Mitglied der Helmholtz-Gemeinschaft

STE Preprint **8/2019**

Shamon, Hawal, D. Schumann, W. Fischer, S. Vögele, H. U. Heinrichs und W. Kuckshinrichs

Changing attitudes and conflicting arguments: Reviewing stakeholder communication on electricity technologies in Germany

Institut für Energie- und Klimaforschung
Systemforschung und Technologische Entwicklung (IEK-STE)

JÜLICH
FORSCHUNGSZENTRUM

Changing attitudes and conflicting arguments: Reviewing stakeholder communication on electricity technologies in Germany

Hawal Shamon[1)], Diana Schumann[1)], Wolfgang Fischer, Stefan Vögele[1)], Heidi U. Heinrichs[1)], Wilhelm Kuckshinrichs[1)]

1) Forschungszentrum Jülich, Institute of Energy and Climate Research - Systems Analysis and Technology Evaluation (IEK-STE), D-52425 Jülich, Germany

Executive Summary

In Germany, the public is exposed to pro and counter arguments regarding different electricity generation technologies. To assess the attitudinal consequences of these arguments, we presented a balanced set of seven pro and seven counter arguments concerning one of six electricity-generating technologies (i.e., coal power stations, gas power stations, onshore wind power stations, offshore wind power stations, open space photovoltaics, or biomass power plants) to respondents with heterogeneous socio-demographic characteristics. We asked them to rate the strength of each argument and report their perceived familiarity with each argument. Based on the respondents' answers, we examined the tendencies that underlie the process of evaluating arguments using different theoretical approaches. We found that persuasiveness ratings are driven by arguments' compatibility with respondents' initial attitudes, arguments' quality (i.e., strong, moderate, or weak), and respondents' perceived familiarity with the arguments. Furthermore, we determined the extent to which respondents' initial attitudes towards an electricity-generating technology, measured immediately before evaluation of 14 conflicting arguments, changed after exposure to the arguments. Unlike former studies on attitude polarization, we examined conditional probabilities instead of the absolute level of global attitude change or the marginal probabilities of attitude change and persistence. This allowed for more nuanced (re)examination of the issue and showed, among other results, that attitude polarization is the exception rather than the rule.

Keywords

Biased Processing; Attitude Polarization; Information Campaign; Persuasive Messages; Public Acceptance; Energy Transition

Contribution Energy Research & Social Science

[1] h.shamon@fz-juelich.de, phone: +49 2461 61-3322, fax: +49 2461 61-2540

Reference: Shamon, H., et al., Changing attitudes and conflicting arguments: Reviewing stakeholder communication on electricity technologies in Germany. Energy Research & Social Science, 2019. 55:106-121. https://doi.org/10.1016/j.erss.2019.04.012

1 Introduction

The German energy transition, known as the "Energiewende" [cf. 1] mainly includes a reduction in energy demand by using energy more efficiently, a nuclear power phase-out, and a decarbonization of the energy supply by switching from fossil to renewable sources [2]. In this respect, the Energiewende represents a fundamental "shift in the nature or pattern of how energy is utilized within a system" [3] and requires public to accept far-reaching changes in how electricity and heat are produced within the energy system, as well as changes in their own behavior patterns in terms of energy consumption. As elite actors and especially political parties play a crucial role in influencing public attitude, stakeholders may promote or even impede the transition of the energy system to renewable energy [4].

In the case of electricity production, which is the focus of this study, different stakeholders inject themselves into the societal debate on the benefits and risks of the energy transition by simultaneously running information campaigns with opposing positions on the different electricity-generating technologies that are needed for a successful implementation of the Energiewende. While some stakeholders aim to persuade the public of the benefits of particular technologies, others give reasons against them.[2] Thus, the public is perpetually exposed to a set of partly repeating messages that present opposing arguments on electricity-generating technologies [also referred to as conflicting arguments, cf. also 8].[3] The exposure of the public to these conflicting arguments, and the possible repetition of this exposure, raise questions about the public's evaluation of such arguments as well as the consequences of (repeated) exposure

[2] Stakeholder communication may not only aim to persuade the public by using pro and/or counter arguments that support the stakeholder's advocated position; it may also aim to create public awareness and deepen the public's understanding of complex issues, for instance the capture and storage of carbon dioxide, and thus enable (lay) persons to form an informed attitude towards an issue [cf. 5, 6, 7].

[3] In line with Kobayashi [8], we understand the term "argument" as a claim that is justified by one or more reasons. Liu et al. [9] take a similar perspective when referring to the conclusion (i.e., the argument's advocated position) and the premise (i.e., a reason that supports the advocated position) of an argument.

for public attitudes on these technologies. While answering these questions is particularly relevant for the field of public acceptance research [e.g., 10, 11-13], this task is all the more difficult given the complex interplay of factors that affect whether messages succeed in persuading the information campaigns' target audience (i.e., the message recipients) of the sender's advocated position in the absence of empirical evidence.

DIFFERENT ROUTES TO ATTITUDE CHANGE

The complex interplay of factors relevant for the persuasiveness of messages is effectively described by the Elaboration Likelihood Model (ELM) [cf. 14]. The ELM considers factors that are internal to the recipient – such as his or her motivation (e.g., personal involvement[4], need for cognition) and ability to elaborate on a message in the absence of distractions – as well as factors that are external to the recipient, such as argument quality (e.g., strong vs. weak) and the source of the message (e.g., political party, electric utility, non-governmental organization). The key statement of the ELM is that attitude change can occur on two different routes, known as central and peripheral, that mark the endpoints of a continuum. If the recipient is motivated and able to process the argument(s) of a message, a potential attitude change (i.e., persuasion) occurs on the central route, where the recipient scrutinizes a message's content (e.g., its argument(s)). If the recipient is unmotivated and/or unable to process the message, he or she takes cognitive shortcuts along the peripheral route, where peripheral cues about the source (e.g., source credibility, source expertise) and the message (e.g., number of arguments used) become more important determinants of persuasion than the message's argument(s). Attitude change induced along the central route is more durable than that induced along the peripheral route.

However, even if recipients take the central route of message processing, they may process an incoming message's argument(s) in either an objective or a biased manner. Objective processors

[4] Personal involvement refers to "the extent to which the attitudinal issue under consideration is of personal importance" [15].

are characterized by their motivation "to discover the 'true validity' of the message, and thus strong arguments induce more persuasion and weak arguments induce less persuasion with more processing". In contrast, biased processors are particularly motivated to produce defensive responses to messages that challenge their initial attitudes towards an attitude object (e.g., an electricity technology) and to develop favorable thoughts on attitude-consistent messages, with the result that such messages are accepted rather than critically scrutinized [8, 14, 16]. This tendency is labeled differently in the literature – for example as biased processing [e.g., 14, 17], biased assimilation [e.g., 8, 18], defensive processing [e.g., 19], refutational processing [9] or attitude congruence bias [16]. In this respect, prior attitude-relevant knowledge, which itself tends to be biased in congruence with people's initial attitudes [14], can be expected to increase recipients' ability to counterargue counter-attitudinal messages and to affirm attitude consistent messages if recipients are motivated to defend their initial attitudes [20-23].

ARGUMENT EVALUATION – EVALUATING TENDENCIESIn the context of argument evaluation, which is one specific focus of this study, biased processing manifests in inflating the quality of arguments that conform to a person's initial attitude and deflating the quality of arguments that do not conform. Empirical evidence [e.g., 8, 16-18, 22, 23-26] suggests that biased processing of arguments in accordance with initial attitudes is a robust cognitive mechanism that occurs across different topics and samples when people are exposed to a set of arguments with opposing claims relating to an attitude object.[5] However, when individuals evaluate arguments,

[5] However, Cohen et al. [27] showed that self-affirmation attenuates biased processing of counter-attitudinal evidence in situations where biased processing is rooted in defense motivation [28-30], that is in "a person's desire to reach a preferred conclusion that is congruent with perceived material interests or existing self-definitional attitudes" [28]. The implication of this finding is that biased processing is not triggered automatically whenever individuals are exposed to counter-attitudinal claims or evidence in situations where biased processing allows the person to maintain his or her valued self-image [27]. Instead, individuals have the flexibility to react to a particular self-threat (i.e., the counter-attitudinal claim or evidence) by affirming "other equally valued domains of self-worth" [27] in order to maintain their global level of self-worth.

the evaluating tendency is not only driven by the motivation to defend initial attitudes and is thus not solely a matter of argument compatibility.

The *congruence model of argument evaluation* [9, 28] states that argument evaluation is simultaneously affected by two evaluating tendencies: a compatibility tendency and a quality tendency. Arguments compatible with prior attitudes tend to cause a positive evaluating tendency, while incompatible arguments tend to cause a negative evaluating tendency. In a similar vein, strong or high-quality arguments promote a positive evaluating tendency, while weak or low-quality arguments evoke a negative evaluating tendency. When both evaluating tendencies are congruent in valence (which is the case for arguments that are both compatible and strong, or incompatible and weak), both tendencies complement each other, such that recipients – assumed to be cognitively economical – tend to evaluate arguments as more extreme in strength without any extra processing being required for the argument. However, when both evaluating tendencies are incongruent in valence (which is the case for arguments that are incompatible but strong, or compatible but weak), an intrapsychic conflict emerges which drives recipients to extensively process the argument and reconcile the two opposing tendencies to reach a moderate conclusion. As a consequence, recipients will evaluate incompatible-strong arguments and compatible-weak arguments as more moderate compared to compatible arguments. Liu et al. [9, cf. also 28] find evidence for both the latter postulate and their suggested processing modes by showing that compatible arguments were evaluated faster than incompatible arguments.

Moons et al. [31] take another perspective on argument evaluation by addressing the relevance of argument familiarity.[6] The evaluation model of these authors partially builds on the *illusion of truth effect (IOT)* [36], according to which "statements repeated even once are rated as truer or more valid than statements heard for the first time" [31]. Importantly, in order for the IOT to

[6] Argument familiarity has usually been induced in experimental studies by means of repetitive exposure to arguments [e.g., 32, 33-35].

occur, it has been shown that raters only need to have a perceived feeling of familiarity with a statement, and not necessarily familiarity induced by actual repetition of a statement.

Moons et al. [31] transferred the basic idea of the IOT to the evaluation of arguments. These authors find evidence for their hypothesis that recipients' agreement with arguments depends on two processes of which one occurs automatically (i.e., familiarity process) while the other only occurs, if recipients are motivated and capable of scrutinizing message content (i.e., controlled processing). According to the authors, familiarity with arguments generates a positive feeling of processing fluency that evaluators (mistakenly) attribute to either the validity of the familiar argument or their liking for it. Hence, the familiarity process automatically produces a higher acceptance of familiar arguments, irrespective of argument quality. The more that recipients scrutinize the message content, the greater a role that argument quality plays in the overall acceptance of an argument. Weak arguments produce a negative-signal-inhibiting agreement with the argument, while strong arguments produce a positive-signal-increasing agreement with the argument. Hence, the more that recipients engage in controlled processing, the more that any (automatic) positive familiarity effect is attenuated by the negative effect of the controlled process in the case of weak arguments, and assisted by the positive effect of the controlled process in the case of strong arguments, respectively. Empirical evidence for familiarity effects in the field of energy research has been examined by [37] in a discrete choice experiment concerning arguments on Carbon Dioxide Capture and Storage (CCS), a technology that has not yet been implemented on a large scale. In that study, arguments that respondents perceived as being important in the CCS discussion were more likely to be persuasive when they were familiar to the public.

CONSEQUENCES OF THE PROCESSING OF CONFLICTING ARGUMENTS

Some studies have shown that recipients polarize their beliefs and attitudes when exposed to mixed evidence [e.g., 26] or to a balanced set of conflicting arguments on an issue [e.g., 16]. Attitude polarization refers to a situation where recipients' initial attitudes become more

extreme after exposure to such evidence or arguments. The implication of this phenomenon on the societal level is that the gap between contrasting attitudes in a society widens, despite the fact that society members have been exposed to the same set of conflicting arguments. Put from a dynamical perspective: if attitude polarization is a "necessary" consequence of biased processing – which itself is rooted in the motivation to defend the initial attitude – a vicious circle will result. The more extreme attitudes become due to attitude polarization, the more motivated recipients will be for biased processing and, thus, the more polarizing the exposure to another set of (new) conflicting arguments will be [cf. also 23, 24].

Empirical evidence on attitude polarization is mixed. While some studies find empirical evidence for attitude polarization as a consequence of exposure to conflicting arguments [e.g., 16, 18, 23, 26, 38], other studies report no evidence [e.g., 17, 18, 24].[7] Unfortunately, these studies apply different strategies to investigate attitude polarization. Some apply measures that determine *reported* attitude change[8] [e.g., 26], while others focus on actual attitude change (i.e., difference in attitude measured before and after the exposure to arguments). Moreover, initial and posterior attitudes are either measured using a single attitude item scale [e.g., 24] or an index of multiple attitude items [e.g., 16, 17, 23]. McHoskey [38], Kuhn and Lao [39], and Corner et al. [18] even apply measures that determine both reported and actual attitude change in their studies, though, they come to different results. While McHoskey [38] and Kuhn and Lao [39] find evidence for attitude polarization on the basis of both measures, Corner et al. [18] find evidence for attitude polarization on the basis of reported attitude change only. Hence, despite the fact

[7] Druckman and Bolsen [24] measured attitude change among a subsample of their experimental participants. The majority of participants only took part in the main study in which they reported initial attitudes towards two issues before being exposed to different information on those issues. Only 206 (out of 621) persons also participated in the follow-up study, in which posterior attitudes were measured. Hence, self-selection processes might also explain the lack of attitude polarization in this study.

[8] With measures of reported attitude change, participants are asked after exposure to arguments to report whether or not their attitude had changed since the beginning of the study. For instance, McHoskey [38] applied the following self-report measure: "How would you compare your current attitude toward the assassination of JFK with the attitude you had at the very start of this experiment?" Participants could indicate their answer on a 17-point scale which ranged from "much more in favor of theory that Oswald killed JFK alone" (-8) to "much more in favor of theory that a conspiracy killed JFK" (+8) with a midpoint referring to no change in attitude (=0).

that biased processing has been shown to be a relatively robust cognitive mechanism, empirical evidence on its consequences for attitude change is ambiguous. It seems that studies applying self-reported attitude change measures are more likely to report attitude polarization than studies measuring attitude polarization on the basis of actual attitude change.[9] The lack of robust evidence among the studies focusing on actual attitude change might be explained by the fact that they assess attitude polarization on a global level in absolute terms of the (standardized) attitude scale [e.g., 16, 18, 23, 24]. While this operationalization is suited to investigate whether the attitudinal gap between supporters and opponents of different technologies has increased or decreased at a global level, it is not sensitive enough to identify processes of attitude polarization at the individual level. If both attitude polarization and attitude moderation occur simultaneously among different respondents in a study, the opposite partial effects cancel each other out [cf. also 24].[10] Investigating attitude polarization in terms of probabilities to observe state changes (e.g., a change from a less extreme attitudinal position to a more extreme attitudinal position) is better suited to examine attitude polarization processes at the individual level. In this context, Kuhn and Lao [39] analyzed marginal probabilities of attitude polarization, centration (i.e., movement toward the neutral point of the attitude scale) and side change (i.e., movement from a positive to a negative position, or vice versa) on the basis of a small student sample and found that only a small percentage of their participants polarized in attitudes.[11]

[9] It is important to note that perhaps the most cited study on attitude polarization, by Lord et al. [26], initially intended to assess attitude polarization in terms of actual attitude change on the basis of identical attitude scales. However, as this proved impossible due to participants' very extreme initial attitudes towards the issue, these authors applied a combination of two self-report measures as well as enlarged versions of the initial attitude scale [cf. 26, FN1].

