Impact of Argument Type and Concerns in Argumentation with a Chatbot

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***Abstract*—Conversational agents, also known as *chatbots*, are versatile tools that have the potential of being used in dialogical argumentation. They could possibly be deployed in tasks such as persuasion for behaviour change (e.g. persuading people to eat more fruit, to take regular exercise, etc.). However, to achieve this, there is a need to develop methods for acquiring appropriate arguments and counterargument that reflect both sides of the discussion. For instance, to persuade someone to do regular exercise, the chatbot needs to know counterarguments that the user might have for not doing exercise. To address this need, we present methods for acquiring arguments and counterarguments, and importantly, meta-level information that can be useful for deciding when arguments can be used during an argumentation dialogue. We evaluate these methods in studies with participants and show how harnessing these methods in a chatbot can make it more persuasive.**

***Index Terms*—dialogical argumentation systems, chatbots, argument types, behaviour change, computational persuasion**

I. Introduction

Chatbots are versatile tools that have the potential of being used as agents in dialogical argumentation systems for behaviour change applications. For example, a chatbot could persuade people to do more sports by presenting arguments in favour of exercising and countering the arguments given by the user as to why she is not willing to. The chatbot is thereby engaging in an argumentation dialogue where it acts as the persuader and the user as the persuadee. This calls for the development of methods for acquiring appropriate arguments and counterarguments that reflect the points of view of both parties. The chatbot needs to be aware of the potential arguments people might have for not engaging in the behaviour in question, in order to reply with appropriate counterarguments. However, there can be many counterarguments to choose from, and their degree of impact can vary. Therefore, meta-level information about the arguments could help the chatbot in using them effectively.

In persuasion, the way an argument is communicated is just as important as its message. A persuader who wants to convince a persuadee to do more exercise can present his argument in many different ways. He can, for example, point out the advantages of regular exercise: *"Regular exercise will strengthen your bones, muscles, and joints"*. However, he could also phrase it in a negative way: *"Lack of regular exercise leads to weakening of your bones, muscles, and joints"*. This notion of *framing* is well studied in psychology and health care [11]–[13], [16]. Other persuasion techniques such as referral to authority and social proof [6] have also been used in psychology. We refer to the style of persuasion used in an argument, as argument *type*.

We want to investigate some common argument types used in persuasive dialogues in the behaviour change domain. Despite the extensive psychology literature on the topic of message framing and persuasion techniques, the notion of argument type is underdeveloped in the computational argumentation field. Walton's *argumentation schemes* [18] could be viewed as a non-exhaustive listing of argument types. However, it leaves some important types for behaviour change unconsidered. Also, to the best of our knowledge, no empirical studies with participants have been undertaken to test the effectiveness of argument types in persuasion.

Furthermore, we want to investigate how *concerns* of the persuadee impact on the effectiveness of arguments in persuasion dialogues. The results in [9] show that taking a persuadee's concerns into account improves the persuasiveness of a dialogue. The persuader might present a valid argument the persuadee does not disagree with but which has no impact on her because the argument does not address her concerns.

In this paper we investigate different *types* of counterarguments and their preference with the persuadee based on his or her *concerns*. We propose a method for crowdsourcing arguments and counterarguments and assess a typology of counterarguments and concern assignments to be used by a chatbot. We use meat consumption as a case study. To verify our approach, we developed a strategic chatbot that takes the concern of the user into account and during an argumentation dialogue with the user, presents only those types of counterarguments that address his or her concern. For comparison purposes, we also developed a baseline chatbot that does not address the user's concerns. Our results show that the strategic chatbot outperforms the baseline one, and has a more significant impact on the user's intention to reduce their meat consumption in the future.

The rest of the paper is structured as follows: Section 2 gives some background theory on the notions of *concerns* and *appeal*, different types of counterarguments, and presents the ones we are investigating in this paper; Section 3 presents the aim of the paper and the hypotheses; Section 4 describes the argument and counterargument acquisition process; Section 5 describes the experiments that were conducted with the acquired data, namely the evaluation of the counterargument types and the chatbot that was used for the persuasion dialogues; and in Section 6 we discuss and conclude our findings.

