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Research Article

Developing an *Ad Hominem* typology for classifying climate misinformation

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ABSTRACT

Misinformation produced by various interest groups is a significant contributing factor to public confusion about climate policy. Character assassination against climate scientists and policymakers is the most common type of misinformation strategy used by contrarians in climate debates (Coan, T. G., Boussalis, C., Cook, J., & Nanko, M. O. (2021). Computer-assisted classification of contrarian claims about climate change. *Scientific Reports*, *11*(1), 22320). Despite its widespread use, however, character assassination remains understudied by social scientists, especially in the context of climate change. This study adapts Douglas Walton's (1998. *Ad hominem arguments*. University of Alabama Press) typology of 'ad hominem' attacks – personal attacks targeting an individual's character, competence, or motives – to misinformation campaigns against the climate community. We developed an original codebook for classifying *ad hominem* arguments made by climate contrarians. Drawing on a 553-paragraph sample from a corpus from 55 contrarian blogs and 15 conservative think-tank websites published in English between 2008 and 2020, we then determined the relative prominence of each type of attack using a consensus-coding approach. Bias attacks, which entail accusing climate scientists of political partisanship or having an ideological agenda, were the most common form of contrarian *ad hominem* attack. The dominance of bias attacks can be explained by their strong relevance for scientific credibility. The study found that *ad hominem* attacks, often with bias and moral attacks clustered together, are the most common combination. The article concludes by discussing the implications of these findings for climate policy and future research.

Key Policy Insights:

- Climate misinformation politicizes climate science, further amplifying ideological conflict and fostering ideological polarization;
- Climate misinformation campaigns feature a range of different types of *ad hominem* attacks designed to undermine the credibility of climate scientists;
- The most common type of *ad hominem* attack on climate scientists in our sample was bias attacks, which entail accusing climate scientists of political partisanship or of having an ideological agenda;
- Attacks on the moral character of climate scientists were the only type of *ad hominem* that increased during the period under study (2008–2020);
- Different types of *ad hominems* often appeared together, with the most common combination being bias and moral attacks;
- *Ad hominem* attacks on climate scientists are part of misinformation campaigns designed to stall discussion on climate change and delay the implementation of climate policies.

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1. Introduction

Climate misinformation leads to reduced climate literacy, with such negative implications for society as reduced support for climate policy and environmental regulation (van der Linden et al., 2017). Misinformation can obtain significant attention in the mainstream media (Elsasser & Dunlap, 2013) and polarize politicians when amplified in echo chambers (Jasny et al., 2018). Simply inserting a few misleading statistics into the discussion can serve to reduce people's acceptance of climate change as a phenomenon (Ranney & Clark, 2016).

Contrarians routinely deny the evidence of environmental problems by exploiting scientific uncertainties, misinterpreting peer-reviewed research, and spreading conspiracy theories (Jacques & Knox, 2016; Jacques et al., 2008). According to McCright and Dunlap (2010), the American conservative movement has employed several techniques to make climate change a non-issue and prevent progress on climate policymaking. It has (1) obfuscated and suppressed the results of scientific research; (2) exploited existing media bias; and (3) intimidated or threatened to sanction individual scientists, among other things. Conservative think tanks (CTT) are the main producers of doubt, denial, and dismissal of the scientific consensus on climate change. According to Xifra (2016), more than 90% of papers skeptical about climate change originate from CTTs. An effort to map the climate change counter-movement identified 4,556 individuals with overlapping network ties to 164 organizations that are responsible for most efforts to downplay the threat of climate change in the United States (Farrell, 2016).

Coan et al. (2021) found that character assassination of climate scientists and policymakers is the most popular type of misinformation strategy deployed by contrarians in climate debates. The use of character attacks is common in politicized contexts and is considered instrumental to goal achievement (Benoit, 2017; Pfau & Kenski, 1990). Social media have made it easier for special interest groups and digital activists to produce smear campaigns by increasing connectivity and a greater number of individual and collective contributors (Petkevic & Nai, 2022; Samoilenko & Jasper, 2023). Reputational attacks cause climate scientists to be more cautious in communicating scientific results and discourage them from publicly addressing politicized topics (Biddle & Leuschner, 2015; Lewandowsky et al., 2015; Lewandowsky et al., 2019).

Argumentum ad hominem is a rhetorical strategy that attacks a person's character instead of debating the issue or the substance of an argument (Tedesco & Dunn, 2019). Attacks may include derogatory statements about personal traits, moral standing, or expertise, as well as speculation about motives and special interests. According to Walton (2002, p. 188), 'the argument against the person is often so effective and devastating that it is a conversation-stopper, closing off the possibilities of objective argument and further reasonable discussion of an issue.' Previous studies indicate that *ad hominem* attacks may have the same degree of impact as attacks on the empirical basis of scientific claims, and that allegations of conflict of interest may be just as influential as allegations of outright fraud (Barnes et al., 2018). Despite their pervasiveness, however, climate-related *ad hominem* attacks are understudied in misinformation research. This has implications for climate policy, as the ultimate purpose of climate misinformation is to delay climate action. Consequently, understanding the sources and content of climate misinformation is vital to countering its influence.

