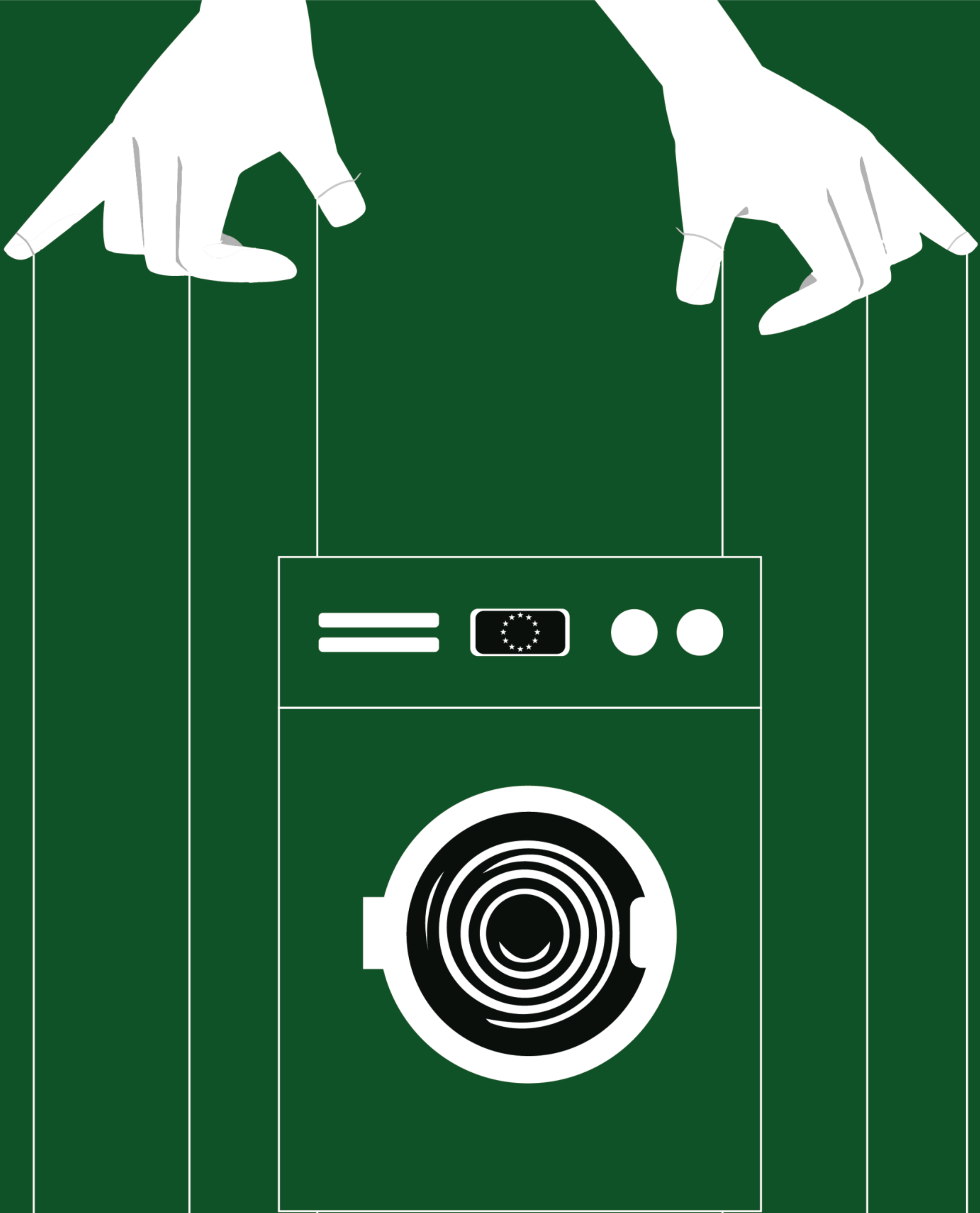

Ludovica Bindi

Designing a semi-automated approach to find potential evidence of corporate greenwashing

Master Thesis

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Arboretica

Designing a semi-automated approach to find potential evidence of corporate greenwashing

by

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An electronic version of this thesis is available at https://repository.tudelft.nl/
Data and codes are published at
https://github.com/LudovicaBindi/collecting_greenwashing_evidence.git

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Executive summary

Greenwashing can be defined as the mismatch between positive green communications that companies have and their actual activities that are counterproductive to the fight against climate change. The need to study this is because greenwashing companies can undermine the success of climate policies by hiding their climate footprints and prevent policymakers from realizing the need for further regulations. The identification of greenwashing in the literature is mainly done with approaches that are manually executed and, therefore, could be ineffective in timely spotting greenwashing companies. Therefore, this research sets out to find a semi-automated approach that can find evidence of greenwashing. Because of time constraints, the scope of the communication of companies to analyze is limited to what companies publish on their official websites and only lobbying in the European Union is considered for companies' actions. Thus, the main research question that this thesis wants to answer is "*To what extent can a semi-automated approach effectively and holistically study companies' communication and lobbying efforts to find potential evidence of corporate greenwashing?*". This approach could then be used by consumers-citizens to become more aware of whether the companies they buy from are greenwashing or not, thus changing their spending behavior and demanding more actions from their elected officials.

In this research, first the objectives (and their matching criteria) that the final approach needs to meet are identified; then a semi-automated approach is created that analyzes companies' communication and their lobbying activities, and then present them together; finally, the approach is demonstrated in a selected case and evaluated according to the previously defined criteria.

The objectives identified as relevant for this approach are accuracy, transparency, reproducibility, and reusability. These objectives are relevant for data science and AI-based approaches.

The created approach has three parts:

- First, a company's online communication on their official webpage is analyzed. The approach is to automatically do deductive coding. The codes used are first created by inductively coding the communication around climate change of six sample companies and are at a sentence level. These codes highlight the difference in the specificity of the communication of companies around climate change, from companies declaring targets and policy to tackle climate change to companies supporting governments' climate policies to companies making general statements regarding the relevance of climate change. The automatic deductive coding part is achieved by using GPT, a Large Language Model (LLM), to deductively code the sentences in a cascade manner according to a label tree (prompts are first tested and optimized for the accuracy of the coding tasks). The final output of this step is the percentage of sentences that fall within each code.
- Secondly, the lobbying activities of the companies at the EU level are scrutinized. The data comes from the EU Transparency Register. First, the total expenditures that companies declare for their lobbying activities at the EU level are gathered. Then, the declared meetings between the company's representatives and European Commissioners and their staff are studied by determining the percentage of meetings that are relevant to climate change regulations. To do so, a list of keywords that contain both general keywords that relate to climate change and the name of key European legislations is first developed and then it is used to filter the meetings based on their brief descriptions. This could be considered as a proxy of the intensity with which the company lobby efforts are concentrated on climate change regulations.
- Lastly, the final output of the approach is produced, a table where the values from the previous two steps are displayed. To aid the comparison the data is color-coded (the higher the values,

the darker the color) in a way that is true to the values that are presented and not so that further biases are introduced: the viewer is left to come to their own conclusions regarding the presence, or the lack thereof, of mismatch between words and deeds which is key to come to a greenwashing accusation. This final table does not tell whether the values represented can be proof of greenwashing: that task is the job of the user. This judgment can be aided by using existing definitions found in the literature: for a company, higher levels of green communication are found in having more sentences in the codes that represent more specific communication and, when compared to higher levels of lobbying (higher expenditures and higher percentage of relevant meetings), this can lead to considering the company as greenwashing (this is true if it can be assumed that the companies are lobbying against climate regulations as in the case of polluting businesses).