[10] For instance, Taber et al. [16] used a change measure that increases with movement towards each of the extreme poles of the attitude scale, while it decreases when attitudes become more moderate. Taber and Lodge [23] regressed posterior attitude extremity on initial attitude extremity and defined an effect size of 1 as cut-off value for either polarization or moderation.

[11] McHoskey [38] analyzed a binary index as an indicator of attitude polarization. According to this indicator, "responses reflecting a more extreme attitude in the direction of the subject's initial position were scored as 1, and all other responses were scored as zero" [38]. Due to the operationalization of the binary index, attitude changes towards the midpoint of the attitude scale could not be examined in this study.

CONTRIBUTION

Liu et al. [9], Liu [28], and Moons et al. [31] made a major contribution to our understanding of the argument evaluation process by theorizing and empirically examining different evaluation tendencies (compatibility, quality, and familiarity) and their moderating factors in randomized laboratory experiments. In this study, we will assess the relative importance of these three evaluation tendencies by examining them within a single study and measuring, rather than experimentally manipulating, the relevant attributes among recipients that are expected to moderate the evaluation tendencies, such as personal involvement and perceived familiarity rather than repetition-induced familiarity. In this way, we aim to contribute to a better understanding by investigating the mechanisms that have been determined in randomized experiments and establishing which of these are practically relevant under the "realistic conditions" of the field.[12] In this respect, we are particularly interested in examining the effects that both attitude extremity and prior attitude-relevant knowledge have on biased processing.[13] The examination of attitude extremity is important, as people can form attitudes on attitude objects spontaneously [cf. e.g., 42], and these attitudes, even if spontaneously formed, become relevant for the way in which recipients process (new) information about a particular attitude object. Finally, our study seeks to provide insights into the dynamics of attitudes towards electricity-generating technologies by examining attitude change in this field. For this examination, we will focus on the conditional rather than on the marginal probabilities of changing or not changing an attitudinal position. This procedure allows us to assess attitude change separately for respondents with initial negative, neutral, and positive attitudes and thus to obtain a nuanced picture of this issue.

[12] This is not to be misunderstood as a general critique of randomized experiments. They are particularly useful for carving out causal mechanisms between explaining factors and target variables [cf. e.g., 40]. However, the explaining factor is randomly manipulated by a researcher and, hence, the examined effect sizes depend, among other things, on the chosen manipulation procedure. Reassessing a causal mechanism in non-experimental settings makes it possible to assess whether or not the mechanism is practically relevant given the associations between attributes that have been measured among individuals, without questioning the mechanism itself.

[13] Attitude extremity refers to "the extent to which an individual's attitude deviates from the midpoint of the favorable-unfavorable dimension" of an attitude [41].

To achieve these objectives, we conducted an online survey (described in detail in Section 2) among respondents from a sample that was much more heterogeneous than most of the above-mentioned studies with regard to the distribution of socio-demographic characteristics.[14] After measuring respondents' initial attitudes towards six different electricity-generating technologies, we randomly assigned participants to one of the six technologies (hereinafter referred to as the focused technology) and exposed them to fourteen conflicting one-sided arguments concerning that focused technology. We subsequently measured respondents' posterior attitudes towards their focused technology as well as towards the other five technologies.[15] We did not differentiate between weak and strong arguments only, but also included arguments of moderate quality in our study; the quality of each argument was rated via an expert assessment which was conducted prior to the online survey. Furthermore, we examined the evaluations and reactions of participants with neutral initial focused attitudes. This is important not only because there may be a substantial proportion of persons with a neutral attitude towards an attitude object in a societal context but also because people with a neutral initial attitude can be expected to be objective evaluators due to their lack of a negative or positive attitude. Including these individuals in a study on conflicting arguments allows us to review the postulates of the congruence model more critically and investigate specific response patterns.

HYPOTHESES

Along with the congruence model of argument evaluation Liu et al. [9], which suggests that argument evaluation is affected by two simultaneous evaluating tendencies (compatibility and quality), we will examine the following three main-effect hypotheses:

[14] Kobayashi [8] and Druckman and Bolsen [24] are the only studies that examine biased assimilation on the basis of a sample consisting not only of students. However, attitude polarization is not examined in the Kobayashi 's study [8].

[15] In the following, respondents' attitudes towards the focused technology will be referred to as focused attitude.

H1: Strong (compatible or incompatible) arguments will be evaluated as more persuasive than moderate (compatible or incompatible) arguments, and moderate (compatible or incompatible) arguments will be evaluated as more persuasive than weak (compatible or incompatible) arguments (*quality hypothesis*).

H2: Compatible arguments will be evaluated as more persuasive than incompatible arguments of equal quality (*compatibility hypothesis*).

Regarding recipients whose initial focused attitude was neutral, the question of argument compatibility is irrelevant, meaning that these recipients base their evaluation exclusively on the quality tendency. If only one tendency applies to these recipients, their argument evaluations should lie in between the evaluations of recipients with incompatible and compatible initial attitudes. With this in mind, we will examine the following hypothesis allowing a critical reexamination of the congruence model's statements:

H3: Recipients with a neutral initial focused attitude will evaluate arguments of equal quality as stronger than recipients with an incompatible attitudinal position and as weaker than recipients with a compatible attitudinal position (*neutral-attitude hypothesis*).

The theoretical considerations of Moons et al. [31] regarding the automatic effect of argument familiarity, and their postulation of a moderation of this effect by controlled processing, justifies the following main-effect and two-way-interaction hypotheses:

H4: Recipients who have a feeling of familiarity with arguments will evaluate those arguments as more persuasive than recipients who perceive the arguments to be unfamiliar (*familiarity hypothesis*).

H5: The more motivated recipients are for controlled processing of arguments, the lower the familiarity effect will be (*attenuating-familiarity hypothesis*).

As recipients with a non-neutral attitude are motivated for biased processing, we expect biased processing to increase with attitude extremity, and will examine the following two-way-interaction hypothesis among recipients with a non-neutral initial focused attitude:

H6: The more extreme the attitude of recipients who are motivated for biased processing, the greater the compatibility tendency for both incompatible and compatible arguments will be (*extremity-compatibility hypothesis*).

Furthermore, as attitude-relevant knowledge has been shown to increase recipients' ability to affirm pro-attitudinal arguments and to counterargue counter-attitudinal arguments, we expect the following hypothesis among recipients with a non-neutral initial focused attitude:

H7: The more attitude-relevant knowledge recipients who are motivated for biased processing have, the less (or more) persuasive they will be to evaluate incompatible (or compatible) arguments (*knowledge hypothesis*).

In the context of the robust findings on biased processing, we will examine the following hypothesis:

H8: We expect the attitudinal position of recipients with positive and negative initial focused attitudes, respectively, to become more extreme after exposure to conflicting arguments on a focused technology (*attitude-polarization hypothesis*).

2 Material and Methods

2.1 Arguments

We developed 84 conflicting one-sided arguments concerning six electricity-generating technologies important for the Energiewende in Germany, namely coal power stations, gas power stations, onshore wind power stations, offshore wind power stations, open-space

photovoltaics, and biomass power plants.[16] The arguments were developed in a multi-stage process (cf. Figure 1) by an interdisciplinary working group at the *Institute of Energy and Climate Research – Systems Analysis and Technology Evaluation (IEK-STE)* at *Forschungszentrum Jülich.*[17] Arguments consisted of a clearly advocated position on an electricity-generating technology, followed by a reason supporting the advocated position. For instance, the wording of one argument in favor of coal power stations was as follows: "The advantages of coal power stations include the fact that they can supply consumers with electricity around the clock and are independent of the weather."[18,19] With the exception of two arguments that consisted of two sentences, all other arguments consisted of a single sentence.[20]

The multi-stage process was organized as follows: first, each working group member was asked in his or her capacity as an expert to brainstorm on an individual basis in order to propose pro and counter arguments for each of the technologies from a technical, ecological, economic, social, and/or political perspective. In doing so, they were instructed to only provide arguments that had been used or might be used by stakeholders to make a case for or against a respective technology.[21] All arguments submitted were in the form of bullet points. Second, two working group members identified arguments that had been mentioned by more than one expert and removed the duplicates. This resulted in a set of unique arguments for each technology. Third,

[16] Due to the decision of the German Federal Government to phase out nuclear energy in Germany by 2022, nuclear power plants were not included in our study [cf. 1].
[17] The working group consisted of engineers and physicists, economists, and social scientists.
[18] The German wording of the argument was as follows: "Für Kohlekraftwerke spricht, dass sie die Bevölkerung rund um die Uhr und unabhängig von der Wetterlage mit Strom versorgen können."
[19] While the survey was carried out in German, the survey elements have been translated into English for the purposes of this manuscript.
[20] One two-sentence argument consisted of an objection to biomass power plants: "The disadvantages of biomass power plants include the fact that the expansion of biomass production raises the price of agricultural land. This inhibits the expansion of organic production." The other two-sentence argument was as follows: "The advantages of gas power stations include the fact that they emit less carbon dioxide (CO_2) than coal power plants. Carbon dioxide (CO_2) is thought to be responsible for climate change." This argument was also adapted and applied to the following technologies: coal power stations, onshore wind power stations, offshore wind power stations, and open-space photovoltaics. Hence, we included a two-sentence argument for each technology.
[21] The restriction to propose arguments that could potentially be used by actual stakeholders was intended to rule out, from the beginning of the study, the possibility of exposing respondents to "fake" arguments in the survey.

the two working group members who had worked on step 2 adjusted the wording of all unique arguments for each technology setting to ensure that they were comprehensible for laypeople and could be used in a survey. Fourth, the resulting unique arguments for each technology were sent back to the other working group members. These were asked to provide feedback on all arguments, including on their wording, with regard to the accuracy of the arguments' content as well as their comprehensibility. In other words, this fourth step ensured that all working group members had the possibility to raise objections to arguments formulated by other members. As a consequence, in the fifth step, arguments that were criticized by at least one working group member were either rephrased in the case of a minor critical remark (e.g., the wording of an issue) or entirely removed from the argument list in the case of a major critical remark (e.g., the argument is incorrect). Arguments that were not criticized were retained on the argument list without being modified. Sixth, we categorized the arguments with respect to the dimension(s) they focus on (technical, ecological, economic, social, and/or political) and assessed them from an expert point of view (expert rating) in terms of their persuasiveness as a weak, moderate, or strong argument (cf. Table 1 ,Table 2, and Table 3).[22] Finally, we selected seven pro arguments and seven counter arguments (84 arguments in total) for each of the six technologies such that all dimensions and all categories of persuasiveness were represented for each technology.[23,24]

Figure 1: Process of argument development

[22] Arguments could also be categorized into more than one dimension. For instance, some were categorized as socio-ecological arguments, while others were categorized as technical-economic arguments.

[23] Previous studies on attitude polarization in the context of biased processing examined at most eight conflicting arguments (i.e., four pro arguments and four counter arguments) per attitude object (cf. Taber and Lodge 2006, Taber et al. 2009).

[24] The application of stricter selection criteria – such as equal length of arguments for all six technology settings or an even distribution of argument quality across all settings – would certainly be relevant if the aim was to examine newly hypothesized evaluating tendencies (e.g., in laboratory experiments). In our case, given that our aim was to measure evaluating tendencies across as many arguments as possible that might be used by actual stakeholders (i.e., in the field), we decided to apply more moderate selection criteria and to account for arguments' characteristics in our (multivariate) analyses.

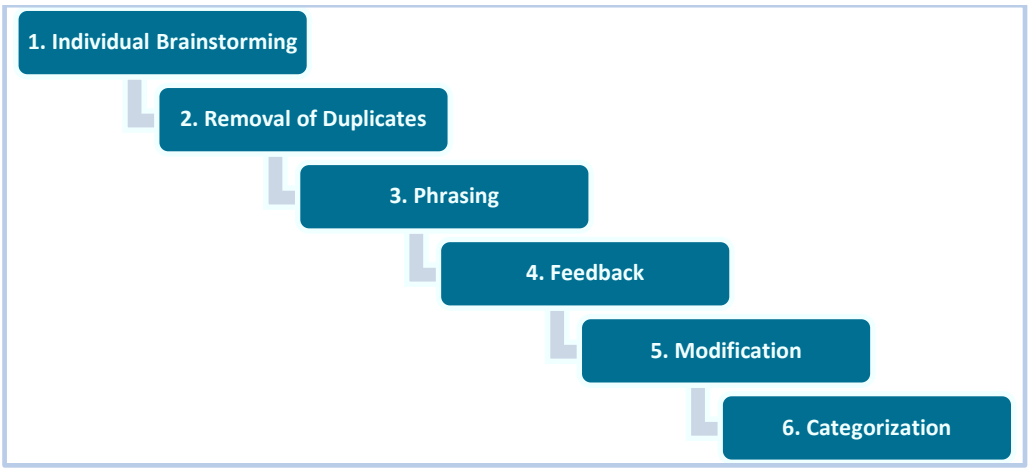


Table 1: Distribution of argument directionality and dimension

		Directionality		
		Pro arguments	Counter arguments	Total
Dimension	Ecological	12	9	21
	Social	5	9	14
	Economic	5	6	11
	Political	5	4	9
	Technical	1	4	5
	Economic/Social	5	1	6
	Economic/Technical	7	4	11
	Economic/Ecological	n.a.	2	2
	Social/Ecological	2	3	5
	m	42	42	84

Note: n.a. = Does not apply.