The purpose of our study was to identify the types of *ad hominem* attacks used in CTTs' materials and the frequency of each type of online attack. The study applies Douglas Walton's argumentation approach (Walton, 1998) to create a system for classifying *ad hominems* against climate scientists and environmental leaders that appear in a content analysis of CTTs' articles. The dataset was computer-generated by Coan et al. (2021). Computational social science has been used actively in recent years to detect and understand climate misinformation, finding that there are recurring thematic patterns (Farrell, 2019) and major themes in CTTs' articles (Boussalis & Coan, 2016). Studies demonstrate that machines can detect deceptive content more reliably than most human judges (Atanasova et al., 2019). Along the same lines, researchers have used machine learning to classify *ad hominem* fallacies (Delobelle et al., 2019). The findings of the present study suggest directions for future research to expose the rhetorical weaknesses of such attacks and develop critical responses.

2. Theoretical background

The literature on *argumentum ad hominem* has identified several categories into which such attacks may fall (Blair & Johnson, 2006; van Eemeren & Grootendorst, 1984; Walton, 1998). The *direct* (abusive) *ad hominem* is used when the attacker claims that the target's argument should not be accepted due to a certain personal imperfection, whether a moral failing or a character flaw. *Guilt by association* is a popular sub-type of direct (abusive) *ad hominem*. It involves transferring alleged guilt to a person for their association with a supposedly discreditable or socially demonized individual, group, or doctrine.

The *bias ad hominem* occurs when the accuser points out that the target is partisan or prejudiced in favour of a particular cause. As such, the attack goes, they will not objectively consider the arguments presented to them, instead seeking only to win at all costs. Finally, the *circumstantial ad hominem* is based on evidence of behaviour inconsistent with previous positions, convictions, or actions. Typically, an allegation of inconsistency takes the form of an argument that the respondent 'does not practice what he preaches.'

There is a dearth of research into *ad hominem* attacks on climate scientists, a striking lacuna given the relative prominence of this form of misinformation. In his analysis of online publications by the CTT Heartland Institute, Cann (2015) found that the texts blended arguments about the scientific uncertainty of climate change with attacks on the moral character of climate researchers. Character attacks targeting scientists have been found to have an impact on public opinion comparable to attacks on the empirical basis of scientific claims, with allegations of conflict of interest potentially just as influential as allegations of outright fraud (Barnes et al., 2018). Allegations of misconduct, conflicts of interest, and incompetence on the part of researchers can be used to attack and undercut science claims (DeAngelis, 2000; Wohn & Normile, 2006).

Little is known about what type of *ad hominem* attacks are most frequently used to undercut climate science claims. Research based on framing theory has limitations when it comes to explaining the pragmatics of such attacks and their credibility with different audiences in different settings (Druckman, 2001; Knight & Greenberg, 2011). A different conceptual framework is needed to understand and critically assess *how* and *why* these attacks undermine scientific dialogue in a given context.

Next, we discuss Walton's approach to *ad hominem*. This approach is similar to the critical thinking methodology used by Cook et al. (2018) to assess the validity of climate misinformation campaigns.

2.1. Walton's approach to Ad Hominem

Traditionally, *argumentum ad hominem* has been described as an informal fallacy of argumentation when used in situations where an opponent's character is not relevant to the issue being discussed (Minot, 1981). This view of *ad hominem* argument is challenged by Douglas Walton's pragmatic theory.

Walton (1998) indicates that while some arguments grounded in personal attacks can definitely be judged fallacious, many others are quite reasonable when evaluated in the appropriate context. There are also arguments that should be evaluated as weak (insufficiently supported) but not fallacious. *Ad hominem* argument can be legitimate when a character critique is directly or indirectly related to the point being articulated (Walton, 1999). Similarly,Benoit (2017) argues that an attack on character can be useful when it exposes wrong-doing and creates awareness of offensive actions. This unwanted publicity is intended to embarrass perpetrators and force them to change their behaviour. Persuasive attacks can also help voters make decisions in contexts where criticism of political candidates is relevant and reasonable. In political contests, defending one's reputation and refuting attacks is celebrated as a critical skill. Hence, *ad hominem* attacks allow voters to see how candidates perform under pressure. Finally, persuasive attacks can help consumers to think critically about products and services; pointing out the weaknesses of a given product may influence consumers' buying decisions.

Walton's (1998) typology lists 21 types of *ad hominem* attacks (see Figure 1). Unlike related classification systems (e.g. Benoit & Harthcock, 1999), this typology is prescriptive in nature. It is also more comprehensive than other similar frameworks (e.g. Benoit, 2017; van Eemeren & Grootendorst, 1984). Walton's work has been used to prepare legal arguments (Walton & Macagno, 2015), to counter irrelevant arguments in