Afterwards, the approach is demonstrated by studying the communication of two companies, ExxonMobil and Shell, that have been found to be greenwashing because of their communication and their lobbying activities in the EU. Based on this demonstration, the approach is evaluated: there are issues of accuracy with the deductive coding part of the approach; there is partial lack of transparency and reproducibility because of GPT, a proprietary and non-deterministic algorithm; reusability is guaranteed because the data used and produced is properly shared with the public.

To answer the research question of this thesis, it can be concluded that the created approach has potential because it is indeed semi-automated, can holistically study communication and lobbying because it combines the results of these two analyses in the final output which then can be used for a greenwashing appraisal, but the issues with accuracy and the other criteria point out to the fact that this approach doesn't fully run its analysis effectively, and, therefore, it is not the best approach that could be created since some of its validity issues are intrinsic to the approach choices made. The research is able to partially fill the gaps in the greenwashing literature and advance the research in the use of GPT for classification purposes and in the field of climate lobbying in the EU.

Future research could work on overcoming the limitations of the created approach by, for example, improving the deductive coding part of the approach by using open-source LLMs or using machine or deep learning models that are deterministic once trained, or by introducing the studying of indirect lobbying to understand the positions of companies on climate regulations. This research can teach to the implementation of new EU regulations that aims at banning greenwashing: the more detailed the definitions of greenwashing that are used, the easier to find greenwashing in an automatic way, and, therefore, the faster the enforcement of the ban can be. Even with regulations, consumers-citizens should still be vigil of greenwashing because it can nonetheless take many forms and slip through these regulations.

Acknowledgements

Completing this thesis is an important achievement for my academic career. And it is, also, a personal one. But I wouldn't have made it without *a lot* of people that I want to thank on this page.

First, I want to thank my graduation committee. James Zhang, from Arboretica, for giving me the chance to tackle this thesis and for its expert input that made me look beyond the academic perspective and out of my comfort zone. Nihit Goyal, my first supervisor, deserves much praise for his knowledgeable and moral support, for teaching me how to approach this thesis rigorously, and for keeping me on track with my ideas and ambitions: for all of this I want to thank him. I also want to thank Amineh Ghorbani for her input that challenged me with her on-point feedback to improve my work.

I wouldn't have been here, in the Netherlands, writing these words if it hadn't been for my parents, Laura and Paolo. They have supported me morally and financially throughout my whole academic career allowing me to study in Italy, the Netherlands, and in the US (both in Kansas and in Pittsburgh). If I am the person that I am today it is because of all the experiences I had, therefore, because of my parents. I am extremely grateful for having them as my parents. *Grazie di tutto*!

There are so many people whose support I could always count on throughout this master and whom I want to thank now. My brothers, Federico and Edoardo, my grandmas, Francesca and Carla, and the rest of my very Italian family. The friends that I made in the Netherlands that have made life here great and that have become my family abroad: Miriam (big shout-out to her cooking skills and all the times that she cooked for me a lovely meal), Dorukhan, Manjula, Aspasia, Yaren, Alex, Zeeshan, Maanav, and all of my Lacrosse family (Go Diamonds!). And the friends that bear with me throughout the years: Giorgia, Chiara, Andrea, Martin, Anduena, and the friends from the Mufloni family.

I learned a lot from this master, Engineering and Policy Analysis. I want to thank the TU Delft professors and staff who made these years fun, tiring, interesting, and full of discoveries. A special thanks to the CMU staff and faculty that welcomed me in Pittsburgh and from whom I learned a lot as well (special thanks to CMU in general for giving me access to some papers that have been used for this thesis that otherwise I would not have read).

This thesis is the conclusion of my TUD (and overall) academic career (at least for the foreseeable future) and it represents a change of era for me: it is indeed a bittersweet moment. But I look forward to the challenges ahead knowing that with the experiences gathered in these past two years and a half, I am well equipped to turn them into adventures.

Ludovica Bindi,
Delft, January 2024

Contents

1. Introduction

The effects of climate change are becoming more evident with the new highest temperatures reached this past summer in the Northern Hemisphere (Weise and Coi, 2023). To effectively challenge climate change, polluting companies need to rapidly reduce their own emissions. However, problems arise if these companies make misleading claims about their environmental efforts or take covert actions that are counterproductive to reduce emissions without making significant efforts to change their polluting business models. This is called "greenwashing". Examples of such practices that companies can undergo range from something as simple as using nature-based imagery on their products even if these products remain polluting (*What is greenwashing?* 2023) to actively lobbying against climate regulations even if they publicly support climate actions. A striking example of this latter greenwashing activity is shown in a study conducted by InfluenceMap (2019), an NGO focusing on corporates' climate lobbying: even if they all publicly supported the 2015 Paris Agreement, the big five oil companies - ExxonMobil, Royal Dutch Shell, Chevron, BP and Total - spent more than $1 billion on misleading climate-related branding and lobbying in the three years after the signing of the treaty.

Companies may use greenwashing activities to "profit off well-intentioned, sustainably minded consumers" (*What is greenwashing?* 2023). Indeed, consumers can be fooled by greenwashing claims ("Protecting Consumers From Greenwashing," 2022) since differentiating between truly sustainable companies and misleading ones can be a "difficult task for the average consumer" (Parafiniuk and Smith, 2019). This is especially alarming since an increasing number of consumers are found to be considering more the environmental impacts of the products being sold when they shop: for example, a multi-country survey found that more than a third of consumers are willing to pay more for sustainable products ("Recent Study Reveals More Than a Third of Global Consumers Are Willing to Pay More for Sustainability as Demand Grows for Environmentally-Friendly Alternatives," 2021), and this percentage can increase to around 70% when only Gen Z are considered (*The State of Consumer Spending: Gen Z Shoppers Demand Sustainable Retail*, n.d.). Thus, if consumers are on board with taking climate action, their efforts may become counterproductive if they are misled by greenwashed claims. In general, it is important to remember that corporations are "powerful economic and social actors, with the ability to shape public and policy discourses" with their communication (Thaker, 2019).