Table 2: Distribution of argument directionality on expert assessment

		Directionality		
		Pro arguments	Counter arguments	Total
Expert rating	Weak	7	11	18
	Moderate	18	15	33
	Strong	17	16	33
	m	42	42	84

Table 3: Distribution of argument quality on technology settings

	Argument quality			
	Weak	Moderate	Strong	Total

Technology	Coal power stations	3	4	7	14
	Gas power stations	4	6	4	14
	Wind power stations (onshore)	1	5	8	14
	Wind power stations (offshore)	4	5	5	14
	Open-space photovoltaics	3	7	4	14
	Biomass power plants	3	6	5	14
	m	18	33	33	84

2.2 Questionnaire

The 84 arguments were integrated into an online questionnaire in which we first asked respondents for their attitudes towards electricity-generating technologies and then randomly assigned them to one of six settings. The settings differed in terms of the technology they focused on: Setting 1: coal power stations; Setting 2: gas power stations; Setting 3: wind power stations (onshore); Setting 4: wind power stations (offshore); Setting 5: open-space photovoltaics; Setting 6: biomass power plants (cf. Figure 2). Within each setting, we then exposed respondents to seven pro and seven counter arguments concerning that technology.[25] In order to prevent response-order effects [43], we randomized the order of the argument blocks (block of pro arguments followed by a block of counter arguments vs. a block of counter arguments followed by a block of pro-arguments) as well as the order of arguments within each block. Before each of the two argument blocks, we provided respondents with a clarification stating that the arguments which followed were not fictitious and might genuinely be used in the actual discussion about the relevant technology.[26,27] For each argument, respondents were

[25] The presentation of arguments occurred identically in all settings. On a page of the online questionnaire, we exposed respondents to a single argument and two survey items measuring their persuasiveness rating and familiarity statement (as will be described below in more detail).

[26] We designed the clarification to be as neutral as possible in the context of an online survey to avoid providing participants with motivation for biased processing due to the wording of the presented clarification [e.g., 44, 45, 46]. Figure 11 in the appendix depicts the first clarification presented to respondents who were randomly assigned to Setting 4 (offshore) and who were presented, based on a random decision rule, with the block of seven pro arguments prior to the block of seven counter arguments. Figure 12 in the appendix depicts the second clarification regarding the upcoming block of seven counter-arguments presented to these respondents.

[27] Previous research on carbon dioxide capture and storage (CCS) has shown that the communication source (e.g., individual stakeholder vs. collaborating stakeholders) providing the factual information on CCS affects how individuals perceive the quality of the provided information (ter Mors et al. 2010). As we

asked to rate its persuasiveness as well as their perceived familiarity with the argument. The following survey items were included in the online survey:

1. *Initial and Posterior Attitudes Towards Electricity Generating Technologies*: Immediately before and after exposure to conflicting arguments, we asked our respondents in an item battery about their attitudes towards the focused electricity-generating technology as well as towards the other five electricity generating technologies that are relevant to our study. Respondents' answers were registered on a bipolar nine-point scale (0: strongly against the technology; 4: neither against nor in favor of the technology; 8: strongly in favor of the technology). Respondents were also offered an exit option (cannot choose).
2. *Attitude Extremity*: Individuals' motivation for biased processing depends on their initial attitude [14]. While the attitude dimension is characterized by a range from a negative (i.e., strongly against the technology) to a positive (i.e., strongly in favor of the technology) through neutral (i.e., neither against nor in favor of the technology) points, the motivation for biased processing is expected to increase with increasing attitude extremity. This means that such motivation is highest at the extreme poles of the attitude scale and lowest at the midpoint, with the direction of biased processing (i.e., positive or negative) of a pro or counter argument depending on argument compatibility. Therefore, we used respondents' initial attitudes towards the focused technology to create an *attitude extremity index* ranging from 0 to 4. Respondents with a neutral attitude are coded 0, while respondents indicating a 3 or a 5 on the attitude scale show a "very moderate attitude"; respondents indicating a 2 or a 6 on the attitude scale show a "moderate attitude"; respondents indicating a 1 or a 7 on the attitude scale show an "extreme attitude"; and respondents who are strongly against or strongly in favor of the focused technology show a "very extreme attitude" (4).

---

did not intend to examine source effects in our study, we did not provide respondents with the source of the information.

3. *Change Indicator*: For our examination of attitude change, we coded respondents with an initial negative or positive attitude as follows: 0 for polarization (i.e., the posterior attitude is more extreme than the initial focused attitude), 1 for a stable negative or positive attitude, and 2 for centration and side changes. Respondents with an initial neutral attitude were coded as follows: 0 for those whose initial neutral attitude position changed to a negative attitude, 1 for those with a stable neutral attitude, and 2 for those whose initial neutral attitude position changed to a positive attitude.
4. *Argument Type*: For the operationalization of argument type, we considered argument quality (strong, moderate, or weak), argument directionality (pro vs. counter), and respondents' initial attitude position towards the focused technology (negative, neutral, positive), resulting in nine different argument types: incompatible-weak (0), incompatible-moderate (1), incompatible-strong (2), neutral-weak (3), neutral-moderate (4), neutral-strong (5), compatible-weak (6), compatible-moderate (7), and compatible-strong (8).[28] This means that, argument type is defined on the basis of the different strengths of evaluating tendencies that an argument elicits among a respondent with a particular initial attitude. While arguments of type 0 to 2 as well as type 6 to 8 simultaneously elicit the evaluating tendencies of quality and compatibility among respondents, arguments of type 3 to 5 are expected to elicit only the quality tendency. Hence, we expect the persuasiveness ratings of these arguments to range between incompatible (type 0 to 2) and compatible arguments (type 6 to 8).
5. *Persuasiveness Ratings*: For the measurement of respondents' *persuasiveness ratings*, we used a one-dimensional endpoint-verbalized nine-point scale for each argument (0: the argument is not at all persuasive; 8: the argument is very persuasive) which was placed immediately below the relevant argument.

[28] This operationalization basically follows that applied by Liu et al. [9] and Liu [28]. However, these studies used two different argument qualities (strong vs. weak) and measured initial attitudes using a response scale where participants could not indicate a neutral attitude (two-alternative forced choice). These studies examined four different argument types: incompatible-weak, incompatible-strong, compatible-weak, and compatible-strong.

6. *Balance of Ratings:* For each respondent, we calculated his or her individual balance of persuasiveness ratings by subtracting his or her average persuasiveness rating for the seven counter arguments from the average persuasiveness rating for the seven pro arguments. A positive (or negative) persuasiveness balance means that a respondent rated the seven pro arguments as more (or less) persuasive than the seven counter arguments on average. Specifically, the balance of persuasiveness ratings ranges from -8 (meaning that a respondent rated all seven counter arguments with 8 while rating all pro arguments with 0) to +8 (meaning that a respondent rated all seven pro arguments with 8 while rating all counter arguments with 0). The balance of ratings serves as a proxy variable for respondents' engagement in biased processing [cf. also 38].
7. *Perceived Familiarity*: Next to the persuasiveness rating scale, we presented respondents with a nominal scale allowing us to measure their *perceived familiarity* with each of the 14 arguments (0: I am not aware of this argument; 1: I am aware of this argument).[29]
8. *Need for Cognition:* Along with the ELM [47], the motivation to scrutinize arguments is expected to increase with a respondent's need for cognition. In our heterogeneous respondent sample, we used a short scale on the need for cognition, with four items measuring respondents' engagement in cognitive tasks (cf. Table 4, items one and four inversely coded) and enjoyment of such tasks (cf. Table 4, items two and three). Beißert et al. [48] selected and validated the items from a longer need-for-cognition scale designed by Cacioppo and Petty [49]. Respondents' answers to the items were measured on a seven-point scale (0: does not apply at all, 6: applies completely) and allowed for the calculation of a mean score index for respondents' need for cognition.
9. *Personal Involvement:* In line with the ELM [47] (cf. also [15]), it is expected that personal involvement increases respondents' interest in and, thus, motivation to elaborate systematically on the presented arguments. Experimental studies on this issue frequently

[29] In the German questionnaire, we used the wording "Kennen Sie dieses Argument schon?" This does not necessarily imply that someone has knowledge about (the background of) an argument, but rather indicates whether or not he or she perceives familiarity with the argument.

operationalized personal involvement by manipulating whether or not a message has consequences for participants (e.g., introduction of tuition fees for current undergraduates vs. introduction of tuition fees for the next cohort of students). In standardized surveys, personal involvement is measured rather than manipulated. For instance, Southwell [50] operationalized personal involvement by asking respondents about their past drug behavior in a survey of evaluations of anti-drug public service announcements. We asked our respondents whether, according to their knowledge, the focused electricity generating technology was being constructed or is planned to be constructed in future (=1) near their place (or not (=0)).

10. *Attitude-relevant knowledge:* We formulated four statements (cf. Table 5 intended to measure respondents' knowledge about energy (i.e., their attitude-relevant knowledge). We asked respondents to indicate for each statement whether the statement was "definitely not true", "probably not true", "probably true", or "definitely true". Only those answers that respondents specified as "definitely not true" for items 1 and 3 or as "definitely true" for items 2 and 4, respectively, were judged to be correct. Finally, we counted the number of correct answers for the four items, such that attitude-relevant knowledge can vary between 0 (limited attitude-relevant knowledge) and 4 (extensive attitude-relevant knowledge), i.e. when all questions are answered correctly.
11. *Age and Gender:* We asked respondents to state their age in an open answer format. Regarding gender, we offered respondents the categories of male and female as well as a third option for respondents who did not want to categorize themselves as either male or female.

Figure 2: Survey design

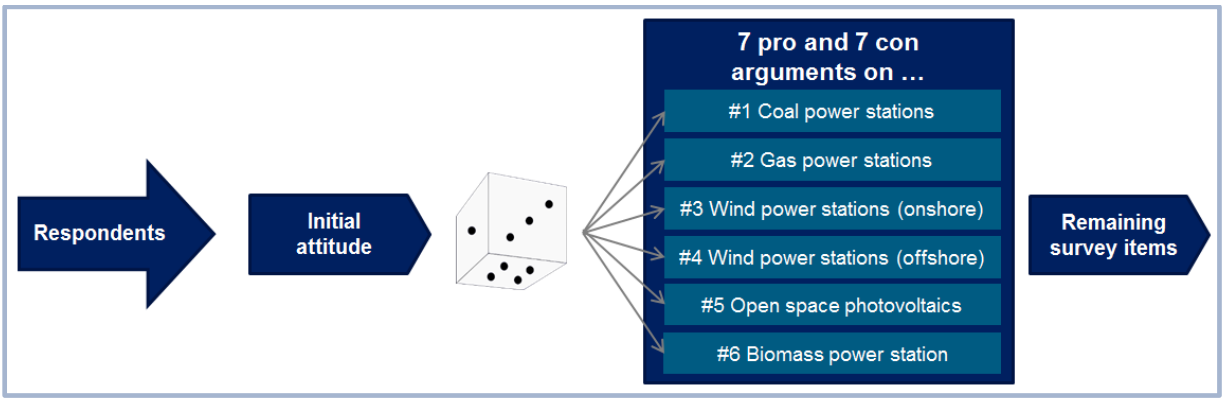


Table 4: Short scale on need for cognition

Item no.	**We would like to know more about you as a person. The following statements may apply more or less to you. In general, to what extent do you think each statement applies to you personally?**
1	Simply knowing the answer rather than understanding the reasons for the answer to a problem is fine with me.
2	I prefer my life to be filled with puzzles that I solve.
3	I would prefer complex to simple problems.
4	I primarily think because I have to.

Source: Beißert et al. [48]

Table 5: Scale for measuring attitude relevant knowledge

Item no.	**One cannot know everything in life. Nevertheless, we would like to ask you to tell us whether you consider the following four statements to be" definitely not true", "probably not true", "probably true", or "definitely true".**
1	An ozone hole will never heal.
2	Every time we burn oil, coal, or gas, carbon dioxide (CO_2) is released.
3	Some electricity producers abroad use magma or molten rock energy to generate electricity.
4	In a private household, most of the energy is used for space heating.

Source: Authors' own.

2.3 Data description

We administered the survey online using a paging design [cf. 51] to members of a German access panel in March 2017. The survey was targeted at persons with a residential address (principal address) in Germany at the time of the survey. We did not pay or promise any monetary incentives in the invitation e-mail, but presented respondents with the prospect of receiving a summary of the survey results upon request. In total, 1,245 respondents were randomly assigned to one of the six settings and completed the survey. We excluded 76

respondents from the sample for quality reasons.[30] Furthermore, we restricted our analysis sample to those respondents who performed both tasks – i.e., persuasiveness rating and perceived familiarity statement – for each of the 14 arguments in his/her assigned setting.[31] Hence, analyses for the arguments are based on the group sizes depicted in Table 6 (cf. Analytical dataset column).[32] Respondents' average age in the final sample is 40.8 years (SD = 15.7), and 49.3 percent of respondents are female, 49.4 percent are male, and 1.3 percent refused to classify their gender.[33] Furthermore, 77.7 percent of the respondents had received a secondary-school leaving certificate and 5.3 percent stated that they are employed in the energy sector.

Table 6: Gross sample & data base

Setting	Gross sample	Analytical dataset
Coal power stations	203	170
Gas power stations	207	171
Wind power stations (onshore)	207	172
Wind power stations (offshore)	207	189
Open space photovoltaics	213	197
Biomass power plants	208	179
n	1,245	1,078

[30] Six respondents stated that they did not live in Germany (primary residential address) and thus they did not belong to the predefined target group. In addition, 67 respondents completed the survey in a relatively short time (less than half of the 5 percent trimmed mean survey completion time in the sample) and a further three respondents answered two or more of the four relevant item batteries with the same answer option (also referred to as non-differentiation [cf. 52]); it can therefore be assumed that these respondents assessed the items without paying attention to their content [cf. 53].

[31] Three respondents in Setting 1, four respondents in Setting 2, two respondents in Setting 3, one respondent in Setting 4, and one respondent in Setting 6 were removed from the analysis sample because they left the persuasiveness rating and/or the awareness statement blank for at least one argument. Furthermore, we removed a total of 80 respondents from the analysis sample who did not provide a valid answer to the items regarding initial and/or posterior attitude towards the focused technology, personal relevance of the focused technology, age, and/or gender. These respondents would have been ignored in the upcoming multivariate analyses in any case due to the listwise deletion procedure.

[32] Mean differences between the six settings regarding initial attitudes, attitude relevant knowledge, and age were not significant either before or after the elimination of respondents (Sidak Tests, $\alpha = 0.05$).

[33] We registered the answers of the 14 respondents who did not classify their gender as either male or female as a substantial answer reflecting the respondent's self-concept of their gender [cf. e.g., 54].

2.4 Methods

2.4.1 Persuasiveness Ratings

We analyzed the answers of respondents in a multivariate regression for all settings jointly.[34] Multivariate regressions allow estimating unbiased estimates for each of the evaluating tendencies. Since each respondent was asked to give answers (persuasiveness ratings and familiarity statements) to 14 arguments (level 1), and respondents with specific characteristics – e.g., initial focused attitudes, need for cognition – (level 2) were randomly assigned to different settings (level 3), our data are hierarchically structured.