II. Conceptualising Argumentation

In our study we chose the topic *meat consumption* and were interested in different argument types in favour of reducing meat consumption which we could present to meat eaters as counterarguments to their arguments in favour of eating meat. It is important to point out that we acquired our arguments by crowdsourcing. We opted for this method because there exists no central repository of all possible counterarguments on the topic. Crowdsourcing offers a fast and efficient way to gather a large number of diverse arguments without introducing the researcher's bias into the selection of arguments if gathering them by hand.

Argument Types: A persuader who wants to convince a persuadee to do more exercise can present his argument in many different ways. We refer to the style of persuasion used in an argument, as argument *type*. We investigate six argument types in total. The most common type of counterargument used in the computational argumentation literature is the *negation* of an argument. We, therefore, included a type which we call *direct counterargument* which negates the given argument.

In our previous study [4], when people were asked to provide a counterargument to their given argument, people mostly gave arguments in the form of suggestions. Suggestions are often enthymemes and do not explicitly negate the argument. They, however, imply that changing the behaviour is advantageous (therefore attacking the argument) and provide a solution on how to achieve that. For this reason, we include suggestions, or *suggestion based arguments* in our argument types assessment.

As mentioned above, arguments can be framed in a positive or negative way, either referring to a gain or a loss (i.e. positive or negative consequence for the persuadee). We, therefore, included *positive* and *negative consequences* into our list of argument types. Further, a certain behaviour often has consequences not just for the person engaging in that behaviour but on others as well, which we call *personal* and *impersonal* consequences respectively. Smoking, for example, is not just bad for the smoker but also imposes a burden on the health care system if the smoker becomes sick due to his behaviour. Therefore, we end up with six argument types we want to investigate. We give the definition and an example for each type in Table I.

Concerns: Arguments can raise or address various concerns for the persuadee that need to be accounted for. A persuader might present a perfectly valid argument, e.g. *"Meat consumption has a negative impact on the environment as it causes deforestation as huge tracts of rain forest are burned for pasture"*. The persuadee might not even disagree with this argument, however, if she is not concerned about the environment, this argument may have no impact on her intention to change her behaviour. If, however, the persuadee is concerned about her health, then the argument *"Some meats are high in saturated fat. Eating a lot of saturated fat can raise cholesterol levels, which raises your risk of heart disease"* is more likely to change her intention to consume less meat. Whilst this is a simple and intuitive idea, there is a lack of a general framework for using concerns in making strategic choices of move in the way suggested by the above example [9].

From preliminary investigation which involved researching the most common arguments against meat consumption on the internet, we discovered that most arguments revolve around two major *concerns*: *Health* and *Environment*. Note, we can view the health concern as a *personal* concern and the environment concern as an *impersonal* concern.

Appeal: In this study we are interested in the appeal of the argument *type*, not the argument itself. As pointed out by [14] an appealing argument might not necessarily be a convincing one. The argument that education should be free might be very appealing, but at the same time, we can acknowledge that universities need resources to function and therefore not be very convincing. We, however, are interested in the appeal of the *type* of argument and not in the appeal or convincingness of the *message* of the argument. We believe that one type of argument cannot be more convincing than another type per se, but one type can indeed be more appealing to the persuadee than another.

III. Hypotheses

In this paper, we show how the persuader's choice of argument type and concern influences the persuadee's intention to change his or her behaviour. Firstly, we explore different *types* of counterarguments and evaluate their appeal to the participants in the behaviour change domain. Secondly, we investigate whether the persuadee's concerns have an impact on the argument types the persuadee found most appealing. Thirdly, we use a chatbot in order to test whether presenting only those counterarguments that address the persuadee's concern is more likely to change his or her intention positively than presenting counterarguments that address other concerns in the domain as well. We summarise these points in the following three hypotheses:

- **H1** When a person is presented with counterarguments of various types, some types are perceived as more appealing than others.
- **H2** When a person is presented with counterarguments that address different concerns in that domain, people find those counterarguments more appealing that address the concern that they perceive as more important.
- **H3** A chatbot with no natural language understanding, just by presenting the type of counterarguments that take the user's concern into consideration, is more likely to have a positive impact on changing the user's attitude, than a chatbot that presents the type of counterarguments that ignore the user's concern.