Moreover, greenwashing can create micro- and macro-financial risks: it can "undermine the effectiveness of prudential policies as market participants would be able to circumvent regulations by hiding, for instance, their climate footprint. Furthermore, supervisors might not be able to identify early on the likely transition pathway the economy has entered, which can have important implications for financial stability" (Bingler et al., 2023). Thus, consumers and policymakers need to be able to identify greenwashing to avoid being misled by companies.

That's why greenwashing has recently become at the center of policy discussions: in 2021 the European Commission carried out a screening of websites focusing on "greenwashing" (and found that more than half of websites displayed some greenwashing-related practice) (European Commission, 2021). In 2022, the Commission started collecting opinions from stakeholders on greenwashing features, determinants, and risks via some of its agencies (European Insurance and Occupational Pensions Authority, 2022). In 2023, the European Parliament and the European Council reached an agreement on "new rules to ban misleading advertisements and provide consumers with better product information" such as sustainability labels that have not been approved or created by public authorities (European Parliament, 2023).

The literature around greenwashing presents multiple definitions of this phenomenon because they focus on different objects of focus (marketing, single environmental claims, sustainability reports, data shared, discourse, environmental activities). One of the most influential and general definitions seems to be the description of greenwashing as the difference between what a company communicates and what a company does regarding the environment (e.g., Gatti et al., 2021): this mismatch is essential to make a greenwashing accusation. While the variety of definitions may be because the greenwashing phenomenon is vast, these different definitions make its identification “more complex" (Moodaley and Telukdarie, 2023).

This identification problem is the focus of this thesis. More specifically, the *semi-automated* identification of greenwashing will be researched. Such an automatic or semi-automatic approach doesn’t yet fully exist in the literature when it comes to greenwashing. The focus of past research has shifted toward understanding the determinants of greenwashing rather than to the development of approaches to identify it. If there are methods or approaches to identify greenwashing, they mainly focus on understanding the communication side of the greenwashing phenomenon, excluding the need to identify a mismatch between this communication and companies’ actions. Moreover, these are more qualitative and time-consuming analyses because they are manually executed. There is a limited use of AI and ML techniques (which could speed up the analysis) in the identification of greenwashing whereas these techniques have shown promising results in the automatic analysis of sustainability reports.

Therefore, the scope of this research will be on creating a semi-automated, AI-based approach that finds evidence of greenwashing from companies’ communications and their lobbying activities, a kind of action that has been identified as relevant in greenwashing studies and which is yet to be the focus of greenwashing identification approaches.

Creating an approach that can identify greenwashing can be helpful to consumers. Now, it can be a time-consuming matter for them to detect greenwashing: among what consumers can do, they could check for third-party certification about companies’ sustainability, check reports on what companies do in terms of the environment, check what campaigns companies contribute to, research the companies they invest in, and so more (Wong, 2019). It seems infeasible that all consumers can have the time to do so. That’s why a semi-automated or automated approach could help bring more transparency in the market: consumers could become more aware of such greenwashing activities and consequently react to them. In this way, consumers could avoid being misled by companies and, therefore, the financial risks that greenwashing introduces could be prevented. Therefore, policy makers could also be interested in the development of such an approach.

Indeed, the potential target users of such an approach will be consumers, “conventional” stakeholders (Contreras-Pacheco and Claasen, 2017): somebody who is not an expert in the subject of companies’ sustainability reports, who is not a scientist, etc. Examples of previous studies done by NGOs on this focus, companies greenwashing to mislead consumers, can be found in BEUC (2023) and Amelang (2022).

I believe this research has both societal and scientific relevance which then leads to relevance for the master this thesis is being carried out as its partial fulfilment, the MSc in Engineering and Policy Analysis (EPA).

Regarding the former, this research deals with climate change, one of the most pressing grand challenges of our time, and its goal is to support decision-making by making companies’ actions (a bit) more transparent (if the such an approach were to be publicly used, e.g., via a web tool): everyday consumers, who are also citizens, could become more aware of whether the companies they buy from are greenwashing or not, thus changing their spending behavior and demanding more actions from their elected officials; policymakers may become more aware that there is a big deal of greenwashing happening, thus changing regulations for, e.g., how the companies communicate online.

My research also has scientific relevance because it will advance research methods since what I propose is new and would (partially) fill current research gaps in the fields of climate policy studies, in particular in the subfield of greenwashing, and ML/AI studies. Moreover, its comprehensive approach to greenwashing (by not only focusing on the communication of companies as done in the literature this far) will give this research a systemic view on the topic. The scientific community could benefit from my approach in several ways: other researchers could use the input of my approach for their own research (e.g., in studies that want to study the determinants of greenwashing, they could use the results of my approach to construct the dependent variable "greenwashing"); this approach could be used alongside with what other researchers already have since greenwashing can be so vast (for example, if someone were to have an approach that looks at the environmental reporting, then they could use the results of my approach alongside what they already have to have a greater picture of greenwashing).

Therefore, this focus on a grand challenge of our times, combined with a systemic view of the greenwashing phenomenon and the use of cutting-edge analysis in the form of AI with the goal of supporting decision-making makes this thesis EPA relevant.

From these considerations, the objective of this thesis will be to develop a semi-automated approach that detects greenwashing as the mismatch between words and deeds of companies. Therefore, the main research question for this thesis will be *"To what extent can a semi-automated approach effectively and holistically study companies' communication and lobbying efforts to find potential evidence of corporate greenwashing?".* To answer this research question, in this thesis, steps of design research approach will be used to come to a semi-automated approach that is able to provide evidence for a greenwashing appraisal of companies. First, the requirements that such a solution should meet will be identified. Then, an approach inspired by past literature will be created. Finally, the use of this created approach will be demonstrated on new data and the approach will be evaluated according to the previously identified requirements.

The rest of the report is structured as follows: first, the state of the art of greenwashing studies and the research questions that stem from its gaps will be presented in Chapter 2; Chapter 3 will discuss the research design and its scope, the requirements to be used to evaluate the final approach and a review of literature that can inform the creation of the approach; afterward, the development of and the details of the approach created in this research will be shown in Chapter 4; Chapter 5 will display the demonstration of the approach and the results of the evaluation that will follow; finally, this report will conclude with Chapter 6 where a thorough reflection on this research will be presented.

2. Greenwashing, literature review and research questions

In this section, I will present the results of the literature review that is conducted to understand the state of the art of greenwashing identification. From there, a gap in current research will be identified and finally, the research questions will be presented.

2.1 Literature review

In this section, I will first present the research strategy for the literature review, and then its results.