To appropriately address the hierarchical data structure in a multivariate regression model, we applied multilevel analysis [55, 56]. Multilevel analysis requires sufficiently high numbers of units at each level to avoid biases in point estimates and/or interval estimates [57-59]. In our case, the number of level-3 units (i.e., the six settings) is critical. To overcome any potential problems due to the low number of level-3 units, we applied a two-level multilevel analysis in which we estimated fixed effects for the settings by using weighted effect coded variables [60]. These weighted effect coded variables account for potentially different means in the persuasiveness ratings between the six settings. We used Stata 14.2 to estimate the following model, using a Restricted Maximum Likelihood estimation procedure and estimating cluster-robust standard errors:

$$Y_{ij} = ß_{0j} + ß_{1j}X_{ij} + r_{ij} + a_k \quad (1)$$

where the unstandardized regression coefficients of this level-1 model can be substituted by the following models applying to the respondent level (level 2):

$$ß_{0j} = \gamma_{00} + Z_j + u_{0j} \quad (2)$$

$$ß_{1j} = \gamma_{10} + Z_j + u_{1j} \quad (3)$$

[34] This is unproblematic as the evaluation tendencies hypothesized to be relevant during the process of argument evaluation do not depend on the attitude object itself but rather on the interplay of a respondent's prior attitude towards an attitude object, his or her perceived familiarity with an argument, and the directionality and quality of the argument.

and where

i	denotes an argument,
j	denotes a respondent,
k	denotes a setting,
Y_{ij}	refers to the persuasiveness rating of respondent *j* for argument *i*,
X_{ij}	refers to the characteristic of argument *i* (e.g., argument type, dimension),
Z_j	refers to the characteristic of respondent *j* (e.g., need for cognition)
$ß_{0j}\ and\ ß_{1j}$	denote a respondent's unstandardized regression coefficient for the intercept ($ß_{0j}$) and the slope ($ß_{1j}$) of the predictor variable X_{1j} at the argument level,
$\gamma_{00}\ and\ \gamma_{10}$	denote the grand mean (average unstandardized regression coefficient) for the intercept (γ_{00}) and the slope (γ_{10}) of the predictor variable X_{1j} at the argument level,
a_k	denotes the residual at the setting level,
$u_{0j}\ and\ u_{1j}$	denote the residuals (random terms) at the respondent level,
r_{ij}	denotes the residual at the argument level.

To test our hypotheses, we estimated two models (hereinafter referred to as Model 1 and Model 2). Model 1 is based on the answers of all respondents (n= 1,078) and is used to test H1 to H5. Subsequent to the estimation of Model 1, we computed the average adjusted persuasiveness rating predictions (hereinafter referred to as average adjusted predictions) for each argument type using Stata's margins command [61]. Testing H1 to H3 required the ability to account for the multiple pairwise comparisons between the nine different argument types (i.e., incompatible-weak, incompatible-moderate, incompatible-strong, neutral-weak, neutral-moderate, neutral-strong, compatible-weak, compatible-moderate, and compatible-strong). Therefore, we compared the resulting average adjusted prediction for each argument type on a pairwise wise basis using the Sidak Test. The Sidak Test is a test for pairwise multiple comparisons that is based on a t-statistic and accounts for multiple comparisons in the significance level [62]. To test H6 and H7, we excluded persuasiveness ratings from respondents who had a neutral initial attitude towards their focused technology prior to the estimation of Model 2. We used Stata's margins command to compute the average adjusted predictions for

the six relevant argument types (i.e., incompatible-weak, incompatible-moderate, incompatible-strong, compatible-weak, compatible-moderate, and compatible-strong) and Stata's marginsplot command to illustrate the estimation results of the two two-way interactions.

2.4.2 Attitude Change

To examine attitude change, we separately estimated multinomial logistic regressions for respondents with initial negative attitude, initial neutral attitude, and initial positive attitude. With *change indicator* as the dependent variable (y) and *balance of ratings* (x_1) as the independent variable, these models allowed us to examine the relationship between biased processing and the probability of attitude polarization, attitude change towards the opposite pole, and attitude persistency. We estimated the following model:

$$ln\frac{P(y_i=m)}{P(y_i=r)} = \alpha_m + \beta_{m1}x_{i1} + \beta_{m2}x_{i2} = Z_{mi} \quad (4)$$

where *r* represents the reference category and *m* represents the remaining two categories of the dependent variable [cf. e.g., 63, 64].

This model allows us to calculate the probability of observing attitude change and persistency [cf. e.g., 64]. Technically, the probability of observing attitude polarization (category 0 of the dependent variable) and attitude moderation or side change (category 2 of the depend variable) reflect transition probabilities: $Pr(attitude_{t2} = p \mid attitude_{t1} = q)$ [cf. e.g., 65]. That is, they reflect the probability of observing a posterior attitude with position *p* given an initial attitude with position *q*. In cases of attitude polarization, *p* is located closer than *q* to the closest extreme pole of the initial attitude position. In cases of attitude moderation or side change, *p* is located further than *q* from the closest extreme pole of the initial attitude position. In contrast, the probability of attitude persistency reflects survival probability: $Pr(attitude_{t2} = q \mid attitude_{t1} = q)$ [cf. e.g., 65]. That is, it reflects the probability of observing a posterior attitude equal to the initial attitude. After model estimation, we computed the average adjusted predictions of

transition and survival probabilities (hereinafter referred to as average adjusted probabilities) based on the *balance of ratings* using Stata's margins command.

3 Empirical Results

3.1 Descriptive Results

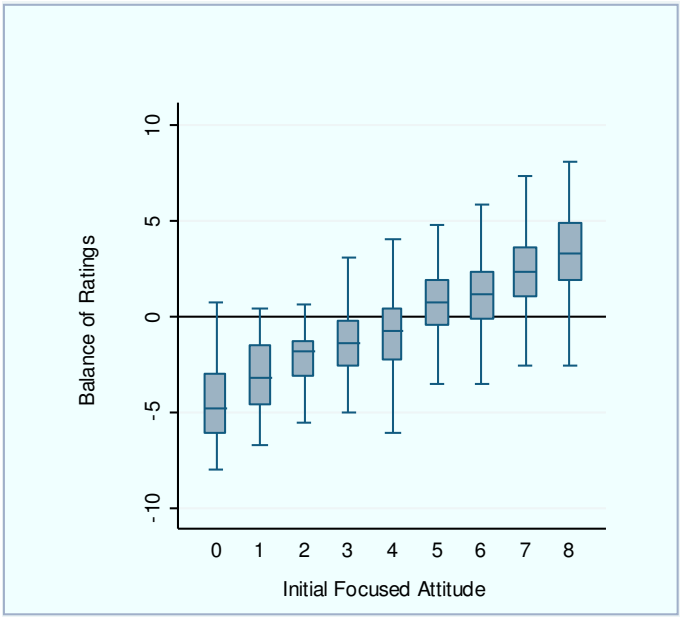
Before we turn to the results of the multilevel analysis, we will analyze the distribution of the initial focused attitudes in our sample (n=1,078). Table 7 shows that about 23.47 percent of the respondents reported a negative attitude, 8.53 percent reported a neutral attitude, and 68 percent reported a positive attitude towards the focused technology before the presentation of 14 arguments. As can be seen in Figure 3, on average, the majority of respondents with initial negative focused attitudes rated counter arguments as more persuasive than pro arguments and the majority of respondents with initial positive focused attitudes rated pro arguments as more persuasive than counter arguments. This finding is in line with the compatibility hypothesis (H1). Furthermore, the stepwise pattern of this relationship aligns with our extremity compatibility hypothesis (H3), as the distribution of individual balances of ratings increases steadily with attitudinal position (cf. Figure 3). This result suggests that biased processing occurs as a consequence of initial focused attitudes. Participants tended to support compatible arguments and counterargue incompatible arguments.

Table 7: Distribution of initial focused attitudes in the sample (n=1,078)

Attitude scale	Verbalization of attitude scale	Proportion of respondents (%)
0	strong in disfavor	8.35
1		5.01
2		5.84
3		4.27
4	neutral	8.53
5		9
6		16.7
7		16.23
8	strong in favor	26.07

Table A.1 in the appendix provides an overview on average attitudes towards all six technologies in each setting.

Figure 3: Box plots of balance of ratings for different attitudinal positions



Notes: The box indicates the lower and upper quartiles of *balance of ratings.* The length of the box represents the interquartile range (IQR). The line subdividing the box represents the median. The lines span all data points within 1.5 IQR of the first and third quartiles.

Table 8 shows the marginal and conditional probabilities of change and persistency in the reported attitudinal positions before (t1) and after (t2) evaluation of 14 conflicting arguments by respondents with initial negative, neutral, and positive focused attitudes. In total, 21.43 percent of the 1,078 respondents shifted their attitudes towards the negative pole of the attitude scale, and 21.99 percent of the respondents shifted their attitudes towards the positive pole of the attitude scale. About 56.59 percent of the respondents did not change their attitudes.

Attitude polarization occurs if the initial negative (or positive) attitudinal position becomes more extreme after exposure to the conflicting arguments. In our study, 14.23 percent (or 18.55 percent) of the 253 (or 733) respondents with an initial negative (or positive) attitude indicated a posterior attitude that was more negative (or positive) compared to their initial attitude after evaluating the arguments. This finding corroborates thus far our *attitude-polarization* hypothesis

(H8). However, at the same time, we observe that 28.85 percent (or 22.78 percent) of our 253 (or 733) respondents with an initial negative (or positive) attitude changed their attitude in the direction of the positive (or negative) pole of the attitude scale, and therefore became less extreme in their attitudes after evaluating the 14 arguments. Interestingly, among respondents with an initial negative attitude as well among respondents with an initial positive attitude, the proportion of respondents who articulated a less extreme posterior attitude (22.78 percent and 28.85 percent) is larger than the proportion of respondents who experienced a polarization effect (14.23 percent and 18.55 percent). In sum, these results suggest that the exposure to conflicting arguments lead to attitude persistency and to less extreme attitudes rather than to attitude polarization. Finally, among 92 respondents with an initial neutral attitude, changes towards the positive or negative pole of the attitude scale are balanced. Of these respondents with initial neutral attitude, 30.43 percent articulated a positive and 30.43 percent articulated a negative attitude after the evaluation of 14 arguments.

Table 8: Marginal and conditional probabilities of attitude change and attitude persistency

Initial attitude (t_1)	Attitude change: Negative ($t_2 - t_1 < 0$)	Stable ($t_2 - t_1 = 0$)	Positive ($t_2 - t_1 > 0$)	n
Negative	14.23 %	56.92 %	28.85 %	253
Neutral	30.43 %	39.13 %	30.43 %	92
Positive	22.78 %	58.66 %	18.55 %	733
Total	21.43 %	56.59 %	21.99 %	1,078

Note: In total, 45 respondents changed the valence of their initial attitude. That is, 23 (or 22) of those surveyed with initially negative (or positive) attitudes changed to a positive (or negative) attitude after the evaluation of arguments.

3.2 Results of the multilevel analysis among all respondents

Table 9 shows the results of the multilevel analysis based on the persuasiveness ratings of all 14 arguments for all (n= 1,078) respondents (Model 1). 27.8 percent of the variance in the persuasiveness ratings is explained on the argument level (level 1) and 15.8 percent on the respondent level (level 2). The analysis of argument type, where compatible-strong arguments were chosen as the reference group, reveals that the effect sizes of the dummies of all other argument types are significantly smaller (α=0.001). This means that compatible-strong arguments received the highest persuasiveness ratings. For instance, compatible-moderate arguments were rated as 0.77 scale points less persuasive than compatible-strong arguments, and incompatible-weak arguments were rated as 3.55 scale points less persuasive than compatible-strong arguments.

In line with our *quality hypothesis* (H1), compatible-strong arguments are rated as stronger than both compatible-moderate arguments and compatible-weak arguments. At the same time, compatible-moderate arguments are rated as more persuasive than compatible-weak arguments. This gradation pattern is also prevalent in the group of incompatible arguments (i.e., incompatible-strong arguments > incompatible-moderate arguments > incompatible-weak arguments). We also find evidence for the *compatibility hypothesis* (H2) among all three quality levels. That is, compatible-strong arguments were rated as more persuasive than incompatible-

strong arguments, compatible-moderate arguments were rated as more persuasive than incompatible-moderate arguments, and compatible-weak arguments were rated as more persuasive than incompatible-weak arguments. Furthermore, the results of Model 1 provide evidence in favor of the *neutral-attitude hypothesis* (H3). The effect sizes for the group of neutral arguments lie in between the effect sizes for the group of incompatible and the group of compatible arguments. However, as mentioned in Section 2.3, an appropriate test of the *quality hypothesis* (H1), *compatibility hypothesis* (H2), and *neutral-attitude hypothesis* (H3) requires a consideration of the multiple pairwise comparisons between the nine different argument types regarding the significance levels. Therefore, we computed the average adjusted persuasiveness ratings for each argument type on the basis of Model 1 and compared these predictions on a pairwise basis using the Sidak Test.

Table 9: Results of Model 1 (dependent variable *persuasiveness ratings*)

Level 1 (15,092 arguments)	R^2 27.8 %		
Level 2 (1,078 respondents)	R^2 15.8 %		
	ß		*se*
Intercept	6.11	***	0.25
Respondent characteristics:			
Unfamiliarity	*Reference*		
Perceived familiarity	0.56	**	0.21
Personal irrelevance	*Reference*		
Personal relevance	-0.23		0.17
* Perceived familiarity	0.11		0.16
Need for cognition	-0.11	*	0.06
* Perceived familiarity	0.00		0.05
Female	*Reference*		
Male	-0.44	+++	0.09
Preferred not to say	-0.43		0.38
Age	0.00		0.00
Argument characteristics:			
Compatible strong	*Reference*		
Compatible moderate	-0.77	***	0.05
Compatible weak	-1.42	***	0.07
Neutral strong	-1.35	***	0.16
Neutral moderate	-1.97	***	0.14
Neutral weak	-2.41	***	0.16
Incompatible strong	-2.53	***	0.08
Incompatible moderate	-2.96	***	0.08
Incompatible weak	-3.55	***	0.09
Economic	-0.05		0.05
Social	0.17	++	0.05
Political	0.62	+++	0.07
Technical	0.85	+++	0.05
Ecological	1.03	+++	0.05
Coal power station	-1.27	+++	0.10
Gas power station	0.59	+++	0.10
Wind power stations (onshore)	-0.37	+++	0.10
Wind power stations (offshore)	-0.05		0.08
Open space photovoltaics	0.03		0.10
Biomass power plants	1.02	+++	0.10

Variance component	σ^2	*se*	Bounds of 95%-Confidence interval	
			Low	Up
Argument type	0.06	0.01	0.05	0.07
Familiarity	0.59	0.08	0.45	0.77
Personal relevance	0.18	0.24	0.01	2.47
Economic	0.19	0.07	0.10	0.38
Technical	0.14	0.09	0.04	0.52
Level 2	1.00	0.12	0.79	1.27
Level 1	3.60	0.08	3.44	3.76

Notes: The model was estimated in Stata 14.2 using a Restricted Maximum Likelihood estimation; se = standard error; * p<0.05, ** p<0.01, *** p<0.001 based on one-tailed hypothesis tests; $^{+}$ p<0.05, $^{++}$ p<0.01, $^{+++}$ p<0.001 based on two-tailed hypothesis tests; empty model ICC was 0.071[35]; the pseudo-R^2 was calculated using the "multilevel tools" Stata package; age mean centered; weighted effect coded dummies for settings.

