a consequence of cognitive dissonance is often experienced when individuals are confronted with conflicting beliefs, attitudes or opinions (Li et al., 2020). People are motivated to reduce the discomfort brought on by cognitive dissonance (Covey, 2009). In order to alleviate the discomfort brought on by conflicting beliefs and behavior, two paths can be taken by an individual. One option to alleviate cognitive dissonance is by employing a diverse set of moral disengagement strategies to deny or avoid the fact that beliefs and behavior are misaligned (Alfnes et al., 2010; Buttlar & Walther, 2019). Examples include pro-meat justifications, scientific skepticism, downplaying the individual impact, and avoiding to recognize the issue (Rothgerber, 2015). When this path is chosen cognitive dissonance acts as a barrier against behavior change. The other option is to change the behavior to align with beliefs, facilitating behavior changes. Especially, when cognitive dissonance is triggered routinely, it could be a motivator to change behavior, since continuously having to employ moral disengagement strategies takes effort.

This concept of cognitive dissonance is a well-known sociological and psychological concept on how behavior changes surrounding meat consumption can be facilitated or complicated on an individual level. However, it does not show how this concept would theoretically influence the spread of beliefs and opinions surrounding meat consumptions within social networks. Opinion dynamics modelling (ODM) is a method which creates simulation models to simulate the theoretical impact of social concepts on different opinion structures within fictional social networks. It is assumed opinions and beliefs withing networks develop and change over time due to social diffusion processes in which participants of social groups interact with each other (Schenk, 2014).

This thesis attempts to contribute to opinion dynamics modeling (ODM) by proposing a way to incorporate the concept of cognitive dissonance for opinions surrounding meat consumption in opinion dynamics modelling. As far as we are aware, the concept of cognitive dissonance is relatively unexplored in opinion dynamics modeling. The only ODM model trying to simulate cognitive dissonance specifically is proposed by Li, et al. (2020), which focuses on letting agents update and change their connections within networks as a result of cognitive dissonance (Li et al., 2020). Therefore, focusing on applying one method of moral disengagement strategies. The model in this thesis tries to encompass a wider variety of moral disengagement strategies. Furthermore, not all social interactions which threaten specific behaviors or opinions are a direct cause to disregard social connections. Besides, sometimes it is not possible to update connections and encounters in such a way that you can prescreen and filter out other individuals based on their beliefs. The behavior surrounding meat consumption is highly social and cultural (de Boer et al., 2017) and confrontations with other people's meat consumption behavior cannot be avoided completely, when having social interactions with friends, colleagues, business or other social connections. It is unlikely to go through life and never interact with a vegetarian and discuss the topic of meat consumption in some capacity.

Three simulation models were compared. The first model is a social influence model based on Sun and Müller (2013) without any type of cognitive dissonance. Social influence threshold d, seems to influence the final distribution's degree of fragmentation or polarization. The second cognitive dissonance model combines this first social influence model with cognitive dissonance. It assumes that cognitive dissonance occurs for both small and large opinion difference, but has different likelihoods of employing moral disengagement strategies. This is due to the fact that small behavior changes are often considered easier (Tosun & Gürce, 2018). Furthermore, more exposure to large opinion differences in previous encounters, does reduce the likelihood of employing moral disengagement strategies in subsequent encounters. The model of cognitive dissonance seems to lead to significantly different final distributions compared to the social influence model when the social influence model resulted in some form of polarization or fragmentation that could not be overcome within the social influence model. The cognitive dissonance model had a general trend where final opinion distributions, where starting to converge towards consensus around the mean. The third model is an idealism model, and adds the concept of idealism to the second model. Idealists in this model can only be influenced by other idealists. When there was more than one idealist in the initial distribution, the idealism model led to a significantly different final distribution compared to the cognitive dissonance model in our scenarios.

If cognitive dissonance combined with social influence indeed impacts an individual's beliefs around meat consumption behavior, then this simulation model suggests that there will also be an effect on the belief and opinion structure of the social networks. For the parameters, distributions and social network chosen in this thesis, the simulation model suggests cognitive dissonance will push opinions surrounding meat consumption to homogenize and reach consensus over time. Beliefs and opinions are often suggested to indirectly effect or partly inform consumption decisions and consumption behavior. Thus, cognitive dissonance might indeed be one of the social mechanisms, pushing behavior changes surrounding meat consumption over time. Furthermore, our simulation model suggests, that when the cognitive dissonance mechanism is combined with a simplified version of idealism, opinions will move towards the idealism threshold over time. Thus, resulting in a lower attachment to meat over time. Of course, this is only a simulation model and shows the theoretical impact of cognitive dissonance, in practice many other factors contribute to opinions surrounding meat consumption and the actual behavior surrounding meat consumption. Chapter 2 gives an overview of some of these factors indicated by the literature. Therefore, these findings can of course not be extrapolated towards the real world. However, it may help us to better understand the concept of cognitive dissonance on a social network level and the potential for belief and behavior changes it possesses, at least in theory.