2.1.1 Queries and research strategy

Since the problem that this research will focus on is helping in the identification of greenwashing in a semi-automatic way, in the literature review I look at how researchers *define* and then *measure* greenwashing. The database used for conducting such research is Scopus.

A summary of the queries used for the literature review can be found in Table 1. The initial focus on the definitions is to better understand the greenwashing phenomenon at the heart of the problem being tackled in this thesis (first query) and to understand how researchers approach to measure greenwashing consequently (other queries). To review the kind of measurements of greenwashing in the literature, I search the database with the words "measure", "identify" and "spot" because they all relate to the measurement of greenwashing (I use "identify" because when looking at the query using "measure", I find papers that also used "identify" as a synonym of "measure". I search using the word "spot" because when looking at NGOs' and consumer organizations' websites, "spotting greenwashing" is one of the most common ways to describe the act of identifying greenwashing). The research on the greenwashing measurements also yields new results on greenwashing definitions.

The abstracts of the papers resulting from these queries are analyzed and the ones that discuss definitions of greenwashing, propose methods or approaches to spot greenwashing, or use a measurement of greenwashing are analyzed further (as a general rule to pick the most promising papers, greenwashing needs to appear as a clear theme of the paper). Moreover, when reading a paper, if one of the papers cited is deemed relevant for my research or seems a well-regarded paper in the field, then that paper is also read. Of the 106 papers resulting from the queries, 23 are further read. Five papers that are mentioned in at least one of these 23 papers are deemed of interest and, therefore, are further analyzed. Moreover, 3 non-academic resources are included in this review since they are regarded as influential in academic papers for academic research. These papers are TerraChoice (2010), Futerra (2009), and Greenwashing Index (n.d.)

No.	Query	Results number	Goal of the query
1	(TITLE-ABS-KEY (greenwashing) AND TITLE-ABS-KEY (definition*))	34	To understand the basic definitions of greenwashing.
2	(TITLE-ABS-KEY (greenwashing) AND TITLE-ABS-KEY (measur*)) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (EXACTKEYWORD , "Greenwashing")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (SRCTYPE , "j"))	40	To understand how greenwashing is measured.
3	(TITLE-ABS-KEY (greenwashing) AND TITLE-ABS-KEY (spot*))	10	To understand how greenwashing is measured.

4	(TITLE-ABS-KEY (greenwashing) AND TITLE-ABS-KEY (identify*)) AND NOT ((TITLE-ABS-KEY (greenwashing) AND TITLE-ABS-KEY (measur*))) AND (LIMIT-TO (SRCTYPE , "j")) AND (LIMIT-TO (PUBSTAGE , "final")) AND (LIMIT-TO (DOCTYPE , "ar")) AND (LIMIT-TO (LANGUAGE , "English")) AND (LIMIT-TO (EXACTKEYWORD , "Greenwashing"))	22	To understand how greenwashing is measured.

Table 1. Description of the queries run on Scopus for the literature review discussed in this Chapter: query, number of results generated, and intended goal for the query are described.

It is worth mentioning some technicalities regarding these queries. The second one is limited to finding just articles that are finalized and whose keywords do contain greenwashing to reduce the number of results to process because of time constraints (simply searching for “greenwashing” and “measur*” results in 123 documents which are deemed to be too many to be analyzed for the timespan of this thesis). I focus on finalized articles because those are the ones expected to be the most complete and easiest to access. And the keywords are set to having to contain “greenwashing” to guarantee that greenwashing is one of the main focuses of the article (and not, for example, briefly mentioned). The last query looks at how researchers *identify* greenwashing, but to save time, the results obtained from the second query (which was about *measuring* greenwashing) are excluded. Moreover, this last query has the same limitations as the second one for similar reasons (searching for “greenwashing” and “identify” would have yielded 76 new results).

I am confident of the results of this review because after reading some papers, in the new articles I analyze I keep finding references to previously analyzed papers: thus, I believe I am able to find and study relevant papers in the field of greenwashing.

2.1.2 Results

The results can be divided into three categories: definitions of greenwashing, potential general definitions of greenwashing, and measurement of the phenomenon. In the following sections, I will discuss the results for each section.

2.1.2.1 Definitions of greenwashing

The main takeaway from the literature review is that there is no single definition of greenwashing that prevails in the literature. Greenwashing can take many shapes and forms and can happen at different levels of the business, etc. A list of the definitions found in the literature follows. The different definitions are grouped according to what is understood as a common theme between the different definitions: this simple “categorization” doesn’t fully reflect discussed groupings in the literature (which will be discussed in the following section), but it is believed to facilitate the understanding of the current discussion on the definitions of greenwashing.

The more immediate form of greenwashing that is discussed in research is the one that relates to the marketing of products that does not reflect a matching environmental responsibility of the company (Jones, 2019; Nemes et al., 2022). This can take the form of “ad bluster” (Contreras-Pacheco and Claasen, 2017) which is the act of using advertising to divert attention from the sustainability issue at hand by exaggerating what the company has done or present programs that are not related to the issue. Greenwashing can be more specific to the marketing of physical products or services (Sensharma, Sinha, and Sharma, 2022; Yu, Van Luu, and Chen, 2020). A more specific case is the use of misleading visual imagery (e.g., the use of natural images on packaging) (Lyon and Montgomery, 2015; Futerra, 2009; *About Greenwashing*, n.d.).

A good portion of the definitions found in the literature focus on the single environmental claims (even just sentences) that a company can make. TerraChoice (2010), an environmental marketing firm, formulates the "seven sins of greenwashing", a list of characteristics that make an environmental claim a greenwashed one. These features are widely used and cited in the academic analyzed papers. The other two non-academic but still relevant for research resources also share aspects of the report developed by TerraChoice. The "sins" of a greenwashing claim are the following: having "hidden trade-offs" (that is considering a narrow set of attributes when discussing a product, thus missing out on other important environmental aspects) (TerraChoice, 2010); not showing any kind of proof (which is easily accessible or verified by a third party) (TerraChoice, 2010; Nemes et al., 2022; Futerra, 2009; *About Greenwashing*, n.d.; Berrone et al., 2015); being vague (so loosely defined that it could be misunderstood) (TerraChoice, 2010; Nemes et al., 2022; Futerra, 2009); being irrelevant (while being truthful, it is unimportant for the environmental concern at hand) (TerraChoice, 2010; Nemes et al., 2022; Futerra, 2009); asserting to be the "lesser of two evils" (saying that something is better than its peers while it is still environmentally dangerous) (TerraChoice, 2010; Futerra, 2009); "fibbing" (an outright false claim) (TerraChoice, 2010; Wei et al., 2023; Nemes et al., 2022; Futerra, 2009); lastly, "worshiping false labels" (using fake third-party verification labels) (TerraChoice, 2010; Wei et al., 2023; Nemes et al., 2022; Lyon and Montgomery, 2015; Futerra, 2009).