In the remainder of this paper we describe the methods for acquiring the main arguments why people eat meat, different types of counterarguments for meat consumption and explain

TABLE I: Definitions of six investigated argument types with examples. The argument countered in the examples is *"I eat meat because it tastes good."*.

Argument Type	Definition	Example
Direct Counter-argument	This argument is counterargument that directly negates a previously given argument by referring to it.	*A raw, unprepared chunk of meat doesn't taste good. It's about the way of preparation and seasoning.*
Suggestion-based Argument	This argument gives a suggestion that may implicitly refer to a previously given argument and suggests how to change the behaviour in question	*You could introduce one day a week where you don't eat meat. Overtime you can increase the number of days.*
Positive Personal Consequence	This argument gives a positive consequence for the persuadee personally, if he or she continues the behaviour in question.	*Eating less meat will decrease your cholesterol level which will ultimately lower your risk of stroke and heart disease.*
Positive Impersonal Consequence	This argument gives a positive consequence for someone/ something apart from the persuadee, if he or she continues the behaviour in question.	*Eating less meat will lead to the reduction of the water foot print on the earth.*
Negative Personal Consequence	This argument gives a negative consequence for the persuadee personally, if he or she continues the behaviour in question.	*Most processed meats are loaded with artificial chemicals, including flavourants, colourants and preservatives that might be bad for your body.*
Negative Impersonal Consequence	This argument gives a negative consequence for someone/ something apart from the persuadee, if he or she continues the behaviour in question.	*Much land is needed to raise cattle for which forests have to be cut down, therefore causing deforestation.*

the experiments conducted with them in order to test our hypotheses.

IV. Argument & Counterargument Acquisition

Our study consisted of two parts: the argument and counterargument acquisition, described in this section, and the experiments (described in the next section) which we conducted with the acquired data in order to test our hypotheses. The participants for all surveys and experiments were recruited via *Prolific* (www.prolific.ac), which is an online recruiting platform for scientific research studies. For each survey, we recruited from either one of two disjoint groups: meat eaters and vegetarians. We opted for this division in order to obtain counterarguments from people who do not engage in the behaviour in question (in this case, meat consumption) which can then be used by the chatbot that tries to persuade people who do eat meat, to change their behaviour. The general prerequisites for taking part in our study were to be over 18 and fluent in the English language. We used Google Forms for all surveys.

Argument Acquisition and Clustering In order to find the most popular arguments for eating meat amongst the participants, we recruited 40 meat eaters and asked them in a Google Form to give their main reasons for eating meat. This way we acquired 111 arguments which can be found in Appendix I [1]. The average length of an argument was 7 words with a standard deviation of 5.

TABLE II: Summary of the arguments acquired in Step 1. Cluster name, number of arguments (A) in that cluster and representative argument for that cluster.

Cluster	No of A.	Representative Argument
Nutrition	15	*For its nutritional value and source of protein*
Filling	6	*It's filling*
Taste/Like	40	*It tastes good*
Easy	6	*Quick and easy to prepare*
Health	11	*It's healthy and contributes to a balanced diet*
Variety	3	*It offers more variety to my meals*

We used the algorithm described in [4] to automatically preprocess and cluster the arguments. The algorithm can be found in Appendix VI [1]. Arguments were clustered by similarity, in order to identify the most popular arguments for eating meat. As a representative argument for each cluster, we randomly picked one of those that contained the highest number of *most common words* in that cluster. In the rest of the paper, those will be referred to as "the most popular arguments" for eating meat. The size of the clusters and the representative argument of each are given in Table II. The name of each cluster is the most common word found in that cluster (excluding stopwords).

Counterargument Acquisition After identifying the most popular arguments for eating meat, we started with the direct counterargument acquisition. For each of the six most popular arguments we created one survey. We recruited 10 vegetarians per survey and asked them to counter the given argument by giving a single argument. This way we acquired 10 direct counterarguments for each of the most popular arguments.

We were interested only in the "best" counterarguments. We, therefore, created six surveys (one for each of the six most popular arguments) and recruited 20 participants for each survey, who identified themselves as meat eaters. The participants were presented the argument and the 10 acquired counterarguments for that particular argument. Since we were not interested in the message of the counterargument (e.g. its believability or convincingness) but still wanted clear, understandable and appropriate representatives of each counterargument type, we asked the participants to select those counterarguments that they found best at communicating their message. We counted the number of times each counterargument was voted for and ordered them by the number of votes. All counterarguments can be found in Appendix II a [1].