10. Reflection

This thesis has proposed a new way to introduce the concept of cognitive dissonance in opinion dynamics modelling (ODM). This concept is as far as we are aware only specifically explored within ODM by Li, et al. (2020), where the focus is on the moral disengagement strategies related to changing and updating connections within social networks to create networks with likeminded people. This leads to a model where cognitive dissonance is only seen as a barrier against behavior change. This thesis takes a broader approach, and allows for cognitive dissonance to be both a barrier and a facilitator for changing opinions, which might indirectly affect behavior changes. Furthermore, cognitive dissonance is often described as a social mechanism for individuals to induce change. This thesis hopes to contribute at least some additional understanding to how cognitive dissonance can theoretically affect different types of opinion distributions over time. Or at least provide a simulation model which could add more understanding about the effect of cognitive dissonance on network opinion distributions in the future.

In order to expand on the simulation models presented and to add more understanding about the effect of cognitive dissonance on network opinion distributions in the future, several avenues of further research could be explored. A closer look at the effects of changing parameter values on a more continuous scale with many runs, could inform more robust conclusions about the sensitivity of the model to certain parameters. This would allow for more detailed statements about the effects of every parameter. Focusing on a specific parameter, allows for more scenarios focused on one specific parameter, rather than having to consider the effect of all parameters to confirm the proof of concept of the presented simulation models. Another interesting avenue to explore is to widen the time horizons and focus on when opinion distributions start to stabilize. Finally, incorporating this approach to modeling cognitive dissonance in different network structures would be interesting, to see what the effect of cognitive dissonance is through multiple connected networks, where not all agents are directly linked to each other. It would be interesting to see, whether adding cognitive dissonance will also reduce polarization and fragmentation between networks that are only loosely connected.

Another big question, as with all simulation models, is how to bridge the gap between the simulated model and the real world. This, if attempted, will definitely not be an easy task. Opinions are often not directly observable or directly measurable, and can be influenced by multiple factors and social mechanisms at the same time. Therefore, social sciences have developed tools to ascertain the actual beliefs people hold. Questionnaires are one of the main tools to ascertaining opinions, and are often standardized (Lavakras, 2011c). Questionnaires could ask people to indicate the importance they attach to the importance of meat, i.e., on a Likert scale. The Likert scale is the most common approach to measuring attitudes in surveys, and results in ordinal data (Lavakras, 2011a). There are some potential response distortions associated with the Likert scale. Some people might have a central tendency bias, due to a reluctance to choose the most extreme response options. Acquiescence bias can occur when people try to pick the "correct" or most appropriate answer, rather than convey their actual attitudes. Social desirability bias, can occur when people try to paint themselves in a positive light or they respond in a manner that they think the questionnaire would like them to answer (Lavakras, 2011a). Other biases may occur due to people having different associations with the language in the questionnaire. I.e., What does one consider strongly agree? Furthermore, socially undesirable behavior may be underreported, while socially desirable behavior is overreported.

Therefore, good questionnaire design is vital. Measuring attitudes surrounding meat consumption and its environmental, ethical and health impacts is likely a challenge and should be done with care (Lavakras, 2011b).

Therefore, while actual opinions might be difficult to determine, an individual's meat consumption and food practices are possible to measure. Perhaps, measuring meat consumption and food practices in conjunction with attitudes can provide useful information to verify the measurement of attitudes. The question is then how to research the link between the stated attitudes, food practices and social interactions. Perhaps some experimental set ups might be possible to research this link further. Perhaps one such experimental set up could determine people's attitudes and meat attachment as well as their current meat consumption. If it is possible social interactions can be facilitated and observed between people with different meat consumption practices and different beliefs around the environmental, ethical and health impact of meat consumption. Afterwards, determine whether people's beliefs, meat attachment and meat consumption have changed as a result of these social interactions. If people's beliefs and meat consumption have changed, this might be due to a combination of social influence and cognitive dissonance, which is what the cognitive dissonance model and idealism model attempt to represent. This might lead to some interesting results, although very difficult to set up properly.

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