Furthermore, claims can be considered as "not credible" (Nemes et al., 2022; Futerra, 2009) if a highly controversial practice (or product, service, etc.) is described as environmentally friendly. Contreras-Pacheco and Claasen (2017) go further: if a company has an "inherently unsustainable" business model but promotes sustainable business practices that can't be feasible for the company, then that company can be considered as greenwashing.

Lastly, claims that use specific jargon or information that consumers cannot understand nor verify are also considered to be a form of greenwashing (Nemes et al., 2022; Futerra, 2009).

While the previous part of the literature focuses on more specific claims, some papers define greenwashing as when a company makes a more exhaustive set of claims, for example when they publish environmental reports. In this case, the most popular definition of greenwashing is "selective disclosure" which is the act of disclosing part of the information regarding the company's environmental performance, withholding the more negative information, thus creating a positive image of the company itself (Lyon and Montgomery, 2015; Wei et al., 2023; Nemes et al., 2022; Kurpierz and Smith, 2020; *About Greenwashing,* n.d.; Blanco et al., 2021; Sensharma et al., 2022; Yu et al., 2020; Siano et al., 2017; Vollero et al., 2016; Moodaley and Telukdarie, 2023). Wu et al. (2020) more specifically say that the undisclosed information are "unobservable aspects" of the company (these aspects are more hidden to the general public). Wu et al. (2022) describe this kind of greenwashing performed by companies as "conceal[ing] their actual ESG (environmental, social and governance, *ed.*) performances".

Another important definition says that greenwashing happens when companies exaggerate their good environmental performances (Wang et al., 2023; Santos et al., 2023; *About Greenwashing,* n.d.; Yu et al. 2020; Contreras-Pacheco and Claasen, 2017; Li et al., 2022; Wu et al., 2022). An example of this kind of greenwashing is given by Sensharma et al. (2022): companies share large volumes of complicated non-financial data in order to mislead stakeholders and consumers and to boost the valuation of the company. Similarly, Yu et al. (2020) say that greenwashing companies disclose large quantities of ESG data to appear more transparent when in reality they perform poorly (these large quantities of data become "smoke and mirrors" to stakeholders because, for example, this data can be unaudited). Lyon and Montgomery (2015) define this kind of greenwashing as "empty green claims" if the company issuing them fails to live up to these exaggerated talks. Siano et al. (2017) go further in saying that this communication is a "deliberate manipulation of business practices aimed at making tangible statements regarding corporate sustainability" which can be seen as "deceptive manipulation".

If the focus is specifically on reports (such as the ESG ones), then Contreras-Pacheco and Claasen (2017) use the words "fuzzy reporting" to describe when companies exploit the one-way communication nature of sustainability reports to manipulate the truth and shed a positive light on their corporate practices.

Literature tries to come up with ways that could generalize the past two sections on greenwashing in communication. The first I encountere is called "misleading narrative and discourse" as described by Lyon and Montgomery (2015) where green or environmental narratives are used as a rhetorical deception tool. Such discourse-setting techniques could be used both in reports produced by the companies and on social media. Another general definition is given by Oppong-Tawiah and Webster (2023): greenwashing messages are false messages which can be called "fake news" (disinformation, malinformation, misinformation). Greenwashing can be disinformation if the message involves "bald-faced lying" (this is also discussed in Nemes et al., 2022, and Seele and Gatti, 2017); it can also be considered "malinformation" if (more or less) truthful information is published with the intention to deceive; finally, greenwashing is a form of misinformation when companies make mistakes (e.g., because they are lacking information on their own) when communicating their sustainability practices.

Since greenwashing deals with (misleading) communication, Seele and Gatti (2015) mention that for a message to be considered as greenwashing, there must be an accusation of such: that is, the falsity is not enough, somebody (stakeholders, NGOs, the media) must perceive the message as misleading. Thus, the authors say that there could be instances where a company engages in misleading practices that are not perceived as such by others and, therefore, there is no greenwashing. This idea that greenwashing must exist in the "eye of the beholder" is also found in Lyon and Montgomery (2015).

Another branch of literature focuses on how companies can be accused of greenwashing because of how their environmental claims relate to the companies' organizational practices.

The first definition says that a company commits greenwashing by making a claim that is not consistent with organizational practices (Nemes et al., 2022). Lyon and Montgomery (2015) propose as an example a company that creates a "Sustainability Department", but which has no actual power within the organization. Thus, these kinds of promises can be considered "empty green policies" because companies do not follow through (Lyon and Montgomery, 2015). Another example is given in *About Greenwashing*. (n.d.): a company that invests more in marketing the whole organization as green rather than using that money for the implementation of practices that do minimize environmental impacts. This greenwashing category is also called "decoupling" which is when a company claims to meet the expectations of stakeholders, but it doesn't make any actual changes in the organization (Siano et al., 2017; Mateo-Márquez et al., 2022; Oppong-Tawiah and Webster, 2023; Moodaley and Telukdarie, 2023). The last example worth mentioning is a company that does produce a green product, but the rest of the company processes are heavily polluting (Futerra, 2009; *About Greenwashing*, n.d.).

Looking at the political actions that a company can take, there is greenwashing if a company pledges to environmentalism while this organization or other organizations such as think tanks, trade organizations, or other groups that the company is affiliated to lobby against environmental legislation (Nemes et al., 2022; Lyon and Montgomery, 2015) or to influence policymakers to obtain benefits from sustainability regulations (Contreras-Pacheco and Claasen, 2017). This "political spin" is warranted by companies because of their large tax-payer nature (Contreras-Pacheco and Claasen, 2017).

Another "action" that can yield greenwashing accusations is when a company endorses another organization's greenwashing claims (Nemes et al., 2022). And NGOs can also fall prey to such accusations because of their partnerships (Lyon and Montgomery, 2015).

The last greenwashing definition that deals with organizational practices is when a company markets its practices, accomplishments, or commitments as green and sustainable while these actions are already required by current legislation: thus, the company is simply abiding by the law (Contreras-Pacheco and Claasen, 2017).

2.1.2.2 Potential general definitions of greenwashing

As the previous section tells us, there are multiple ways of defining greenwashing. A "more" general definition is given by Nemes et al. (2022): "greenwashing is an umbrella term for a variety of misleading communications and practices that intentionally or not, induce false positive perceptions of an organization's environmental performance". This definition captures the main themes covered in the previous section: greenwashing involves communications and practices of companies, and the goal is to present the company as caring for environmental concerns in the eyes of the consumers; a company may result as doing greenwashing even unintentionally. Lyon and Montgomery (2015) present a similar definition.