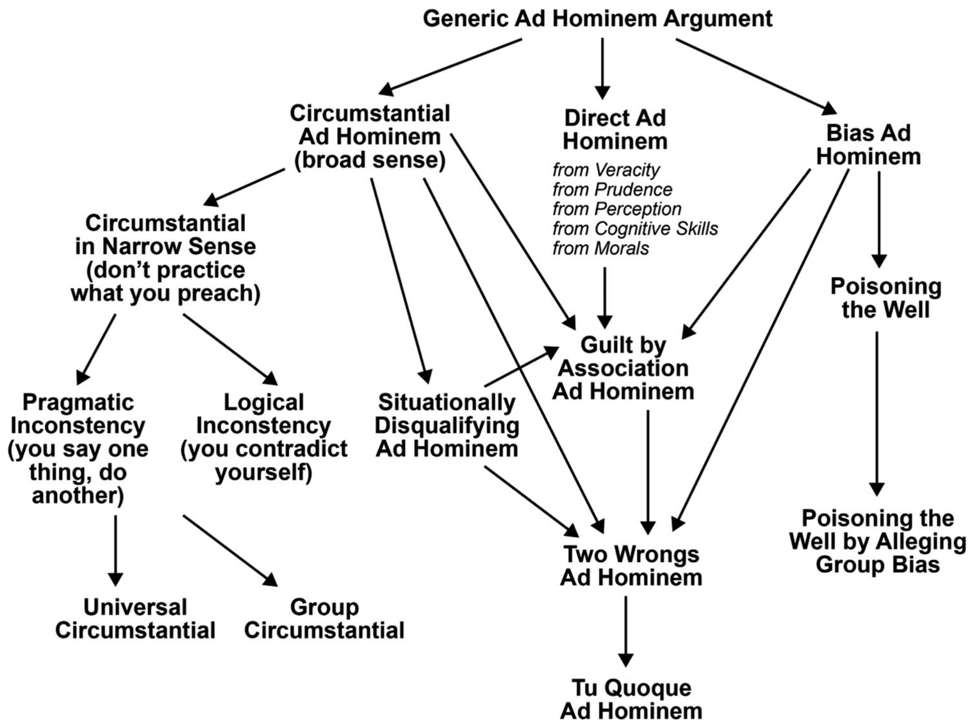

Figure 1. *Walton's Typology of* Ad hominem *Arguments* (amended for simplicity).

debates regarding genetic engineering of humans (Walton, 2017), and to help develop artificial intelligence (Walton, 2005).

Other studies support the view of *ad hominem* attacks as a pragmatic strategy (Walton et al., 2008). These attacks can be especially damaging when they question the competence and integrity of scientists (Barnes et al., 2018). By challenging a speaker's authority, they undercut those arguments that depend for their credibility on the expertise of the speaker (Macagno, 2013). Even if an *ad hominem* attack is considered fallacious, it can still be effective because it can undermine public trust in scientific expertise.

Despite the widespread nature of the phenomenon, the use of *ad hominem* attacks in contrarian misinformation campaigns and their effects remain understudied by social scientists in the context of climate policy. The present study attempts to fill this void. Analyzing a sample of character attacks detected on contrarian blogs and websites using a machine-learning approach, we aim to determine *what types* of attacks are used and *how frequently* they occur. Online platforms are a popular means of disseminating misinformation, as platforms can target audiences and users can self-select platforms, producing polarizing echo chambers (Treen et al., 2020). The findings of the present study may inform efforts to assist people in recognizing the *ad hominem* attacks often lodged against climate scientists, thereby reducing the effectiveness of future contrarian misinformation campaigns.

3. Methodology

3.1. Materials

The final sample for our content analysis was a set of 553 paragraphs containing attacks on climate scientists. We derived this from a dataset produced by Coan et al. (2021), who created custom software to harvest a corpus of 287,000 documents from 55 contrarian blogs and 15 North American CTT websites published in English between 2008 and 2020. The list of contrarian blogs built upon an existing list of blogs that posted contrarian content about climate change (Sharman, 2014). These blogs and think tanks are prolific and influential sources of climate misinformation that seek to discredit climate science and further free-market fundamentalism. In Coan et al. (2021), a subset of climate misinformation was found to target four groups perceived to be part of the climate movement: climate scientists (e.g. scientists publishing research about climate change), environmentalists, politicians, and the media. For our content analysis, we used machine learning to identify 553 paragraphs from this larger corpus that contained *ad hominem* attacks against people involved in the climate movement.

Coding of narrative data is an established research method to improve the generalizability of findings, ensuring that conclusions can be applied to other contexts (McLean & Syed, 2015). Quantitative content analysis allows us to determine the prevalence of attacks on climate scientists. The paragraph was used as a unit of analysis to identify, enumerate, and analyze occurrences of specific messages embedded in texts. We coded more than one type of attack in each paragraph under study. Differing types of *ad hominem* attacks were seen to cluster together in distinct combinations (e.g. allegations of immorality and bias).

The targets of attacks were environmentalists, climate scientists, journalists writing about climate issues, and policymakers concerned about climate change (e.g. Al Gore). These four target types are discussed by Coan et al. (2021) in more detail. We did not observe contrarian attacks targeting skeptics or CTT members.