For the remaining counterargument types, we created one survey for which we recruited 10 vegetarians and asked them to provide one counterargument of each type. They were given the same examples of these argument types as given in Table I. Using the same approach as for the direct counterargument acquisition, we again received a ranking which allowed us to identify the best counterarguments (those ranked the highest).

V. Experiments

The experiments were split into two parts: the first was concerned with the evaluation of the different argument types according to their appeal, and their concern assignment. We wanted to test whether there is a correlation between the concerns of the participants and their preferred argument type. In the second part, we used a chatbot in order to test whether presenting counterarguments that take the user's concerns into account was more likely to change the user's attitude positively compared to a chatbot presenting counterarguments that ignore the user's concerns.

We used the three counterarguments that were ranked the highest by meat eaters. This resulted in a total of 18 direct counterarguments (three for each of the six most popular arguments for eating meat) and the top three ranked of the remaining five types. These counterarguments can be found in Appendix II b [1].

A. Evaluation of Argument Types

In this part of the experiment, we evaluate the six different argument types according to their appeal to the participants and show the correlation between preferred argument type and the concerns of the participants in order to investigate hypothesis H1 and H2.

1) Methods: We created a survey where the participants were asked what their main reason for eating meat was. There was a choice of the six most popular arguments (Table II) and the option "other". Then they were presented with the 3 highest ranked counterarguments of each type. They were asked to pick all the counterarguments that appeal to them. Note, that if they selected the option "other" in the previous step, no direct counterarguments were presented. At the end, they were asked to provide a short explanation of why they chose those counterarguments. We recruited 100 meat eaters.

2) Results: We were interested in two things: Firstly, whether there is a difference in popularity of argument types. And secondly, whether there is a correlation between the preferred argument type of the participants and any of the information that they provided in their explanation which the chatbot could take into consideration when presenting the arguments during an argumentation dialogue. Table III shows how many of the shown argument types were selected overall by all participants, i.e. there were 3 arguments of each type, since 33% of the *Suggestion-based arguments* (SUG) were selected it means that on average each participant selected one SUG. One can clearly see that *Direct Counterarguments* are much less popular compared to the others[1]. The four types of consequential arguments were the most popular. The results support our H1, that different types of counterarguments differ in their appeal.

We observed that the explanations of most participants raised concerns about their health or the environment, or both, which further supports our choice of concerns for this domain. To investigate this, we automatically assigned concerns to the explanations. Every explanation that contained the word *health* was assigned the concern *Health* and those that contained the words *animal, environment, planet* were assigned the concern *Environment*. Explanations that contained words from both concerns, were labeled *Both*. We observed a high statistical correlation between the participants' concerns and their preferred argument type. Participants who gave an explanation that was labeled with the concern *Health* preferred the *personal* consequences, whereas those with *Environment* preferred the *impersonal* consequences. Participants who gave an explanation that was labeled with both concerns preferred all consequential counterarguments equally. We used the Chi-Square test in order to calculate statistical significance by comparing the numbers of the available counterarguments with the number of the selected ones[2]. The p-values for all three groups were below 0.001. The results are summarised in Table IV. The results support our hypothesis H2, that people strongly prefer argument types that relate to their concern.

TABLE III: Results from the evaluation of argument types. *DIR = Direct Argument, SUG = Suggestion, NIC = Negative Impersonal Consequence, NPC = Negative Personal Consequence, PIC = Positive Impersonal Consequence, PPC = Positive Personal Consequence*.

Arg Type	NPC	PPC	NIC	PPIC	SUG	DIR
Votes	55%	51%	50%	47%	33%	6%

B. Evaluation of Chatbot

We developed two versions of the chatbot, one that took the concern of the user into account when presenting counter-arguments (strategic chatbot), and one that did not (baseline chatbot). The purpose of the chatbot was twofold: firstly, to test whether presenting counterarguments that take the user's concern into consideration is more likely to change the user's attitude positively, than presenting counterarguments that ignore the user's concern. Secondly, to test whether a chatbot, that has no natural language understanding can engage in an argumentation dialogue and influence the user's attitude about the discussed topic. With natural language understanding we mean, that the chatbot does not "understand" what the user writes, i.e. no keyword matching or machine learning. So this experiment was to investigate hypothesis H3.