Another general pattern that comes out of the literature is described by Gatti et al. (2021): greenwashing happens when there is an "inconsistency between environmental-related words and deeds". The mismatch between environmental misbehavior and communication by a company is a "lie" to stakeholders (Gatti et al. 2021). Along these lines a typology to classify greenwashing and non-greenwashing companies is found in Li et al. (2022) (and a similar categorization can be found in Contreras-Pacheco and Claasen, 2017): by comparing their "green communication" and "green practices", companies can be classified as "greenwashing", "vocal green", "silent brown", and "silent green" (Figure 1 is the union of the tables that describe such definition contained in these two papers). Indeed, the definition of greenwashing as the difference between what is communicated to stakeholders and what is done by the company is fairly reported in other papers as well (Santos et al., 2023; Lyon and Montgomery, 2015; Futerra, 2009; Li et al., 2022; Moodaley and Telukdarie, 2023). Kurpierz and Smith (2020) define this kind of behavior as "fraud" because both "require a reporter that makes statements that are … misleading … with the intent to deceive". A more "elegant" definition is given by Blanco et al. (2021) (a similar definition is also discussed in Contreras-Pacheco and Claasen, 2017): greenwashing is the "existence of a difference between two behaviors: symbolic and substantive actions" (with the actions being, respectively, the environmental communication and practices). Mateo-Márquez et al. (2022) also reframe this definition as the "intersection" between poor environmental results of the company's practices and positive communication around these performances.

		Green practice	
		Negative	**Positive**
Green communication	Positive comm.	Greenwashing	Vocal green
	No comm.	Silent brown	Silent green

Figure 1. Typology of companies based on their green practice and green communication. The table is created by the author and is based on the tables found in Li et al. (2022) and Contreras-Pacheco and Claasen (2017).

Other papers mention that there is a possible classification of greenwashing based on where it happens within a company's structure. A first distinction is made between firm-level greenwashing (which may involve ESG reports) and product-level greenwashing (advertising on the single product) as can be seen in Oppong-Tawiah and Webster (2023), Sensharma et al. (2022), and Yu et al. (2020). Jones (2019) goes further in the classification: other than specifying that firm-level greenwashing can also include political actions of companies (such as lobbying) and long-term environmental impacts (sustainability practices), the author adds the industry level for greenwashing where the focus of the analysis is the actions taken by the industry groups that want to represent the interests of all the companies that belong to the same sector.

2.1.2.3 Ways to identify greenwashing

In this last section of the literature review, the focus will be on ways to identify greenwashing that are used and discussed in the current literature.

Some papers try to identify greenwashing by only looking at the communication done by companies.

Jones (2019) uses advertisement campaign pictures (found on Google Images) of different companies and analyzes them with an analytically inductive approach to understand the narratives of such campaigns. The goal is to find shared patterns among the companies. Along similar lines, Plec and Pettenger (2012) analyze ExxonMobil's advertising using framing theory.

Another paper that analyzes greenwashing in communication is Contreras-Pacheco and Claasen (2017). In their paper, the authors manually collect (online) all the social and environmental reporting (e.g., press releases, media communication) of a company following a single environmental incident the firm under scrutiny was involved in. Then, they proceed to analyze such material via a qualitative content analysis. The added value of this paper is their focus on firm-level greenwashing and on a single, specific incident. They also argue that research which studies sustainability reports is only accessible to "specialist" stakeholders, like NGOs, that have the prerequisites to analyze such kinds of reports because "conventional" stakeholders (the general public) are "not prepared to effectively interpret them": according to the authors, methods that have a linguistic and discursive perspective can overcome this issue of accessibility.

Bricker and Justice (2022) use a rhetorical approach to identify greenwashing. They focused on a speech given by the CEO of ExxonMobil, and they demonstrate it was an instance of greenwashing by using a rhetorical technique called "conciliatio" which is "noting internal contradictions within pro-environmental rhetoric of corporations, using the corporation's words against itself".

The last paper that falls into this category is Oppong-Tawiah and Webster (2023). This paper is deemed of special interest since it is the only result that uses an automatic approach to identify greenwashing, which is aligned with what this research is about. The goal of this paper is to determine whether the communication of companies on social media platforms (in this case Twitter) around environmental sustainability is misleading and an instance of greenwashing. To do so, they draw from fake news studies because greenwashing messages can be seen as fake messages (as discussed earlier). To study the Tweets, they measure certain linguistic cues, the "lexical and syntactic features of language that are independent of content", that are described in the literature as good indicators of deceptiveness. An example of linguistic cues in this research is "quantity", the text length: according to the literature the authors review, deceptive messages are expected to be shorter in length compared to truthful ones. One of the reasons could be that the deceiving authors want to avoid adding incriminating information. In their method, they first selected Tweets of companies related to the environment and then classified them using the linguistic cues identified in the literature. The value of this approach is that it does not require an algorithm to be trained: as described by the authors, trained algorithms that would be able to perform automatic detection would need ground-truth data whose quality dramatically impacts the final quality of the results. The authors also conducted different validation tests and, according to their results, there is strong evidence of the validity of their method.

Another branch of the literature focused on using the definition of greenwashing as the difference between what is said by a company (disclosure) and what the company does (actions). This is in line with the more comprehensive definitions of greenwashing on the mismatch between words and actions discussed in the previous section. Moreover, this part of the literature uses already existing databases to give a score on these two parts of the "greenwashing equation" or other quantitative techniques. It is important to highlight that the goal of many of these papers isn't to develop methods to identify greenwashing, but they mainly use already existing data in order to study something else like possible determinants of greenwashing in an econometric way. These papers are Zhang (2022a), Yu et al. (2020), Blanco et al. (2021), Sensharma et al. (2022), Zhang (2022b), Feng et al. (2022), Li et al. (2022), Zhang (2023), and Mateo-Márquez et al. (2022). The used scores could be normalized (Zhang, 2022a; Yu et al., 2020; Zhang, 2022b) or standardized (Li et al., 2022). Also, the scores of a company could be adjusted to the ones of its peers (difference between the company's score and the mean of its peers' scores): this is considered to evaluate the degree of how sustainable the company is (Zhang, 2022b; Zhang 2022a).

There are different ways to quantify disclosure and actions. Regarding the disclosure scores, the databases used are the Bloomberg ESG database to get the ESG disclosure score (Zhang, 2023; Zhang, 2022a; Sensharma et al., 2022; Yu et al., 2020; Zhang, 2022b) and the results of the 2015 Carbon Disclosure Project (Mateo-Márquez et al., 2022). Some papers are able to quantify the disclosure of companies using other techniques: Feng et al. (2022) manually code interviews using categories previously developed in the literature; Blanco et al. (2021) carry out a manual content analysis on companies' sustainability reports using a framework and formula previously defined in the literature as well; finally, Li et al. (2022) do a manual content analysis, too, on sustainability reports but they develop their own framework first.