Computer-assisted detection was used to identify those paragraphs with the highest probability of containing *ad hominem* attacks. Coan et al. (2021) trained a machine-learning model to categorize climate misinformation into different categories of misinformation, with one sub-category being 'Climate movement is unreliable' (with 'climate movement' including climate scientists, environmentalists, journalists, and politicians who accept mainstream climate science and support climate action). The machine-learning model provided a sample of 4,506 paragraphs with the highest probability of containing 'climate movement is unreliable' claims. From this sample, we randomly selected 650 paragraphs for our study: 50 paragraphs per year between 2008 and 2015. The number of paragraphs was later reduced to 553 to eliminate duplicates, paragraphs with garbled text due to scraping issues (that is, superfluous words such as page headings), and paragraphs that did not meet the criteria of our coding book (e.g. not climate-related or not a complete sentence).

3.2. Procedure

The theory-driven approach taken in this study involves deconstructing Walton's (1998) argumentation theory into codes that can be applied to the data (Marcia, 1966). Walton's typology emerged in a humanistic scholarly field, namely argumentation (e.g. van Eemeren & Grootendorst, 1984); additional steps were therefore required to transform his scholarship into a social-science instrument. Specifically, a codebook was needed to establish a reliable system for classifying *ad hominem* arguments with acceptable intercoder reliability. To increase the usability of Walton's typology for social-scientific classification of these attacks, we first reviewed 21 forms of argument significant for defining the various subtypes of *ad hominem* argument, as well as related forms of argument. We then narrowed our scope to the relevant *ad hominems*, targeting the abovementioned four target types. These *ad hominem* categories were subsequently scaled down and streamlined for content analysis purposes.

The coding manual for this project was developed iteratively by the principal investigator and the second coder for two years between May 2018 and May 2020. The process of developing a reliable coding scheme involves balancing parsimony and nuance (Syed & Nelson, 2015). One of the most important decisions made in coding development is the number of codes to be used. A large number of codes allows for greater complexity but comes with the possible cost of decreased reliability. This decision must be made on a case-by-case basis, with attention paid to the reliability and usefulness of the data (Campbell et al., 2013). Initial coding attempts resulted in poor intercoder reliability, reflecting both the difficulty of the coding task and the need to further refine the codebook. The difficulty of the task was due to the nature of the corpus, with attacks on scientists often containing incomplete sentences, innuendo, sarcasm, and ambiguity. The iterative process continued until the codebook was sufficiently refined and intercoder reliability established. Walton's

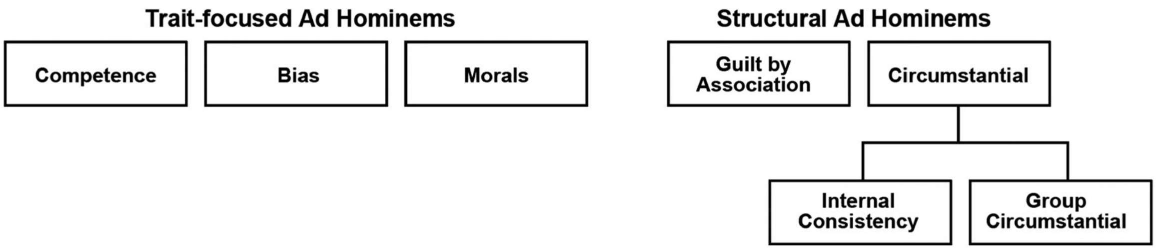

Figure 2. *Typology of* Ad Hominem *Arguments Found in Climate Change Character Attacks.*

21 forms of *ad hominem* attacks were streamlined by selecting the attacks that were coded with the greatest reliability.

From this process, we derived three major types of trait-focused attacks – that is, *ad hominem* attacks that label a target with a specific negative trait (shown in Figure 2). These were allegations of incompetence, immorality, and bias.

From this process, we derived three major types of trait-focused attacks – meaning *ad hominem* attacks that paint a target with a negative trait (shown in Figure 2). They included allegations of incompetence, immorality, and bias. Additionally, we identified two structural *ad hominem* arguments: inconsistent behaviour (circumstantial guilt) and guilt by association. These attacks were structured in a certain way but could be used to label targets with any type of negative trait. Two main types of circumstantial attack were detected: logical/pragmatic inconsistency and group circumstantial.

The first type of inconsistency can result from either logical mismatch or practical inconsistency between a target's words and his/her actions. Pragmatic inconsistency attacks entail contrasting the target's current behaviour or statements with past behaviour or statements in order to establish a lack of consistency. An example in a climate context would be 'the EPA and IPCC insist they rely entirely on scholarly peer-reviewed source material. However, fully 30% of the papers and other references cited in the IPCCs Fourth Assessment Report (AR4) were not peer reviewed; many IPCC lead authors were graduate students or environmental activists; and many sources were actually master's degree theses or even anecdotal statements by hikers and mountain guides.'

The second type of circumstantial attack, group circumstantial, involves contrasting the target with the idealized behaviour of a group to which they belong. For example, 'the IPCC is supposed to be an objective scientific body, but […] writes forewords for Greenpeace publications and has accepted a green crusader award.' Table 1S summarizes documents the codebook developed for categorizing different types of *ad hominem* attacks (see Supplementary Material for the full version). The codebook included examples for each category, as well as some exclusion examples of text that did not fall into that category.