Figure 4 depicts the average adjusted predictions for each argument type. As can be clearly seen, respondents evaluated incompatible-weak arguments as least persuasive (2.86 on the persuasiveness rating scale) while they evaluated compatible-strong arguments as most persuasive (6.4 on the persuasiveness rating scale). Table 9 provides the corresponding results of the Sidak Test on the multiple pairwise comparisons of the average adjusted predictions. For instance, the average adjusted predictions of compatible-strong arguments is 3.55 (≈ 6.4 - 2.86) scale points stronger than that of incompatible-weak arguments. All differences in the average adjusted predictions between the argument types are significant, except for two argument type combinations (neutral-weak arguments vs. incompatible-strong arguments and neutral-strong arguments vs. compatible-weak arguments). As a result, in the statistical sense, respondents with a neutral initial focused attitude evaluated weak arguments as persuasive to the same extent that respondents with incompatible attitudes rated strong arguments; and respondents with a neutral initial focused attitude evaluated strong arguments as persuasive to the same extent that respondents with an compatible attitude rated weak arguments. In sum, the gradation pattern depicted in Figure 4 is perfectly in line with the *quality-hypothesis* (H1), *compatibility hypothesis* (H2), and *neutral-attitude hypothesis* (H3) and the results of the Sidak Test corroborate these hypotheses.

Table 9 provides further interesting details on the relative importance of the evaluating tendencies of quality and compatibility in the persuasiveness ratings of the 84 arguments. The differences in the average adjusted predictions in the groups of incompatible arguments, neutral

[35] ICC refers to intra class coefficient. An ICC of 0.07 means that around 7 percent of the variance in the persuasiveness ratings is due to differences across respondents, with the remaining 93 percent attributable to differences in the arguments. Hence, respondents are relatively homogenous regarding the persuasiveness ratings.

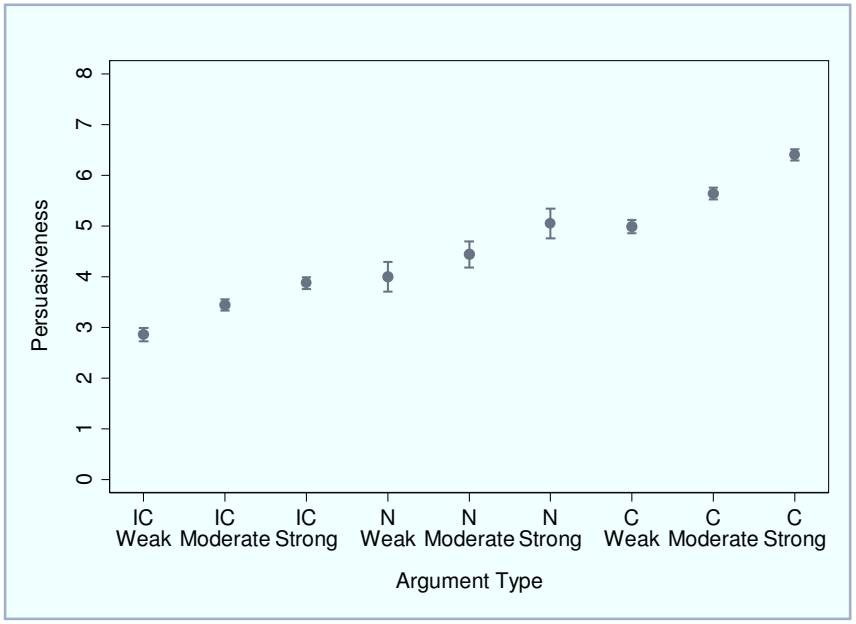
arguments, and compatible arguments, respectively, refer to the impact of argument quality on persuasiveness ratings. For instance, we observe that incompatible-strong arguments were rated as 1.02 scale points more persuasive than incompatible-weak arguments. This difference in the average adjusted predictions resembles the difference in the corresponding ratings between neutral-weak and neutral-strong arguments, amounting to 1.06 scale points. The largest quality effect can be found among the group of compatible arguments. Here, the difference in the average average adjusted predictions between strong and weak arguments amounts to 1.42 scale points. These effects are smaller than the effects resulting from the compatibility tendency. The average adjusted prediction of compatible-weak arguments is 2.13 scale points higher than the comparable of incompatible-weak arguments. The difference in the average adjusted predictions between compatible-strong and incompatible-strong arguments amounts to as many as 2.53 scale points. Hence, whether or not an argument is compatible with a recipient's initial attitude has more implications for argument evaluation than the quality of the argument.

Regarding the effect of familiarity on argument evaluation, the results of Model 1 present a divided picture. First, we find evidence for our *familiarity hypothesis* (H4). Respondents rated arguments that they perceived to be familiar as 0.56 scale points more persuasive than arguments that they did not perceive to be familiar (α=0.01). However, we did not find evidence for the *attenuating-familiarity hypothesis* (H5). Neither the two-way interaction between perceived familiarity and need for cognition nor the two-way interaction between perceived familiarity and personal involvement proved to be significant (α=0.05).[36] Hence, the automatic positive effect of perceived familiarity is not moderated by any controlled processing effect. Finally, our analysis reveals that addressing an ecological aspect increased persuasiveness

[36] We also tested a three-way interaction between perceived familiarity, personal relevance, and argument type as well as between perceived familiarity, need for cognition, and argument type. However, neither the three-way interaction terms nor the interaction terms of lower order are significant in these models.

ratings by 1.03 scale points. This point to the fact that besides argument quality dimension is another important aspect of argument content affecting persuasiveness ratings.[37]

Figure 4: Average adjusted predictions for each argument type



Notes: IC = incompatible argument, N = neutral argument, C = compatible argument; predictions based on Model 1; confidence interval for level 95 %; robust standard errors.

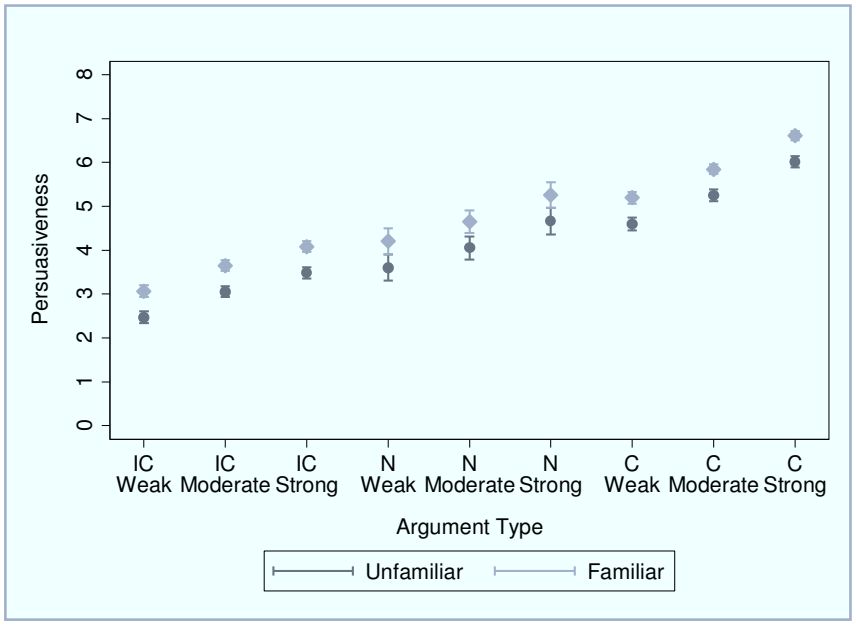
Table 10: Results of the Sidak Test by argument type

		Incompatible			Neutral			Compatible	
		W	M	S	W	M	S	W	M
Incompatible	**M**	0.58							
	S	1.02	0.43						
Neutral	**W**	1.14	0.55*	0.12ns					
	M	1.58	1.00	0.56**	0.45+				
	S	2.19	1.61	1.18	1.06	0.61			
Compatible	**W**	2.13	1.54	1.11ns	0.99	0.55**	-0.07		
	M	2.78	2.20	1.76	1.65	1.20	0.59**	0.65	
	S	3.55	2.96	2.53	2.41	1.97	1.35	1.42	0.77

Notes: W = weak, M = moderate, S = strong; ns = not significant (α=0.05); if not indicated otherwise, all contrast effects are significant; p<0.001, ** p<0.01, * p<0.05, + p<0.10; hypotheses tested with a one-tailed test; a positive sign indicates that respondents rated a particular argument type in a row as more persuasive than a particular argument in a column.

[37] It is important to recall that arguments could also be categorized into more than one dimension only (cf. FN 22 and Table 1). Hence, the effect sizes of the dimensions reported in Table 9 and Table 11 do not refer to differences between the particular dimension and a reference dimension, but to the effect of the particular dimension on persuasiveness ratings.

Figure 5: Average adjusted predictions for argument type – familiarity effect



Notes: IC = incompatible argument, N = neutral argument, C = compatible argument; predictions based on Model 1; confidence interval for level 95 %; robust standard errors.

3.3 Results of the multilevel analysis among non-neutral respondents

As our aim was to examine the impact of attitude extremity as well as recipients' attitude-relevant knowledge on the compatibility and incompatibility tendencies, respectively, we re-estimated Model 1 excluding respondents with a neutral initial focused attitude. Furthermore, we accounted for two two-way-interactions – i.e., between argument type and attitude extremity as well as between argument type and attitude-relevant knowledge – that allowed us to address the *extremity-compatibility hypothesis* (H6) and the *knowledge hypothesis* (H7), respectively. Hence, the results of Model 2 are based on the persuasiveness ratings of (m=) 13,804 arguments by (n=) 986 respondents having either a positive or negative initial focused attitude (cf. Table 11). In Model 2, 32.97 percent of the variance in the persuasiveness ratings is explained on the argument level (level 1) and 15.59 percent on the respondent level (level 2).

Due to the estimation of two two-way-interactions, the effect sizes outlined in Table 11 for particular argument types represent main effects that apply to respondents with very moderate attitude and no attitude-relevant knowledge, and ignoring all other characteristics. For instance, respondents with very moderate attitude and no attitude-relevant knowledge rated compatible-

moderate arguments as significantly less persuasive than compatible-strong arguments (α=0.001) by 0.63 scale points. As can be seen from the sizes of the main effects for argument type, these effect sizes do not follow the gradation pattern found in Model 1. For instance, the effect size of incompatible-strong arguments (=0.43) is significantly positive (α=0.05), meaning that respondents with very moderate attitude and no attitude-relevant knowledge rated incompatible-strong arguments as 0.43 scale points more persuasive than compatible-strong arguments – i.e., the reference argument type.

To address the *extremity-compatibility hypothesis* (H6), we calculated average adjusted predictions for respondents with very moderate and very extreme attitude on the basis of Model 2. Figure 6 illustrates the impact of attitude extremity on the compatibility tendency. Respondents with very extreme attitude rated incompatible arguments as significantly less persuasive than respondents with very moderate attitude; for instance, in the case of incompatible-weak arguments, the difference between respondents with very moderate and very extreme attitude amounts to 1.39 scale points.[38] At the same time, respondents with very extreme attitude rated compatible arguments as significantly more persuasive than respondents with very moderate attitude; for instance, in the case of compatible-strong arguments, the difference between respondents with very moderate and very extreme attitude amounts to 1.70 scale points. We therefore find evidence for our *extremity-compatibility hypothesis* (H6), meaning that the more extreme respondents' initial focused attitudes are, the stronger the compatibility tendency. In the same vein, we tested our *knowledge hypothesis* (H7) by comparing the average adjusted persuasiveness ratings for respondents with no relevant knowledge with those for respondents with extensive relevant knowledge. However, we did not find evidence in favor of our *knowledge hypothesis* (H7), that is to say that respondents with

[38] The significance of the interaction between attitude extremity and argument type can be seen in Figure 6, as the confidence intervals of the average adjusted predictions of respondents with very moderate attitude do not overlap with the average adjusted predictions for respondents with very extreme attitude. Furthermore, we conducted a Sidak Test for pairwise multiple comparisons which yielded significant differences in the average adjusted predictions between both groups.

extensive attitude-relevant knowledge were not more able to affirm compatible arguments and counterargue incompatible arguments than respondents with no attitude-relevant knowledge.

Table 11: Results of Model 2 (dependent variable *persuasiveness ratings*)

Level 1 (13,804 arguments)	R^2 32.97 %		
Level 2 (986 respondents)	R^2 15.59%		
	ß		*se*
Intercept	4.28	+++	0.28
Respondent characteristics:			
Unfamiliarity	*Reference*		
Perceived familiarity	0.72	+++	0.22
Personal irrelevance	*Reference*		
Personal relevance	-0.26	+	0.16
* Perceived familiarity	0.22		0.17
Need for cognition	-0.06		0.06
* Perceived familiarity	-0.04		0.05
Female	*Reference*		
Male	-0.41	+++	0.08
Prefer not to say	-0.47	+	0.30
Age	0.00		0.00
Attitude extremity	0.57	***	0.05
Knowledge	0.04		0.05
Argument characteristics:			
Compatible strong	*Reference*		
Compatible moderate	-0.63	***	0.14
* Attitude extremity	-0.05		0.04
* Knowledge	0.00		0.05
Compatible weak	-1.07	***	0.21
* Attitude extremity	-0.15	**	0.06
* Knowledge	0.06		0.07
Incompatible strong	0.43	*	0.23
* Attitude extremity	-1.03	***	0.07
* Knowledge	-0.06		0.08
Incompatible moderate	0.01		0.23
* Attitude extremity	-0.96	***	0.72
* Knowledge	-0.18	*	0.08
Incompatible weak	-0.41		0.26
* Attitude extremity	-1.03	***	0.08
* Knowledge	-0.15	*	0.09

Table 11 Continued

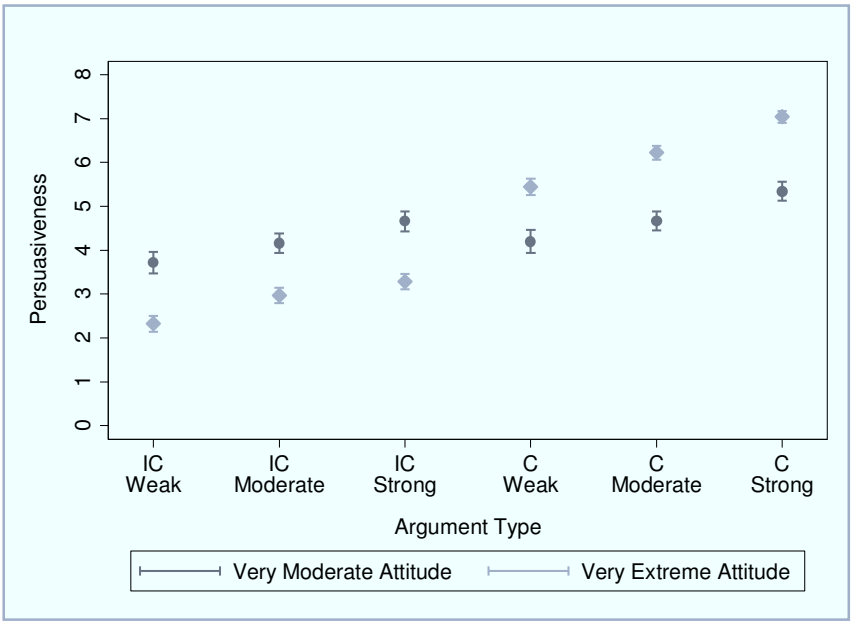
Level 1 (13,804 arguments)	R^2 32.97 %		
Level 2 (986 respondents)	R^2 15.59%		
	ß		*se*
Economic	-0.07		0.05
Social	0.13	+	0.05
Political	0.52	+++	0.08
Technical	0.85	+++	0.06
Ecological	0.98	+++	0.06
Coal power station	-1.04	+++	0.09
Gas power station	0.36	++	0.10
Wind power stations (onshore)	-0.35	+++	0.08
Wind power stations (offshore)	-0.08		0.07
Open space photovoltaics	0.15		0.08
Biomass power plants	0.90	+++	0.09

Variance Component	σ^2	*se*	Bounds of 95%-Confidence Interval	
			Low	Up
Argument type	0.07	0.01	0.05	0.10
Familiarity	0.47	0.08	0.33	0.66
Economic	0.25	0.07	0.14	0.43
Technical	0.17	0.10	0.06	0.52
Level 2	0.58	0.10	0.41	0.82
Level 1	3.70	0.09	3.53	3.88

Notes: The model was estimated in Stata 14.2 using a Restricted Maximum Likelihood estimation; se = standard error; * p<0.05, ** p<0.01, *** p<0.001 based on one-tailed hypothesis tests; $^{+}$p<0.05, $^{++}$ p<0.01, $^{+++}$ p<0.001 based on two-tailed hypothesis tests; empty model ICC was 0.068[39]; the pseudo-R^2 was calculated using the "multilevel tools" Stata package; age mean centered; weighted effect coded dummies for settings.