To measure actions, the main method seems to be using existing databases. The variables used are the ESG performance score from Bloomberg ESG database (Zhang, 2022a; Yu et al., 2020; Blanco et al., 2021), the Asset4 ESG performance score from Thomson Reuters ESG rating (Zhang, 2022a; Yu et al., 2020; Zhang, 2022b), the Thomson Reuter's ESG performance score (Sensharma et al., 2022; Zhang, 2022b), ESG performance score from Refinitiv (Demers et al., 2021), MSCI's ESG performance score (Demers et al., 2021), ESG rating data from the Sino-Securities Index Information Service (Huazheng Database) (Zhang, 2023) and ESG rating score from the WIND database (Zhang, 2023). Mateo-Márquez et al. (2022) use carbon emissions values as a proxy for the action variable and they retrieve the data from Refinitiv Datastream (in this case, a company is considered to be greenwashing if they have positive communication about their environmental performances and a high level of emissions). Feng et al. (2022) and Li et al. (2022) don't use an existing database for quantifying the action variable, but they carry out similar procedures as they do for measuring the disclosure variable.

A general way that is suggested as important when identifying greenwashing is to have an "investigative approach" by focalizing on the "mismatch between words and deeds" as investigative journalists do (Bricker and Justice, 2022).

Another way to give a comprehensive evaluation of greenwashing is proposed by Jones (2019). It is important to mention that the author proposes this approach but does not carry it out. The focus of the approach is based on the relations within and outside the company: a critical analysis of the underlying processes in a company is needed and these must be evaluated at the product, firm, and industry levels. At the product level, the life cycles of products should be evaluated. At the firm level, the author points to different aspects to scrutinize: aggregated lifecycle analysis from the previous level, political actions of the company (e.g., lobbying), the legal history of the firm (fines), various economic ties that a company has (relationship to the parent company and business partners), and the long-term environmental impacts of the company (sustainability practices). Finally, at the industry level, the previous levels should be analyzed for all the companies in the industry and the identification of industry groups that represent the industry's interests. This approach is essential because it recognizes that greenwashing can happen at different levels which came out as an important aspect of greenwashing in the section on the multiple greenwashing definitions in the literature.

2.1.2.4 Conclusions

The literature on greenwashing proposes different definitions of what the phenomenon is and how to spot it. One of the most influential definitions of greenwashing seems to be the description of greenwashing as the difference between what a company communicates and what a company does regarding the environment (e.g., Gatti et al., 2021). This mismatch is essential to make a greenwashing accusation. The actions that a company does can take many shapes and forms, not only what they do with a product, but also how they are organized, and how they relate to other companies and trade associations (Jones, 2019). Thus, the broader the analysis when studying greenwashing practices, the better. While the variety of definitions may be because the greenwashing phenomenon is vast, these "varying definitions of greenwashing make the identification of greenwashing more complex" (Moodaley and Telukdarie, 2023).

2.2 Literature gaps and research questions

In this section, I will identify the literature gaps that result from the literature review described above, and from those, I will identify the main research question (and its subquestions) that this research will answer.

2.2.1 Literature gaps

There are several gaps in the literature described above. The most evident one is that not all the definitions of greenwashing have a matching method that identifies that kind of greenwashing, even if there is a consistent number of papers that use greenwashing measurements. For example, there is no paper that focuses only on identifying selective disclosure. Moreover, there is no study that follows Jones's (2019) footsteps and uses products' lifecycles analysis to understand product-level greenwashing and that looks at the company level (e.g., via studying lobbying and legal history of companies) nor that focuses on the industry-level relations among companies and interest groups.

This gap may happen because a lot of studies that use a measurement of greenwashing focus more on understanding the determinants of greenwashing, rather than on an identification *a posteriori* of the phenomenon. These papers are Zhang (2022a), Yu et al. (2020), Blanco et al. (2021), Sensharma et al. (2022), Feng et al. (2022), Zhang (2023), and Mateo-Márquez et al. (2022). Two papers, Zhang (2022b) and Li et al. (2022) use the quantified greenwashing measure as another independent variable for their econometric models.

Two problems arise from the use of these measurements. The first one relates to the data that is used: it isn't easily accessible; thus, the reproducibility of research is hindered. Of the mentioned data sources, only Refinitiv's ESG performance score is found to be free for the public, while the others (Bloomberg ESG database, Thomson Reuters, MSCI, and Carbon Disclosure Project) are all a paid service. Other data sources may have another kind of accessibility problem: sustainability reports (as studied in, e.g., Li et al., 2022) may be too advanced for "conventional" stakeholders as Contreras-Pacheco and Claasen (2017) point out. Therefore, Contreras-Pacheco and Claasen (2017) suggest that it is better to analyze such material based on linguistic and discursive perspectives these stakeholders have better chances of understanding.

The second problem is more intrinsic to the methodology itself: when using such scores, an inconsistency between a high communication standard and a low environmental performance only indicates *candidates* of greenwashing (Blanco et al., 2021). There is no certainty that the mismatch is on, for example, the same environmental issue.

The studies that propose methods to identify greenwashing focus mainly on the communication side of the phenomenon. While this focus may be easier for the "conventional" stakeholder (Contreras-Pacheco and Claasen, 2017), this approach lacks the study of the actions of the companies under scrutiny and, therefore, it fails to highlight how greenwashing is constituted of a mismatch between actions and words, as the leading general definitions of greenwashing suggest. These studies are Jones (2019), Plec and Pettenger (2012), Contreras-Pacheco and Claasen (2017), Bricker and Justice (2022), and Oppong-Tawiah and Webster (2023).

Another limitation of these papers that propose an identification method for greenwashing (except for Oppong-Tawiah and Webster, 2023) is that they are highly qualitative, especially if they deal with perceptions and narratives such as in Jones (2019), which could hinder the reproducibility of such results. Moreover, these studies are manually executed which means that the identification of greenwashing can only happen when researchers publish their results in papers (or NGOs put out their reports). Indeed, as Oppong-Tawiah and Webster (2023) discuss, manual methods are time-consuming and may not yield results. An example of this is Jones (2019): according to the author, the proposed method (studying advertisement campaigns with an analytically inductive approach) does not work because the narratives that the paper wants to analyze are "too malleable" to be properly studied for their accuracy. The author says that a better understanding of the larger context of the firm (its products, its organizational practices, and its industry relations) is needed to evaluate greenwashing.

In the literature, there is a lack of automatic methods to detect greenwashing. The only paper that proposes such an approach is Oppong-Tawiah and Webster (2023). To confirm this gap, Moodaley and Telukdarie (2023) conduct a literature review to understand the intersection between greenwashing and AI & ML fields and find only one paper that belongs to both fields. However, this paper is not deemed of interest for this research because of its focus on sustainable finance and because it only discusses greenwashing in terms of possible future research questions. In stark contrast to this, the paper finds that the use of AI and ML, especially NLP, on sustainability reporting is far a much more mature (e.g., in terms of the number of documents published) and wider field. Therefore, Moodaley and Telukdarie (2023) conclude that there is a limited use of AI & ML techniques as a methodological tool for greenwashing studies: this is an unexplored field.