3.3. Data analysis

The codebook was used to instruct coders how to assign values to content units. Coders practiced content analysis on paragraphs that were not part of the main analysis until acceptable intercoder reliability was established, then began coding study content (Krippendorff, 2013). Two coders coded content units independently of each other. The central challenge for the coders was deciding how to code when a paragraph could be labelled in several different ways. This is a typical problem during categorization, as codes included in one category may also seem to be a fit for another category. According to Erlingsson and Brysiewicz (2017), overlap between initial categories is common when the data are voluminous and/or complex. Since the reliability check involved two or more coders coding the same content, there were some content units where coders assigned more than one value on which they disagreed. The process for resolving disagreements included a discussion among the coders aimed at reaching consensus. In the event of discrepancies, coders used a consensus-coding approach after each individual session. This enabled them to discuss and reflect on their coding decisions and to reach consensus on the best way forward. Consensus coding is an appropriate approach for establishing reliability when coding narrative data (Syed & Nelson, 2015).

4. Results

Intercoder reliability between the two coders for competence, moral, bias, guilt by association, and circumstantial *ad hominems* is listed in Table 1. Given the imbalanced dataset, with some *ad hominem* types (bias and moral) more highly represented than others, Gwet's AC(1) was chosen as an appropriate intercoder reliability measure (Wongpakaran et al., 2013). Reliability analysis was conducted in R using the irrCAC library (Gwet, 2014). To resolve discrepancies, the two coders deliberated and decided on consensus codings in cases where there were disagreements. Table 1 reflects intercoder reliability before discrepancies were discussed and resolved.

Figure 3 shows the total number of each type of *ad hominem* after the coders reached consensus. This figure therefore depicts the relative prevalence of differing types of *ad hominem* arguments. It shows the clear dominance of bias attacks, followed by attacks on morality. When it comes to structural arguments, the circumstantial structure is used more than the guilt by association structure. Attacks on scientists' competence are the least common form of *ad hominem* in our sample.

Figure 4 shows the prevalence of different *ad hominem* argument types over time. While it likewise reflects the dominance of bias attacks in the sample, it shows that these have remained relatively consistent over the analysis period. Moral attacks, meanwhile, have increased (the only category of *ad hominem* attacks to do so),

Table 1. Summary Statistics for Coding (2008–2020).

Category of *Ad Hominem* Attack	Gwet's AC(1)	Percentage Agreement
Competence	0.85	88
Moral	0.66	83
Bias	0.80	88
Association	0.77	83
Circumstantial	0.71	83