1) Methods: The chatbot was deployed on Facebook via the Messenger Send/Receive API. For more on the implementation of such a chatbot see [3]. For each chatbot we recruited 50 participants. The dialogue protocol is described in dialogue steps DS1 to DS8:

DS1 The participant was asked at the beginning of the chat to select whether they would consider reducing their

[1] only 6 participants chose the option "other" and were therefore not presented any DIR

[2] For example, since 28 participants were concerned about health only, there were 168 (28 x 6) personal consequential arguments to select from and 336 (28 x 12) of the remaining types. 120/168 out of the personal consequential arguments were selected in contrast to only 70/336 of the remaining types.

meat consumption. The choices were: *definitely wouldn't, probably wouldn't, might, probably would* and *definitely would*.

DS2 Then they were asked what they were more concerned about: the impact that meat consumption had on their health or the impact it had on the environment and animals. They were given two options to select: *health* and *environment/animals*.

DS3 Then they were asked to select their main argument for eating meat (see Table II) and the option "other".

DS4 Then the chatbot presented its first counterargument. For the chatbot we only used the four consequential types of counterarguments, since they scored the highest during the first part of the study, described in section 4. The strategic chatbot would present either six positive and six negative personal arguments (if the participant selected *health*), or six positive and six negative impersonal arguments (if the participant selected *environment*) during the course of the chat. The baseline chatbot did not take the concern into account and presented three counterarguments of each type.

DS5 After each counterargument that the chatbot presented, the participant had the choice to select *agree* or *disagree*.

DS6 If the participant agreed, then the response was dependent on the variant of the chatbot. We implemented two slightly different variations of each chatbot.

Variant I Chatbot presented the next counterargument.
Variant II Chatbot asked *"Why do you eat meat then?"*.

DS7 If the participant disagreed, the chatbot asked *"Why?"*. The participant gave an argument and depending on the length, the chatbot either asked the participant to expand or accepted it and presented the next counterargument, to which the participant agreed or disagreed and so on. The query-algorithm is explained in our previous work [4] and can be found in Appendix VI [1].

DS8 At the end of the chat, the chatbot asked the participant again to select whether they *definitely wouldn't/probably wouldn't/might/probably would/definitely would* consider reducing their meat consumption.

Examples of chats with all four chatbots can be found in Appendix IV.

We divided the 50 participants for both variations of the chatbot into two groups depending on which concern they selected. For each concern group, we calculated the change in intention. The change in intention is the final choice of intention minus the original choice of intention. We call the units of this measure *intention points* (IP). For example, if one participant changed her intention from "probably wouldn't" to "might" after chatting with the bot this counts as 1 IP, whereas changing from "might" to "probably wouldn't" counts as -1 IP. Table V shows the number of participants in each concern group and their average intention change within the group, as well as in total. We can see that the total number of IPs for the strategic Variant I is over 3 times higher than for the baseline of Variant I, and for the strategic Variant II the number of IPs is over 4 times higher than for the baseline Variant II.

Interestingly, the total average number of arguments that participants disagreed with while chatting with the baseline chatbot remained the same compared to the strategic chatbot. On average participants disagreed with 3.5 arguments out of 12 when chatting with Variant I and 4 when chatting with Variant II. From this, it follows that participants do not necessarily disagree with counterarguments that do not address their concern. But despite that, those counterarguments do not have an impact on their intention. It is not surprising that overall fewer people changed their intention positively when chatting with Variant II, due to its "annoying" nature. Many people were irritated by the repetitive question of "Why do you eat meat then?" after they agreed with an argument. For an example see Appendix IV [1].

Table VI shows how many participants changed their intention to the worse and to the better, disregarding the number of intention points. We used the number of participants who changed their intention to the better in order to calculate the statistical significance of the difference between the control group that chatted with the baseline chatbot and the group that chatted with the strategic chatbot using Chi-Square test. All results were statistically significant apart from the environment group for Variant I (having a p-value of 0.278) because the increase in the number of participants who changed their intention to the better was not very high (from 7 in the control

TABLE IV: Total number of selected counterarguments per concern and number of participants (p). See caption for Table III for acronyms.