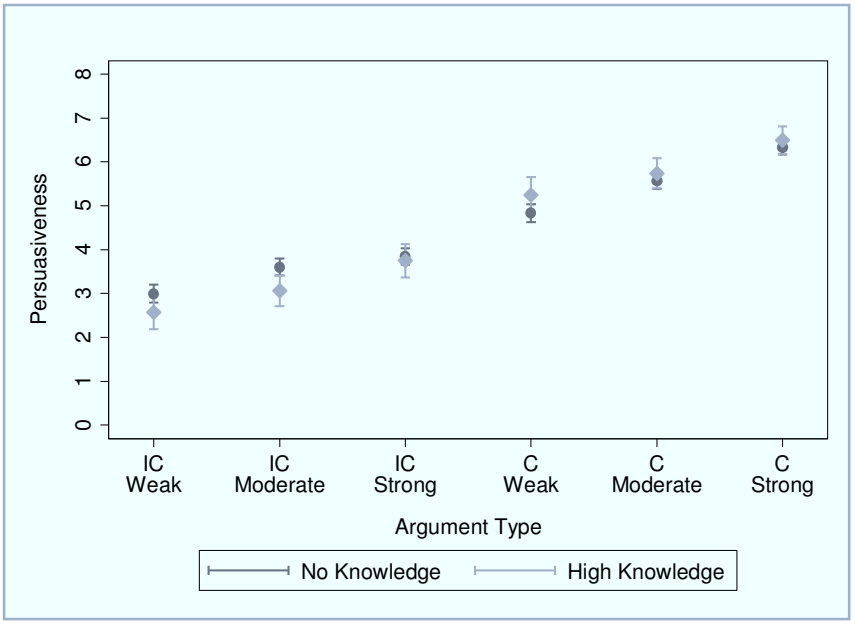
[39] For the meaning of ICC, see footnote 35.

Figure 6: The impact of attitude extremity on the compatibility tendency



Notes: IC = incompatible argument, N = neutral argument, C = compatible argument; predictions based on Model 2; confidence interval for level 95 %; robust standard errors.

Figure 7: The impact of attitude-relevant knowledge on the compatibility tendency



Notes: Predictions based on Model 2; Confidence Interval for level 95 %, robust standard errors.

3.4 Attitude Change

Table 12 shows the results of the multinomial logistic regression estimations, in which *change indicator* was the dependent variable, for each of the respondent groups. In each model, the

likelihood ratio chi-square statistic is significant, and hence, the estimated models are statistically significant (α=0.001) compared to their null models (i.e., models with no independent variable). The coefficient of *balance of ratings* indicates the relationship between the likelihood of attitude polarization and attitude moderation as well as the relationship between *balance of ratings* and the reference group (i.e., respondents who did not change their initial attitude after argument evaluation). For instance, as opposed to respondents with a constant attitude in Model 1, the likelihood of articulating a less extreme attitudinal position after argument evaluation significantly increases with a higher *balance of ratings* (α=0.001). This intuitive result indicates that the likelihood of reporting a less extreme posterior attitude increases participants' evaluations of the strength of the pro arguments compared to the counter arguments. Two issues are important to note here. First, the effect size of *balance of ratings* is not significant in all models (α=0.05) (see Models 2 and 3). Second, even if it is significant, the sign of the effect size might be unexpected. In Model 1, for instance, the effect size of *balance of ratings* is positive among respondents who polarized their initial negative attitudes, meaning that the stronger participants evaluated pro arguments in comparison to counter arguments, the more likely they were to adopt polarized attitudes than maintain their attitudes.

Figure 8, Figure 9, and Figure 10 depict the average adjusted probabilities of attitude change and attitude persistency among respondents with initial negative attitude, initial neutral attitude, and initial positive attitude. The probabilities were calculated based on the multinomial regression models. Figure 8 shows that respondents with a negative *balance of ratings* are more likely to maintain their initial negative attitudes than polarize them. In contrast, respondents with a positive *balance of ratings* are more likely to moderate their initial negative attitudes than maintain them.[40] Among respondents with an initial neutral attitude (cf. Figure 9), a

[40] This pattern does not change substantially if respondents with initial extremely negative attitudes ('0'; n=90) are disregarded from the analysis (cf. Figure A.1). The probability of attitude polarization is higher

negative (or positive) *balance of ratings* substantially increases the probability of adopting a negative (or positive) posterior attitude. In contrast, among respondents with an initial positive attitude, the *balance of ratings* contributed to attitude polarization but not to attitude moderation (cf. Figure 10).[41]

than the probability of attitude moderation, but it is still substantially lower than the probability of attitude persistency.

[41] When 281 respondents with initial extremely positive attitudes ('8') are excluded from the analysis, there is a higher probability of attitude polarization than attitude persistency due to the positive *balance of ratings* (cf. Figure A.2).

Table 12: Results of multinomial logistic regressions (dependent variable *change indicator*)

Model 1: Respondents with Initial Negative Attitude (n=253)		*ß*		*se*	*Model Evaluation*	
Polarized	Balance of Ratings	0.23	*	0.09	Likelihood Ratio Test χ2	40.29***
	Intercept	-0.63		0.33	Pseudo-R^2	0.083
Stable		*Reference*				
Moderated	Balance of Ratings	0.46	***	0.08		
	Intercept	0.59	*	0.26		
Model 2: Respondents with Initial Neutral Attitude (n=92)		*ß*		*se*	*Model Evaluation*	
Neutral to Negative	Balance of Ratings	-0.61	***	0.18	Likelihood Ratio Test χ2	22.52***
	Intercept	-1.06	**	0.37	Pseudo-R^2	0.112
Stable		*Reference*				
Neutral to Positive	Balance of Ratings	0.04		0.14		
	Intercept	-0.24		0.26		
Model 3: Respondents with Initial Positive Attitude (n=733)		*ß*		*se*	*Model Evaluation*	
Polarized	Balance of Ratings	-0.08		0.05	Likelihood Ratio Test χ2	66.07***
	Intercept	-0.96	***	0.15	Pseudo-R^2	0.047
Stable		*Reference*				
Moderated	Balance of Ratings	-0.35	***	0.05		
	Intercept	-0.32	**	0.12		

Notes: se = standard error; * p<0.05, ** p<0.01, *** p<0.001 based one-tailed hypothesis tests.

Figure 8: Probability of attitude change and persistency among respondents with initial negative attitude

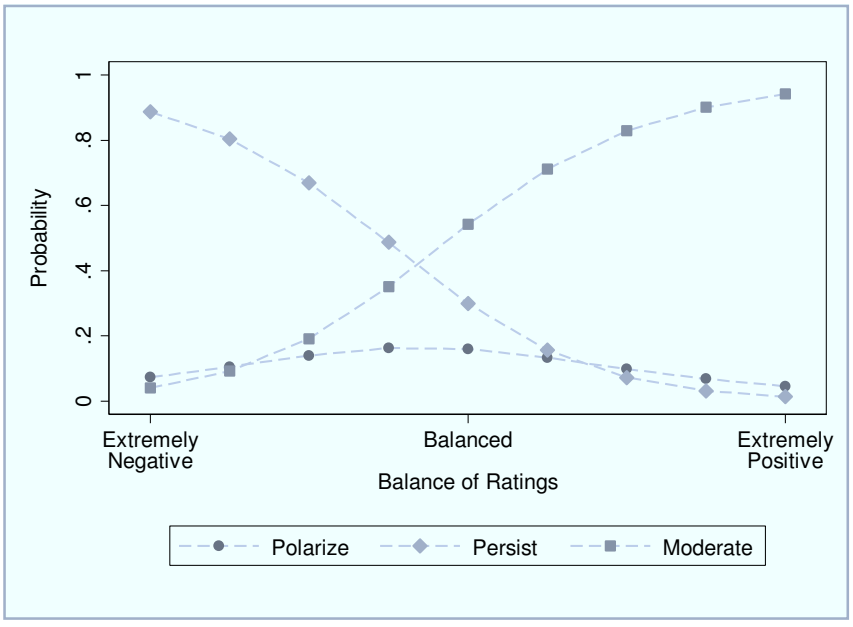


Figure 9: Probability of attitude change and persistency among respondents with initial neutral attitude

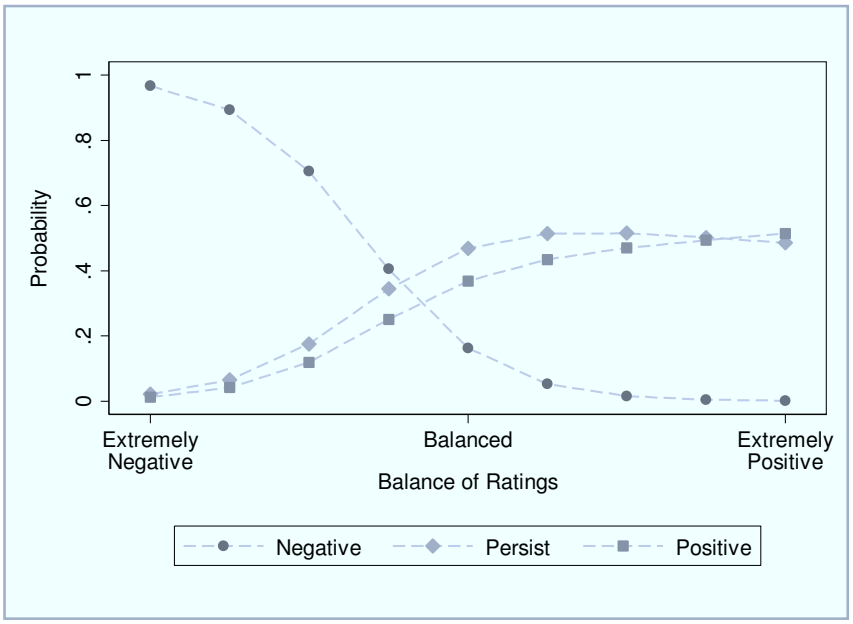
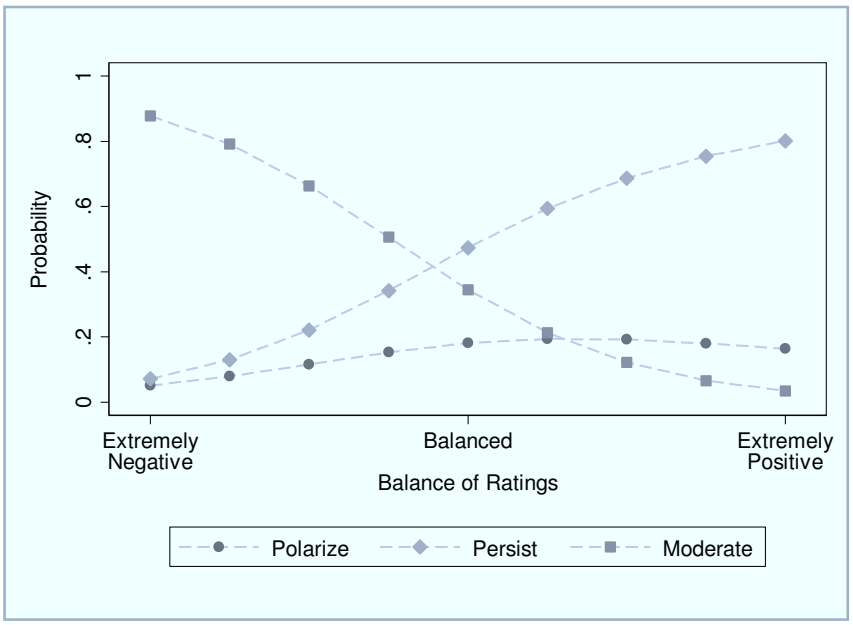


Figure 10: Probability of attitude change and persistency among respondents with initial positive attitude



4 Discussions and Conclusion

In Germany, the public is continuously exposed to arguments concerning electricity-generating technologies that are injected into the public debate by different stakeholders. Previous studies on argument evaluation outlined, by means of randomized experiments, different evaluating tendencies that affect the overall evaluation of arguments. Furthermore, some studies have

shown that biased processing of conflicting arguments contributes to an attitude polarization effect, meaning that initial attitude positions towards an attitude object (in this case, an electricity-generating technology) become more extreme after exposure to information either in favor of or against the particular attitude object. Transferred to the German energy transition, or Energiewende, evidence for an attitude polarization effect would suggest that the use of arguments both in favor of and against different electricity-generating technologies broadens the societal gap between supporters and opponents of different technologies relevant for the Energiewende.

In this study, we bridged the gap between two models on argument evaluation proposing different evaluating tendencies to occur during the process of argument evaluation. For our examination, we exposed participants in an online survey to seven pro and seven counter arguments (i.e., conflicting arguments) concerning one of six electricity-generating technologies (i.e., 84 arguments in total). For each argument, we asked the respondents to rate its persuasiveness and state their perceived familiarity with it. Furthermore, by measuring respondents' attitudes towards the focused technology before and after the arguments were presented, we were able to investigate their actual attitude change towards the focused technology as a consequence of exposure to the conflicting arguments.