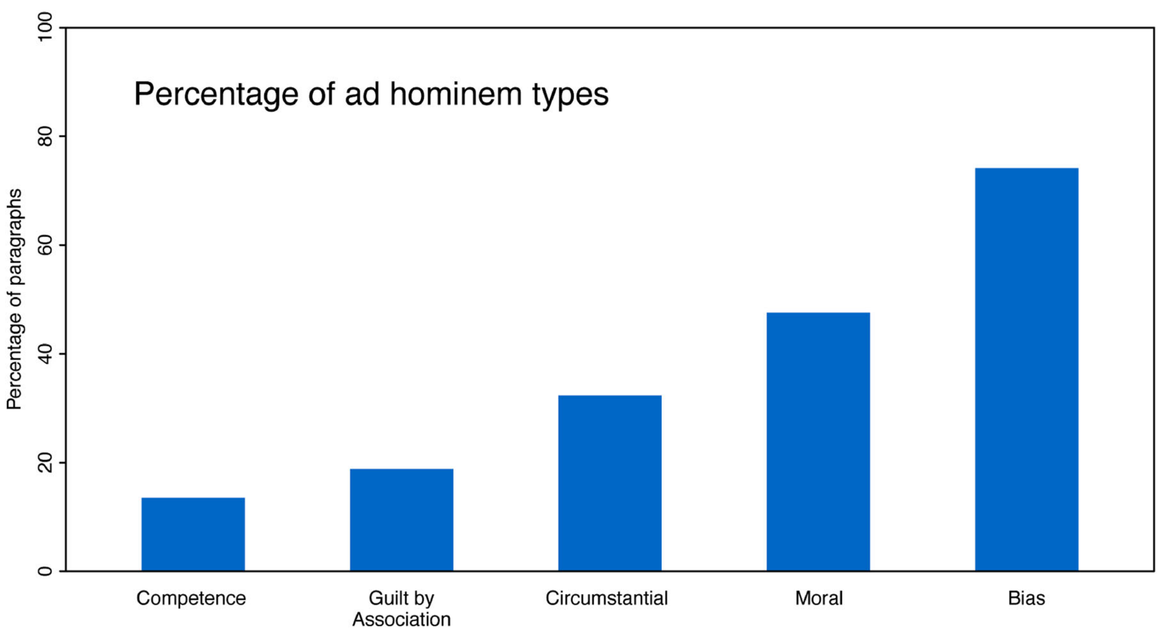

Figure 3. *Percentage of* Ad Hominem *Types in Corpus.*

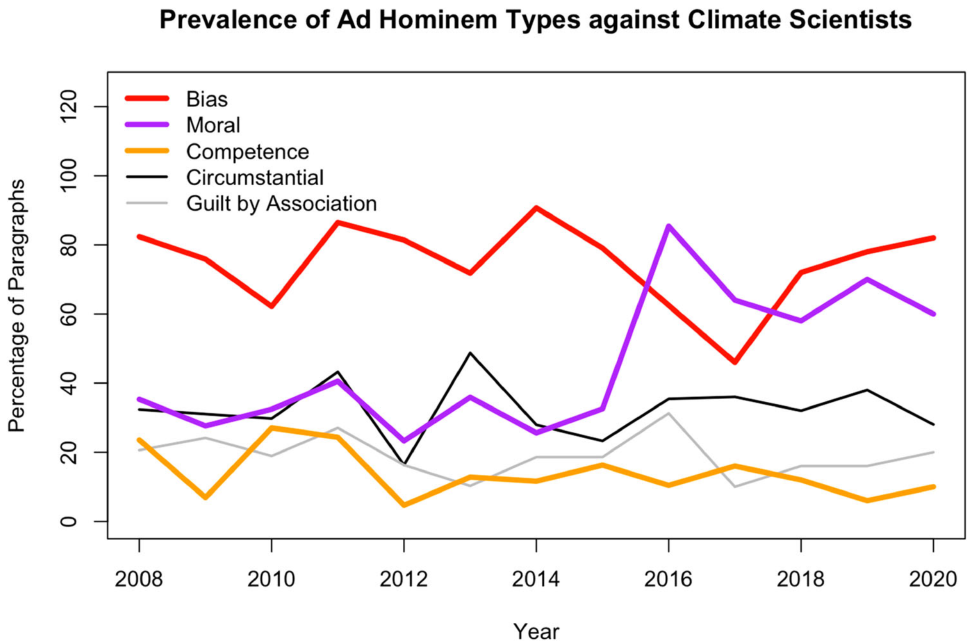

Figure 4. *Prevalence of* Ad Hominem *Types, 2008–2020.*

becoming nearly as prominent as bias attacks by the end of the period under study. This supports the previous observation that attacks targeting moral character have become more prominent in policy debates (Coan et al., 2021).

Table 1S lists the five different types of *ad hominem* attacks identified above and provides climate-relevant examples (see Supplementary Material). The first *ad hominem* type is *bias*. It occurs when the accuser points out that the target is partisan or prejudiced in favour of a particular cause. The target may be also accused of having an agenda/advocacy (typically due to his/her politicalaffiliation/ideology/religion) or of promoting some sort of propaganda or spreading alarmism.

The second type is *moral*. The attacker claims that the target's argument should not be accepted due to the latter's moral failings or bad character. Such attacks may manifest as name-calling or applying ridiculing or demonizing labels. Moral attacks imply that the target is deceptive/corrupt/unethical and deliberately harms others.

The third type is *circumstantial*. It is based on evidence of inconsistency with previous positions, convictions, or actions. *Contra* van Eemeren and Grootendorst (1984, p. 190), the circumstantial *ad hominem* argument in Walton's classification is always based on an allegation of inconsistency and not bias. Group circumstantial arguments contrast the target's behaviour/character with the idealized standards of the scientific/target's community. Arguments of pragmatic/logical inconsistency claim that a target's statement/behaviour conflicts with his/her earlier statements/behaviour. Typically, this type of inconsistency takes the form of an argument that the respondent 'does not practice what he preaches.'

The fourth type is *competence*. The accuser states that target is wrong because he/she lacks knowledge/education/competence/skill. The target is accused of making inaccurate predictions and is generally seen as incompetent.

The fifth type is *guilt by association*. It involves transferring alleged guilt to a person for his/her association with a supposedly discreditable or socially demonized individual, group, or doctrine. It links the target with an external group or individual that possesses a negative trait, thereby tarring the target with the same negative trait.

Importantly, a single character attack often contains multiple types of *ad hominems*. Table 2 shows the most common combinations of different *ad hominem* attacks. The most common combination was bias and moral *ad*

Table 2. *Combination of* ad hominems*: prevalence, description, and examples*.