	Argument Type						
Concern	DIRECT	SUG	NIC	NPC	PIC	PPC	**No of p.**
Health	7	26	22	**65**	15	**55**	28
Env.	2	25	**59**	31	**59**	22	31
Both	3	17	**39**	**40**	**39**	**42**	18

TABLE V: Results for Variant I & II grouped by Baseline/Strategic and the concerns Health/Environment and their totals/averages.

Chatbot	Baseline			Strategic		
Concern	Health	Env.	total/avg	Health	Env.	total/avg
Variant I						
No of p.	27	23	50	26	24	50
Sum of IP	6	4	10 (0.2)	20	12	32 (0.64)
Variant II						
No of p.	29	21	50	28	22	50
Sum of IP	-1	6	5 (0.1)	12	10	22 (0.44)

TABLE VI: Number of participants that changed their intention to the worse (W) and to the better (B) for all four chatbots.

Participant Group	Baseline				Strategic			
Concern	Health		Env.		Health		Env.	
Change of intention	W	B	W	B	W	B	W	B
Variant I	1	5	2	7	0	17	0	11
Variant II	4	3	3	5	0	10	0	12

to 11 in the strategic group). Although in the in the control group most participants changed from "probably would" to "definitely would" whereas in the strategic group more participants changed from "probably wouldn't" to "might" and from "might" to "probably would" which could be argued is harder to achieve since the participants were less likely to consider reducing their meat consumption. However, overall there is a high statistical significance between the control and the strategic chatbots which support our hypothesis H3, that presenting arguments that address the user's concern is more likely to have a positive impact on changing the user's attitude, than presenting arguments that ignore the user's concern. All the chat data can be found in Appendix V [1].

VI. Discussion

Our contribution in this paper is fourfold. Firstly, we have shown that some types of arguments are considered more appealing than others in the behaviour change domain. Direct counterarguments and suggestions were the least popular in our study. Suggestions might not necessarily be unappealing but simply not tailored to the specific argument of the persuadee and therefore not relevant. Direct counterarguments, on the other hand, might trigger negative feelings from the persuadee. For the remaining argument types, there was not a large difference in their appeal.

Secondly, we have shown that people prefer arguments that address the concern that they perceive as more important. This is not surprising, however, *concerns* are often ignored when judging the effectiveness of arguments or choosing a strategy. There are some studies that make use of different personality traits of the user attributes in order to evaluate what sort of argument might be more effective for this particular person (for examples see [7], [10], [15], [17]). However, computational argumentation largely focuses on sentimental [5], rhetorical [8] and structural [2] attributes of the argument, rather than attributes about the user. We have shown that without knowing anything about the personality of the user, and by simply asking them what they are more concerned about, we can present arguments that have a positive impact on their intention to change their behaviour. This leads to our third contribution. We have shown that presenting arguments that address the user's concern is more likely to have a positive impact on changing the user's attitude, than presenting arguments that ignore the user's concern.

And lastly, we considered how a chatbot with no natural language understanding can engage in an argumentation dialogue and influence the user's attitude towards a certain topic. Chatbots that engage in health promotion and behaviour change have recently gained interest in industry and academia. There are chatbots that encourage you to go to the gym more often like *Atlas* (www.facebook.com/getatlasfit/), track your mood in order to make you feel better like *Woebot* (https://woebot.io/) and give you nutrition tips, like *Forksy* (https://getforksy.com/). None of these chatbots, however, use argumentation as a key component. They use a combination of reminders, provision of information and games.

Our approach of crowdsourcing some of the main arguments on why people engage in a certain behaviour and the corresponding counterarguments of various types that are then used by a chatbot to engage in persuasion dialogues is a novel approach in the behaviour change domain. Using crowdsourced arguments does not require professional research but solely relies on the input of participants. Using only the highest ranked counterarguments assures that no inappropriate arguments are chosen for the chatbot. There are, however, also potential risks to consider. For example the spread of invalid arguments which, despite being popular, might contain wrong information.

In the future, we want to explore more argument types and their suitability in the behaviour change domain. Further, we want to use our chatbot in a different domain and research how concerns can be acquired for different domains. We also want to explore potential risks of our approach like the possibility to use factually inaccurate arguments.

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