We found evidence for the predictions of both models on argument evaluation. In line with the *quality hypothesis* (H1), the *compatibility hypothesis* (H2), and the *familiarity hypothesis* (H4), respondents based their persuasiveness ratings on argument quality (i.e., strong, moderate or weak arguments), argument position (i.e., indicating the advantages or disadvantages of a technology), and their perceived familiarity with the presented argument. In general, strong arguments were rated as more persuasive than moderate arguments, and moderate arguments were rated as more persuasive than weak arguments; arguments compatible with respondents' initial attitude position were rated as more persuasive than those incompatible with their initial attitude position; and familiar arguments were rated as more persuasive than unfamiliar

arguments. Opposed to the *attenuating-familiarity hypothesis* (H5), the familiarity effect was neither moderated by respondents' need for cognition nor by their personal involvement. While one may speculate to explain the missing moderating effect with the chosen operationalization of personal involvement in this study, such speculation seems to be erroneous for the operationalization of need for cognition, since we used a validated short scale to measure this concept. Hence, our results speak in favor of three evaluating tendencies that occur simultaneously during the evaluation process: compatibility, quality, and familiarity.

Of these three evaluating tendencies, the compatibility tendency seems to exert most influence on respondents' evaluations. For strong arguments, which can be assumed to be communicators' argument type of choice, the fact whether or not an argument is compatible with respondents' initial attitudes results in a difference of 2.53 scale points on the nine-point persuasiveness rating scale. In contrast, the difference between compatible-strong and compatible-weak arguments (that is, the difference attributable to the quality of a compatible argument) results in a difference of 1.42 scale points, while perceived familiarity contributes to a difference of 0.6 scale points in the persuasiveness ratings.

Another important finding of our analysis in line with our *extremity-compatibility hypothesis* (H6) is that respondents' initial attitude extremity seemingly increases their motivation to defend the initial attitude towards the focused technology. The more extreme a respondent's initial attitude towards a focused technology is, the stronger the compatibility tendency. For instance, in the case of incompatible-strong (or compatible-strong) arguments, the average adjusted predictions for respondents with extreme attitudinal positions (i.e., either strongly against or strongly in favor of a focused technology) is 1.38 (or 1.7) scale points higher than the average adjusted predictions for respondents with a very moderate attitudinal position, located closely to the neutral position on the attitude scale. At the same time, contrary to the *knowledge hypothesis* (H7) attitude-relevant knowledge did not strengthen the compatibility tendency. In other words, the compatibility tendency seems to be strengthened by respondents'

motivation rather than by their ability to affirm compatible arguments and to counter-argue incompatible arguments. However, it might be that attitude-relevant knowledge as measured in this study was too general compared to the arguments used for the various technologies, which were relatively specific. Our study adds to (most of) the existing literature studies, by examining respondents with neutral attitudes. In line with our *neutral-attitude hypothesis* (H3), we found that arguments that were rated by respondents with an initial neutral focused attitude yielded higher persuasiveness scores than incompatible arguments and lower persuasiveness scores than compatible arguments. From our point of view, this result underpins the predictions of the congruence model, as it can be explained with the non-existent compatibility tendency among people with initial neutral attitudes. Hence, only two evaluating tendencies (i.e., quality and familiarity) seem to have applied among these respondents.

Our analysis of attitude change showed the following results. The descriptive transition analysis revealed that a large proportion of respondents did not change their initial attitude position after the presentation of conflicting arguments. Furthermore, we found among respondents with initially negative attitudes as well as among respondents with initially positive attitudes, attitude polarization and attitude moderation simultaneously to occur. As both tendencies have opposing effects on global attitude change in a sample, our finding might explain the missing evidence on attitude polarization in other studies which analyzed actual attitude change on global levels. In this study, the proportion of respondents having less extreme posterior attitudes is larger (22.78 percent of those surveyed with initially positive attitudes and 28.85 percent among those with initial negative attitudes) than the proportion of respondents having more extreme attitudes after the evaluation of conflicting arguments in both respondent groups. Attitude polarization occurred among 18.55 percent of those surveyed with initially positive attitudes and among 14.23 percent of the respondents with initially negative attitudes. Hence, in line with Kuhn and Lao [39] our results clearly point against the idea that attitude polarization is an inevitable consequence of exposure to conflicting arguments.

The bivariate analyses showed that biased processing generally increases the likelihood to observe attitude changes in accordance with the direction of biased processing. However, to induce attitude change, biased processing needs to be sufficiently strong. Furthermore, among respondents with initial negative attitudes, strongly negative biased processing contributed to attitude persistency rather than to attitude polarization. Unfortunately, we can only speculate on the reasons for this finding. Perhaps participants with initial negative attitudes held on average stronger attitudes than respondents with initial neutral or positive attitudes. It is desirable to see future studies investigating the role of attitude strength when analyzing conditional probabilities of attitude change and attitude persistency. These studies might also take into account examining to what degree beliefs and attitudes towards electricity generating technologies, respectively constitute valued sources of persons' identity. To the extent that this is the case, biased processing can be expected to be rooted in defense motivation [cf. 27]. Finally, future studies might also consider examining methodological aspects, for example, the impact of attitude scale width on probabilities of attitude change.

Our findings suggest that when communicators aim to convince target recipients of positions that run counter to those recipients' own positions, any argument that they may use can be expected to lose strength substantially due to its incompatibility with the recipients' initial attitudes. Furthermore, this loss in strength can be expected to become greater the more extreme the recipients' initial attitudinal position is, and does not necessarily require the recipients to have attitude-relevant knowledge. The critical point here is that communicators cannot avoid the problem of biased processing, because the fact whether or not an argument is compatible with recipients' initial attitudinal position lies outside the sphere of a communicator's influence. In this respect, the scope of the significance of initial attitudes is all the more problematic when one considers that attitudes may also be formed spontaneously, for instance when new technologies or products are launched to the market. As initial attitudes

affect the way in which information is processed, e.g., on a new technology, spontaneous attitudes could affect market acceptance of new technologies.

Appendix

Table A.1: Average attitudes towards the technologies in the six settings

Setting	Initial attitudes towards					
	Coal power station	Gas power station	Wind power stations (onshore)	Wind power stations (offshore)	Open-space photo-voltaics	Biomass power station
Coal power station	1.72	3.79	6.28	6.43	6.85	5.78
Gas power station	1.84	3.96	6.30	6.54	6.85	5.85
Wind power station (onshore)	1.58	3.99	6.33	6.45	6.99	5.49
Wind power station (offshore)	2.01	3.93	6.42	6.47	7.04	5.73
Open-space photovoltaics	1.67	3.80	6.20	6.37	7.07	5.58
Biomass power station	1.84	4.32	6.27	6.63	6.96	5.87
Sample average	1.78	3.96	6.30	6.48	6.96	5.72

Notes: Attitudes towards the six technologies were measured on a nine point scale. The extreme points of the continuum indicate a strong attitude against ('0') and a strong attitude in favor of ('8') the relevant technology. A neutral attitude is represented on the answer scale by '4'.

Table A.2: Mean and standard deviation of arguments' persuasiveness

Setting	Persuasiveness			
	Pro arguments		Counter arguments	
	Mean	SD	Mean	SD
Coal power station	2.62	1.86	5.70	1.45
Gas power station	4.64	1.72	5.14	1.63
Wind power station (onshore)	5.65	1.37	3.67	1.56
Wind power station (offshore)	5.51	1.31	3.62	1.44
Open-space photovoltaics	5.54	1.61	3.16	1.63
Biomass power station	5.73	1.50	4.79	1.53

Notes: SD = standard deviation.

Table A.3: Perceived familiarity with pro arguments

Setting	Number of pro arguments perceived to be familiar								
	0	1	2	3	4	5	6	7	Total
Coal power station	1	4	7	22	33	45	27	31	170
Gas power station	7	4	17	24	34	38	23	24	171
Wind power station (onshore)	0	2	6	14	34	51	32	33	172
Wind power station (offshore)	5	4	15	27	30	56	36	16	189
Open-space photovoltaics	2	6	19	25	43	43	31	28	197
Biomass power station	15	5	17	22	39	33	24	24	179
Total	30	25	81	134	213	266	173	156	1,078

Table A.4: Perceived familiarity with counter arguments

Setting	Number of pro arguments perceived to be familiar								
	0	1	2	3	4	5	6	7	Total
Coal power station	3	8	8	24	24	41	34	28	170
Gas power station	5	7	15	21	38	36	25	24	171
Wind power station (onshore)	1	1	7	19	28	44	34	38	172
Wind power station (offshore)	5	7	14	25	39	40	40	19	189
Open-space photovoltaics	4	5	16	26	44	42	43	17	197
Biomass power station	8	9	14	27	40	23	41	17	179
Total	26	37	74	142	213	226	217	143	1,078

Figure A.1: Probability of attitude change and persistency among respondents with initial negative attitude after excluding 90 respondents with initially extreme negative attitudes

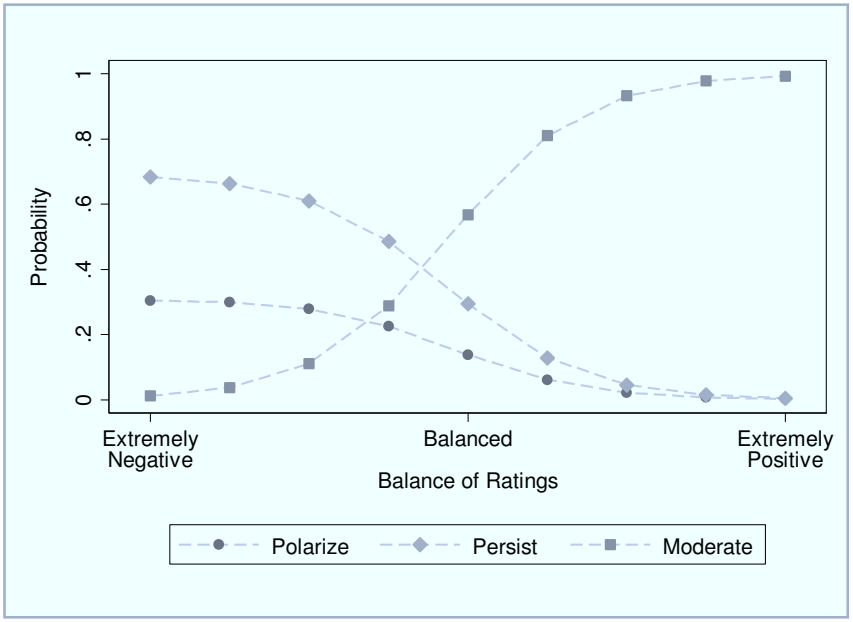


Figure A.2: Probability of attitude change and persistency among respondents with initial negative attitude after excluding 281 respondents with initially extreme positive attitudes

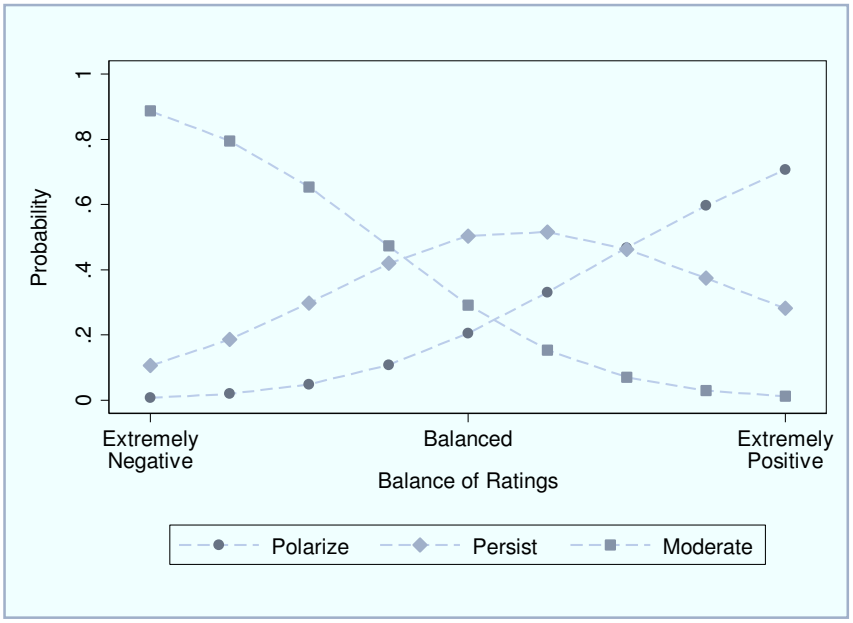
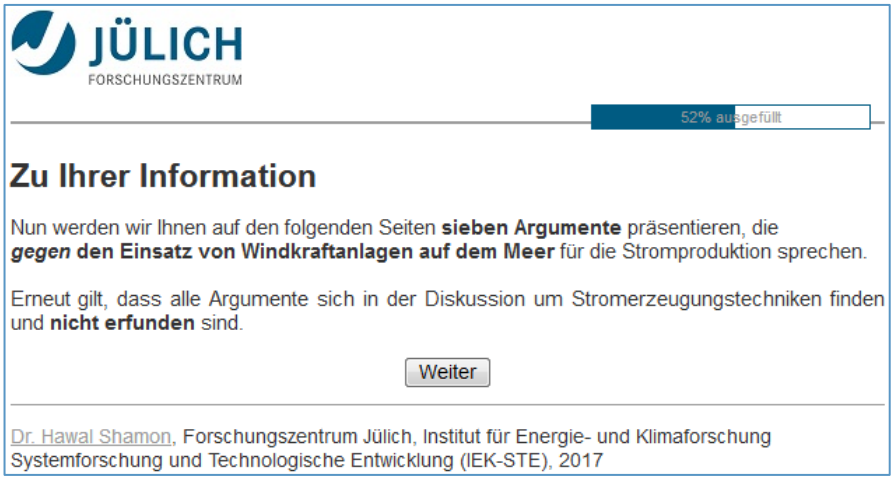


Figure 11: Clarification presented to respondents (here in Setting 4) before the first block of seven arguments (here pro arguments)[42]

Notes: In (online) surveys, a contact person and the name of the institution in whose name the study is being conducted are required (cf. e.g., Couper [66]).

Figure 12: Clarification presented to respondents (here in Setting 4) before the second block of seven arguments (here counter arguments)[43]



Notes: In (online) surveys, a contact person and the name of the institution in whose name the study is being conducted are required (cf. e.g., Couper [66]).

[42] English translation of this clarification: For your information. On the following pages, we will present you with seven arguments in favor of the use of offshore wind power stations for electricity production. All of these arguments are genuinely used in the discussion about power generation technologies and were not fabricated for the purposes of this survey. We would like you to tell us how persuasive you find the different arguments and whether they are new to you or you are already familiar with them.

[43] English translation of this clarification: For your information. On the following pages, we will present you with seven arguments against the use of offshore wind power stations for electricity production. Once again, all arguments are genuinely used in the discussion about power generation technologies and were not fabricated for the purposes of this survey.