Ad hominem combinations	% of paragraphs	Description	Examples
Bias, moral	29.8%	Claiming bias among climate scientists or advocates for climate action motivated them to commit immoral acts.	• Deception (' … alarmists will go to incredible lengths to manipulate and misrepresent objective scientific facts for the cause of promoting their alarmist Climate Delusion') • Profiting from the climate issue ('All of them have turned their fearmongering to quite some business') • Impinging on citizens' freedoms ('Alarmists want to impose a tyranny on others').
Bias, circumstantial	25.3%	Referring to external inconsistency (e.g. being out of line with scientific standards) or internal inconsistency (e.g. not practicing what one preaches).	• Comparing the climate movement to an objective scientific approach ('such attribution is more faith-based than science-based', 'Climate change alarmism is based entirely on speculation, not on science', 'global warming advocates are more interested in pushing a political agenda than actual science', 'propagandists, not scientists') • Pithy labels ('junk science', 'anti-science') combined with bias attacks in the form of single words or short phrases ('alarmist pseudoscientific hype'). • Contrast with idealized behaviour was also applied to other targets such as media outlets, accusing them of bias (' … they don't gather news and information or present views with due impartiality').
Moral, circumstantial	17.2%	Contrasting a moral scientific standard with accusations of immoral activities by climate scientists	• Deception ('Climate scientists are not scientists. They are professional fraudsters') • Fabricating data ('replacing evidence-based policy-making with policy-based evidence-making') • Profiting ('Climate science is not a science. It is a criminal venture intended to extort money from the public'). • Use of air quotes to imply that the target didn't meet scientific standards ('Every single thing these 'scientists' said was fraudulent').
Bias, guilt by association	15.6%	Associating the target with a biased group, in order to paint the original target with the same negative trait.	Listing one or more targets with general climate 'alarmists' ('Climate alarmists in government agencies, in academia, and among radical environmental groups', 'will the Times and its fellow climate alarmists … ', ' … an alarmist narrative by the UN IPCC, Al Gore and other vested interests … '). A common target was scientists, typically associated with perceived biased groups such as left-orientated politicians ('scientists sought political relevance and allowed policy makers to put a big thumb on the scale of the scientific assessment').
Moral, guilt by association	10.5%	Accusing two or more groups of collaborating on immoral activities	• Deception ('Climate scientists, Democrats, and the press have reacted quite predictably by simply ramping up their lies', ' … an alarmist narrative by the UN IPCC, Al Gore and other vested interests is exposed as a deliberate misrepresentation of data … ') • Censoring or suppressing dissenting voices (' … the BBC gathered a group of like-minded elite

(*Continued*)

Table 2. Continued.

Ad hominem combinations	% of paragraphs	Description	Examples
			greenies together and in secret session decided to limit any reporting of science that suggested global warming … was not caused predominately by CO2 … ') • Profiting (' … various parasitical academics, researchers, propagandists and otherwise unemployable environmental studies graduates and postgraduates on the climate change gravy train'). • During the COVID-19 pandemic, health scientists were also associated with climate scientists in order to paint them with the same negative traits ('scientific dissent is not only being suppressed and marginalized in Germany when it comes to climate science but with virology and public health').

hominems, reflecting the prevalence of the individual *ad hominems*. For all of the top five combinations, there is a strong correlation between paragraphs that feature a combination and the individual *ad hominems*. For example, there is a strong correlation between the presence of bias *ad hominems* and bias-plus-moral combinations, $r(551) = .38$, $p < .001$, and a similarly strong correlation between the presence of moral *ad hominems* and bias-plus-moral combinations, $r(551) = .68$, $p < .001$.

The next four most common combinations were structural *ad hominems* (e.g. circumstantial or guilt by association) with *ad hominems* used to paint a particular negative trait (e.g. bias or immoral). Of these, the most common combination was circumstantial *ad hominems* used to portray bias, followed by circumstantial *ad hominems* used to paint a target as immoral. The fourth most common *ad hominem* combination was guilt by association and bias, while the fifth most common was guilt by association and immorality.

5. Discussion

In the present study, we identified the differing types of *ad hominem* arguments used by contrarians in their attacks on climate scientists. The three dominant arguments revealed in this study – attacks on scientists' morality, alleged bias, and inconsistent behaviour (circumstantial guilt) – overlap with the similar categories suggested by Walton (1998, p. 211) as fundamental to political debates. Bias attacks – accusing climate scientists of political partisanship or ideological agendas – were found to be the most common form of contrarian *ad hominem*, followed by attacks on scientists' morality and accusations of inconsistent behaviour, respectively. Guilt by association and attacks on competence appeared less frequently in contrarian climate-related materials.

The study revealed the prevalence of *ad hominem* attacks over time, showing that they have been used stably and consistently in the materials produced by contrarian think tanks. This supports previous findings by Coan et al. (2021) demonstrating the steady prominence of character assassination as a contrarian strategy in climate-related misinformation campaigns.

Ad hominem attacks are instrumental for contrarians because they shift the dialogue from a critical discussion (which has a particular set of rules for debate) to a bargaining type of dialogue (with a different set of rules) in which the accused party must defend himself/herself and win over public opinion (Walton, 1998). Hence, *ad hominem* attacks may lower the perceived status differences between the scientist and the rest of the public.

The dominance of bias *ad hominems* can be explained by the strong relevance of bias to scientific credibility. The science – policy relationship requires trust between climate scientists and policymakers; this is often based on the validity of evidence, which in turn depends on the appropriate application of scientific methods and reporting of research findings (Lacey et al., 2018).

Accusations of bias challenge the authority of a speaker, thereby undercutting those arguments that depend for their credibility on the expertise of the speaker (Macagno, 2013). If scholars are perceived as lacking objectivity and as driven by extrinsic motivation, then they are not regarded as scientists and their advice is no longer compelling. According to Walton (1998), bias *ad hominems* not only call into question a target's impartiality, but also attack the sincerity of the target's participation in the collaborative dialogue. This supports the observations made by Gierth and Bromme (2020), who found that online comments attacking the motivations of scientists were effective in lowering scientists' perceived integrity.