References

[1] Die Bundesregierung der Bundesrepublik Deutschland. 2011. *Gesetzesentwurf Der Bundesregierung – Entwurf Eines Gesetzes Zur Neuregelung Des Rechtsrahmens Für Die Förderung Der Stromerzeugung Aus Erneuerbaren Energie – Drucksache 17/6247.* Drucksache 17/6247, Retrieved June, 29 2018 (http://dip21.bundestag.de/dip21/btd/17/062/1706247.pdf).

[2] Federal Ministry for Economic Affairs and Energy (BMWi). 2015. *Making a Success of the Energy Transition*, Retrieved March 14, 2018 (https://www.bmwi.de/Redaktion/EN/Publikationen/making-a-success-of-the-energy-transition.pdf?__blob=publicationFile&v=6).

[3] Araújo, Kathleen. 2014. "The Emerging Field of Energy Transitions: Progress, Challenges, and Opportunities." *Energy Research & Social Science* 1:112-121.

[4] Kammermann, Lorenz and Clau Dermont. 2018. "How Beliefs of the Political Elite and Citizens on Climate Change Influence Support for Swiss Energy Transition Policy." *Energy Research & Social Science* 43:48-60.

[5] Kinneavy, James L. 1971. *A Theory of Discourse*. New York: W. W. Norton.

[6] Rowan, Katherine E. 2003. "Informing and Explaining Skills: Theory and Research on Informative Communication." Pp. 403-438 in *Handbook of Communication and Social Interaction Skills.* Mahwah, NJ, US: Lawrence Erlbaum Associates Publishers.

[7] Ter Mors, Emma, Mieneke W. H. Weenig, Naomi Ellemers and Dancker D. L. Daamen. 2010. "Effective Communication About Complex Environmental Issues: Perceived Quality of Information About Carbon Dioxide Capture and Storage (Ccs) Depends on Stakeholder Collaboration." *Journal of Environmental Psychology* 30(4):347-357.

[8] Kobayashi, Keiichi. 2016. "Relational Processing of Conflicting Arguments - Effects on Biased Assimilation." *Comprehensive Psychology* 5:1-13.

[9] Liu, C. H., Hung-Wei Lee, Po-Sheng Huang, Hsueh-Chih Chen and Scott Sommers. 2016. "Do Incompatible Arguments Cause Extensive Processing in the Evaluation of Arguments? The Role of Congruence between Argument Compatibility and Argument Quality." *British Journal of Psychology* 107(1):179-198.

[10] Arikawa, H., Y. Cao and S. Matsumoto. 2014. "Attitudes toward Nuclear Power and Energy-Saving Behavior among Japanese Households." *Energy Research and Social Science* 2:12-20.

[11] Gaede, James and Ian H. Rowlands. 2018. "Visualizing Social Acceptance Research: A Bibliometric Review of the Social Acceptance Literature for Energy Technology and Fuels." *Energy Research & Social Science* 40:142-158.

[12] Walker, Benjamin J. A., Bouke Wiersma and Etienne Bailey. 2014. "Community Benefits, Framing and the Social Acceptance of Offshore Wind Farms: An Experimental Study in England." *Energy Research & Social Science* 3:46-54.

[13] Zoellner, Jan, Petra Schweizer-Ries and Christin Wemheuer. 2008. "Public Acceptance of Renewable Energies: Results from Case Studies in Germany." *Energy Policy* 36(11):4136-4141.

[14] Petty, R.E. and J.T. Cacioppo. 1986. "The Elaboration Likelihood Model of Persuasion." Pp. 123-205 in *Advances in Experimental Social Psychology*, edited by L. Berkowitz. New York: Academic.

[15] Petty, Richard E. and John T. Cacioppo. 1979. "Issue Involvement Can Increase or Decrease Persuasion by Enhancing Message-Relevant Cognitive Responses." *Journal of Personality And Social Psychology* 37(10):1915-1926.
[16] Taber, Charles S., Damon Cann and Simona Kucsova. 2009. "The Motivated Processing of Political Arguments." *Political Behavior* 31(2):137-155.
[17] Teel, Tara L., Alan D. Bright, Michael J. Manfredo and Jeffrey J. Brooks. 2006. "Evidence of Biased Processing of Natural Resource-Related Information: A Study of Attitudes toward Drilling for Oil in the Arctic National Wildlife Refuge." *Society & Natural Resources* 19(5):447-463.
[18] Corner, Adam, Lorraine Whitmarsh and Dimitrios Xenias. 2012. "Uncertainty, Scepticism and Attitudes Towards Climate Change: Biased Assimilation and Attitude Polarisation." *Climatic Change* 114(3-4):463-478.
[19] Wood, Wendy, Nancy Rhodes and Michael Biek. 1995. *Working Knowledge and Attitude Strength: An Information-Processing Analysis. Attitude Strength: Antecedents and Consequences*, Edited by R. E. Petty and J. A. Krosnick. Mahwah, NJ: Lawrence Erlbauin Associates.
[20] Cacioppo, John T., Richard E. Petty and Joseph A. Sidera. 1982. "The Effects of a Salient Self-Schema on the Evaluation of Proattitudinal Editorials: Top-Down Versus Bottom-up Message Processing." *Journal of Experimental Social Psychology* 18(4):324-338.
[21] Wood, Wendy. 1982. "Retrieval of Attitude-Relevant Information from Memory: Effects on Susceptibility to Persuasion and on Intrinsic Motivation." *Journal of Personality And Social Psychology* 42(5):798-810.
[22] Biek, M., W. Wood and S. Chaiken. 1996. "Working Knowledge, Cognitive Processing, and Attitudes: On the Determinants of Bias." *Personality and Social Psychology Bulletin* 22(6):547-556.
[23] Taber, Charles S. and Milton Lodge. 2006. "Motivated Skepticism in the Evaluation of Political Beliefs." *American Journal of Political Science* 50(3):755-769.
[24] Druckman, James N. and Toby Bolsen. 2011. "Framing, Motivated Reasoning, and Opinions About Emergent Technologies." *Journal of Communication* 61(4).
[25] Edwards, K. and E. E. Smith. 1996. "A Disconfirmation Bias in the Evaluation of Arguments." *Journal of Personality And Social Psychology* 71(1):5-24.
[26] Lord, C. G., L. Ross and M. R. Lepper. 1979. "Biased Assimilation and Attitude Polarization: The Effects of Prior Theories on Subsequently Considered Evidence." *Journal of Personality and Social Psychology.* 37(11):2098-2109.
[27] Cohen, G. L., Joshua Aronson and Claude M. Steele. 2000. "When Beliefs Yield to Evidence: Reducing Biased Evaluation by Affirming the Self." *Personality and Social Psychology Bulletin* 26(9):1151-1164.
[28] Liu, C. H. 2017. "Evaluating Arguments During Instigations of Defence Motivation and Accuracy Motivation." *British Journal of Psychology* 108(2):296-317.
[29] Chaiken, Shelly, Akiva Liberman and Alice H. Eagly. 1989. "Heuristic and Systematic Information Processing Withing and Beyond the Persuasion Context." Pp. 212-252 in *Unintended Thought*, edited by J. S. Uleman and J. A. Bargh. New York: Guilford Press.

[30] Chen, Serena and Shelly Chaiken. 1999. "The Heuristic-Systematic Model in Its Broader Context." Pp. 73-96 in *Dual-Process Theories in Social Psychology.* New York, NY, US: Guilford Press.
[31] Moons, W.G., D.M. Mackie and T Garcia-Marques. 2009. "The Impact of Repetition-Induced Familiarity on Agreement with Weak and Strong Arguments." *Journal of Personality And Social Psychology* 96(1):32-44.
[32] Claypool, HM, DM Mackie, T Garcia-Marques, A McIntosh and A Udall. 2004. "The Effects of Personal Relevance and Repetition on Persuasive Processing." *Social cognition* 22(3):310-335.
[33] Cacioppo, John T. and Richard E. Petty. 1979. "Effects of Message Repetition and Position on Cognitive Response, Recall, and Persuasion." *Journal of Personality And Social Psychology* 37(1):97-109.
[34] Cacioppo, John T. and Richard E. Petty. 1989. "Effects of Message Repetition on Argument Processing, Recall, and Persuasion." *Basic & Applied Social Psychology* 10(1):3-12.
[35] Garcia-Marques, T. and Diane M. Mackie. 2001. "The Feeling of Familiarity as a Regulator of Persuasive Processing." *Social cognition* 19(1):9-34.
[36] Hasher, Lynn, David Goldstein and Thomas Toppino. 1977. "Frequency and the Conference of Referential Validity." *Journal of Verbal Learning and Verbal Behavior* 16(1):107-112.
[37] Broecks, Kevin P. F., Sander van Egmond, Frank J. van Rijnsoever, Marlies Verlinde-van den Berg and Marko P. Hekkert. 2016. "Persuasiveness, Importance and Novelty of Arguments About Carbon Capture and Storage." *Environmental Science & Policy* 59:58-66.
[38] McHoskey, John W. 1995. "Case Closed? On the John F. Kennedy Assassination: Biased Assimilation of Evidence and Attitude Polarization." *Basic and Applied Social Psychology* 17(3):395-409.
[39] Kuhn, Deanna and Joseph Lao. 1996. "Effects of Evidence on Attitudes: Is Polarization the Norm?". *Psychological Science* 7(2):115.
[40] Sovacool, Benjamin K., Jonn Axsen and Steve Sorrell. 2018. "Promoting Novelty, Rigor, and Style in Energy Social Science: Towards Codes of Practice for Appropriate Methods and Research Design." *Energy Research & Social Science* 45:12-42.
[41] Krosnick, Jon A., Matthew K. Berent, David S. Boninger, Yao C. Chuang and Catherine G. Carnot. 1993. "Attitude Strength: One Construct or Many Related Constructs?". *Journal of Personality & Social Psychology* 65(6):1132-1151.
[42] Fazio, Russell H., Tracy M. Lenn and Edwin A. Effrein. 1984. "Spontaneous Attitude Formation." *Social cognition* 2(3):217-234.
[43] Lavrakas, Paul. 2008. "Encyclopedia of Survey Research Methods."
[44] Wood, Wendy and Jeffrey M. Quinn. 2003. "Forewarned and Forearmed? Two Meta-Analytic Syntheses of Forewarnings of Influence Appeals." *Psychological Bulletin* 129(1):119-138.
[45] Petty, Richard E. and John T. Cacioppo. 1979. "Effects of Forewarning of Persuasive Intent and Involvement on Cognitive Responses and Persuasion." *Personality and Social Psychology Bulletin* 5(2):173-176.
[46] Petty, R.E. and J.T. Cacioppo. 1977. "Forewarning, Cognitive Responding, and Resistance to Persuasion." *Journal of Personality And Social Psychology* 35(9):645-655.

[47] Cacioppo, John T. and R. E. Petty. 1986. *Communication and Persuasion: Central and Peripheral Routes to Attitude Change*. New-York,NY: Springer.
[48] Beißert, Hanna, Meike Köhler, Marina Rempel and Constanze Beierlein. 2015, Retrieved January 23, 2017 (http://www.ssoar.info/ssoar/handle/document/40315). "Kurzskala Need for Cognition Nfc-K." Vol. *Zusammenstellung sozialwissenschaftlicher Items und Skalen.* Mannheim: GESIS - Leibniz-Institut für Sozialwissenschaften.
[49] Cacioppo, John T. and Richard E. Petty. 1982. "The Need for Cognition." *Journal of Personality And Social Psychology* 42(1):116-131.
[50] Southwell, Brian G. 2001. "Health Message Relevance and Disparagement among Adolescents." *Communication Research Reports* 18(4):365-374.
[51] Peytchev, Andy, Mick P. Couper, Sean Esteban McCabe and Scott D. Crawford. 2006. "Web Survey Design: Paging Versus Scrolling." *Public Opinion Quarterly* 70(4):596-607.
[52] Krosnick, John A. 1991. "Response Strategies for Coping with the Cognitive Demands of Attitude Measures in Surveys." *Applied Cognitive Psychology* 5(3):213-236.
[53] Meade, A. W. and S. B. Craig. 2012. "Identifying Careless Responses in Survey Data." *Psychological Methods* 17(3):437-455.
[54] Moleiro, Carla and Nuno Pinto. 2015. "Sexual Orientation and Gender Identity: Review of Concepts, Controversies and Their Relation to Psychopathology Classification Systems." *Frontiers in Psychology* 6(1511).
[55] Snijders, T. A. B. 2012. *Multilevel Analysis: An Introduction to Basic and Advanced Multilevel Modeling*. Los Angeles; London: SAGE.
[56] Raudenbush, S. W. and A. S. Bryk. 1992. *Hierarchical Linear Models: Applications and Data Analysis Methods*, Vol. vol 0001. Newbury-Park,CA: SAGE Publ.
[57] Bell, B.A., J. M. Ferron and J. D. Kromrey. 2008. "Cluster Size in Multilevel Models: The Impact of Sparse Data Structures on Point and Interval Estimates in Two-Level Models." *JSM Proceedings, Section on Survey Research Methods*:1122-1129.
[58] Clarke, P. and B. Wheaton. 2007. "Addressing Data Sparseness in Contextual Population Research: Using Cluster Analysis to Create Synthetic Neighborhoods." *Sociological Methods and Research* 35(3):311-351.
[59] Maas, C. J. M. and J. J. Hox. 2005. "Sufficient Sample Sizes for Multilevel Modeling." *Methodology-European Journal of Research Methods for the Behavioral and Social Sciences* 1(3):86-92.
[60] te Grotenhuis, Manfred, Ben Pelzer, Rob Eisinga, Rense Nieuwenhuis, Alexander Schmidt-Catran and Ruben Konig. 2017. "When Size Matters: Advantages of Weighted Effect Coding in Observational Studies." *International Journal of Public Health* 62(1):163-167.
[61] Williams, Richard. 2012. "Using the Margins Command to Estimate and Interpret Adjusted Predictions and Marginal Effects.". *The Stata Journal* 12(2):308-331.
[62] Abdi, Hervé. 2007. "The Bonferonni and Šidák Corrections for Multiple Comparisons." Pp. 103-107 in *Encyclopedia of Measurement and Statistics.*, edited by N. J. Salkind. Thousand Oaks (CA): Sage.

[63] Kleinbaum, David G. and Mitchel Klein. 2010. "Logistic Regression: A Self-Learning Text." *Statistics for Biology and Health*.
[64] Williams, Richard. 2018. *Multinomial Logit Models - Overview*, Retrieved January, 24 2019 (https://www3.nd.edu/~rwilliam/stats3/Mlogit1.pdf).
[65] Andreß, Hans-Jürgen, Katrin Golsch and Alexander W. Schmidt. 2013. *Applied Panel Data Analysis for Economic and Social Surveys*. Berlin, Heidelberg: Springer.
[66] Couper, Mick. 2008. *Designing Effective Web Surveys*. Cambridge; New York: Cambridge University Press