With so many science-based challenges facing the world, researchers – more than ever before – have a responsibility to make the public and policymakers aware of their research (Woolston, 2016). There is disagreement among scholars as to whether scientists can advocate in some contexts without reputational harm. Some studies suggest that climate scientists who wish to engage in certain forms of advocacy have considerable latitude to do so without risking harm to either their own credibility or the credibility of the scientific community (Kotcher et al., 2017). Other studies indicate that overt displays of science advocacy may harm public perceptions because values generally cannot be eliminated from science (Gray & Campbell, 2009).

Taking a stand perceived as political may negatively affect a researcher's credibility in the eyes of the general public. In the United States, surveys have found wide political differences on attitudes related to the environment, climate change, and energy, with Democrats and Republicans having different degrees of faith in scientists' ability to be unbiased. Moreover, no more than two in ten Americans believe scientists are transparent about potential conflicts of interest with industry all or most of the time (Funk et al., 2019). Awareness that scientists receive funding for research has been shown to harm public trust in science (Critchley & Nicol, 2011; Hargreaves et al., 2003).

In addition, allegations of immorality and inconsistent behaviour (circumstantial *ad hominem*) were found to be popular techniques of contrarian climate-related communication in this study. According to Walton (1998), the public perception of scientists is often based on their social role and ability to demonstrate a stable commitment to objective and value-free research. Any perceived violation of this commitment results in group circumstantial *ad hominem*, contrasting the target with the idealized behaviour of the scientific community to which they belong. Some argue that when they 'disregard scientific norms, scientists allow themselves to become accomplices in the restriction of individual freedom and expansion of government control over people's lives' (Knight & Greenberg, 2011, p. 336).

Some guilt-by-association attacks detected in the sample (e.g. Reductio ad Hitlerum) were used together with other types of attacks, such as direct (abusive) personal attacks. This type of *ad hominem* was infrequent compared to other categories. Most guilt by association attacks were equivocal, conspiratorial, and designed to allow loyal supporters to confirm their biases. Unfortunately, the argumentation literature does not provide a detailed account of such combinations. Walton (1998) briefly addresses the possibility of complex *ad hominems* in the persuasion dialogues common in legal trials and political debates. He says that these attacks appear to be elaborately prepared and to combine argumentation strategies that can be used simultaneously with loaded and leading questions, push polls, and other tricks. In a similar vein, Macagno (2013) concludes that *ad hominem* arguments should be considered as multifaceted and complex strategies that involve not a simple argument but several tactics in combination.

In our study, accusations of incompetence were found to be less prevalent than the other three categories of *ad hominems* discussed above. In this respect, it diverges from the findings of Knight and Greenberg (2011), who demonstrated the popularity of adversarial framing targeting the expertise of participants in climate-related debates. This discrepancy can be explained by the departure of CTTs from their original strategies – which were based on participating in scientific debates and attacking policies and data – in favour of post-truth politics, misinformation, and character assassination (Oreskes & Conway, 2010).

Future research offers several promising lines of development. First, there is a need for experimentation testing the effectiveness of different types of *ad hominems*, including those containing combined character attacks. Clustered attacks require solid empirical investigation, especially in the context of interactive online debates featuring different levels of discursive complexity (Habernal et al., 2018). Sequential combination attacks are examples of what we describe as *Tetris character assassination*. Just as Tetris games feature differently configured tetromino pieces that accumulate and intertwine, solidifying into an ever-growing structure, *ad hominem* attacks can be configured in different combinations and multiple attacks can accumulate to build a negative picture of the target. What reinforcing effect might multiple *ad hominem* combinations have on audiences?

Second, experimentation should test different interventions to neutralize *ad hominems* through either inoculation or reactive corrections. Preemptive inoculation has been found to be an effective strategy for countering climate change misinformation (Cook, 2019). Alternatively, future research could address the application of Walton's argumentation schemes featuring a set of appropriate critical questions for debunking climate misinformation (Walton, 1998). This process of deconstruction may weaken the intended effect of complex attacks. These schemes can be used both to identify fallacies and to respond to both sound and fallacious arguments.

Third, machine learning could be better utilized as a tool for detecting and categorizing *ad hominem* attacks in online misinformation. Machine-learning models have already been effective in detecting climate misinformation (Coan et al., 2021). There have also been attempts to automate the detection of logical fallacies, with *ad hominems* notably among the fallacies that machines detect most reliably (Habernal et al., 2018). As climate misinformation on online platforms is a big-data problem, machine learning offers fruitful avenues for improving our understanding and real-time detection of *ad hominem* attacks in this context.

6. Conclusion

Ad hominem attacks against climate scientists, environmentalists, and policymakers are a dominant feature of misinformation campaigns. Our findings suggest that responding to bias attacks should be considered a high priority, given their prevalence and interplay with other attacks. They often act in combination with other types of *ad hominem* attacks, with bias-plus-moral being the most frequent combination. These attacks have negative consequences for climate science and climate policy, affecting the credibility of scientists and their research, as well as undermining public support for climate action. Interventions countering the influence of such *ad hominem* attacks have yet to be explored in empirical studies. More research is needed to examine how character assassination strategies are employed in the climate change debate and to develop interventions that neutralize or reverse the effects of this misinformation.

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