2.2.2 Research questions

There are many gaps in the literature, but it is unfeasible for this thesis to tackle all of them in the scope of this thesis because of time constraints. Therefore, I will focus on using ML/AI techniques in a semi-automatic approach that finds evidence of greenwashing activities. The focus on finding evidence rather than coming to a complete assessment of greenwashing is chosen because of the variety of definitions of greenwashing: by finding potential evidence of greenwashing, users are free(er) to come to their own conclusion regarding greenwashing. Regardless, it should be possible to use the results that the approach will produce to come to a greenwashing appraisal (that is, the analyses should be informative for greenwashing appraisals).

Moreover, since the literature suggests that both communication and actions from companies must be studied to come to a thorough greenwashing analysis (as discussed in, for example, Gatti et al., 2021), the approach whose development this research is about will take into account both these elements. And, because of time constraints, it is decided to have a specific scope for the development of the design (a more detailed description of the scope will follow in Section 3.2). For the actions, I will focus on the lobbying that companies can do as suggested by Jones (2019), Nemes et al. (2022), Lyon and Montgomery (2015), and Contreras-Pacheco and Claasen (2017): this focus also adds a novelty element to my research since it is still an unexplored field in greenwashing research because in the papers described above, it isn't a specific field of study. Finally, I will focus on EU data because lobbying in the European Union has become a "hot topic" since the Qatargate corruption scandal erupted in December of 2022 (Tidey, 2022). Regarding the communication side, I will focus on what companies say on companies' official channels of communication (such as their official websites) as suggested by Contreras-Pacheco and Claasen (2017). Moreover, the intended user of such an approach is the "conventional" stakeholders (Contreras-Pacheco and Claasen, 2017), that is somebody who is not an expert in the subject of companies' sustainability reports.

From these gaps of interest, what is learned from the literature review, and resource and time considerations, the research question (RQ) for this thesis is as follows:

"To what extent can a semi-automated approach effectively and holistically study companies' communication and lobbying efforts to find potential evidence of corporate greenwashing?"

This question can be answered by answering the following sub-questions (SQ):

- SQ1. "What operationalizable criteria can be used to determine the success of the approach?"
- SQ2. "What semi-automated approach can be created to potentially allow for a holistic study of companies' communication and lobbying efforts?"
- SQ3. "To what extent is the created approach successful to the previously defined criteria when evaluated on a selected case?"

3. Research design

In this chapter, I will present the research design that this research will follow and the scope (including the data that this research will need to use) and requirements for the approach to have. I will also present the literature that the creation of the approach will be based on.

3.1 Design research and this thesis approach

This research will be based on the design research approach discussed in Peffers et al. (2007) because the goal of this thesis is to design an approach that tries to solve an existing problem, the semi-automatic identification of evidence for greenwashing.

According to Hevner et al. (2004), the design science paradigm is "fundamentally a problem-solving paradigm" because it "creates and evaluates IT artifacts intended to solve identified … problems": indeed, at the heart of this approach is the desire to solve "heretofore unsolved and important business problems" (Hevner et al., 2004). The whole approach is rigorous and, therefore, it can lead to created artifacts that are able to solve the observed problems which are thoroughly evaluated and to research contributions (Peffers et al., 2007).

Peffers et al. (2007) describe six activities to be completed for the design research approach. The first one is "problem identification and motivation" which aims at defining the problem to be solved and, therefore, justify the value that the solution to be created can have. From this problem specification, the researcher should determine the objectives for the solution to meet (this activity is called "define the objectives for a solution") which can be quantitative or qualitative. The key activity is "design and development" which is the act of creating the artifact that can solve the identified problem: "conceptually, a design research artifact can be any designed object in which a research contribution is embedded in the design". With the created artifact, the researcher should demonstrate the usability of the artifact in solving one or more examples of the original problem ("demonstration"). This could involve, for example, simulations and case studies. By comparing the obtained results from the demonstration activity to the solution objectives previously determined, the research can measure how well the created solution solves the original problem ("evaluation" activity). The last activity left is "communication" where the researcher shares the problem and its importance, the created artifact, why it is useful, novel, rigorously designed and its effectiveness in solving the problem to researchers and other interested audiences.

As Peffers et al. (2007) highlight, while the way that the activities were presented above seems to suggest the order in which these should be carried out, the researcher could decide to start from almost any of the activities presented and move outward. Moreover, the process doesn't need to be linear: after evaluating the artifact, the researcher can attempt to find a more effective solution by going back to the design step (or can proceed with the communication activity) (Peffers et al., 2007).

This approach is deemed to be suitable for the purpose of this research because its goals align with the ones of this project: the creation of an approach that can enable users to identify corporates' greenwashing in a semi-automated way (the artifact) because such an approach lacks in the literature and it is much needed due to the detrimental impact that greenwashing can have on countries' and peoples' efforts to tackle climate change (the heretofore unsolved problem and its importance). In this way, this research is problem-centered (Peffers et al., 2007) because the idea of the design comes from the observation of a problem (the lack of automating methods and approaches to identify greenwashing).

For time limitations, it isn't feasible to thoroughly conduct all the steps described above. Therefore, the research is limited to properly conducting the "design and development" (Chapter 4), “demonstration” (Chapter 5), and “evaluation” (Chapter 5) activities. The created approach is the answer to SQ2 whereas its evaluation is the answer to SQ3. The first two steps of the design research approach are tackled but not as rigorously as they should be: the first phase of the design process, “problem identification and motivation”, has already been completed in Chapter 2; some objectives and their matching criteria will be discussed as per the requirement of the second step, “define the objectives for a solution”, but this won’t be necessarily an extensive list (see Section 3.3.1). These objectives are the answer to SQ1. The final thesis report coincides with the last phase, “communication”.

Moreover, the choices regarding the “demonstration” and “evaluation” phase can be already discussed. As discussed in Peffers et al. (2007), the final steps of the design methodology involve demonstrating the use of the approach on new data and then evaluating to what extent the designed approach “supports a solution to the problem” by examining the results of the demonstration. For this research, it is chosen to demonstrate the use of the artifact created in a case study fashion as suggested by Peffers et al. (2007) but on only one instance because of time limitations. Therefore, since the goal of these steps is to evaluate the approach on a single demonstration, what is being conducted is called a “small-case evaluation” (Wohlin & Rainer, 2022).

A visual summary of the research approach of this thesis can be found in Figure 1.

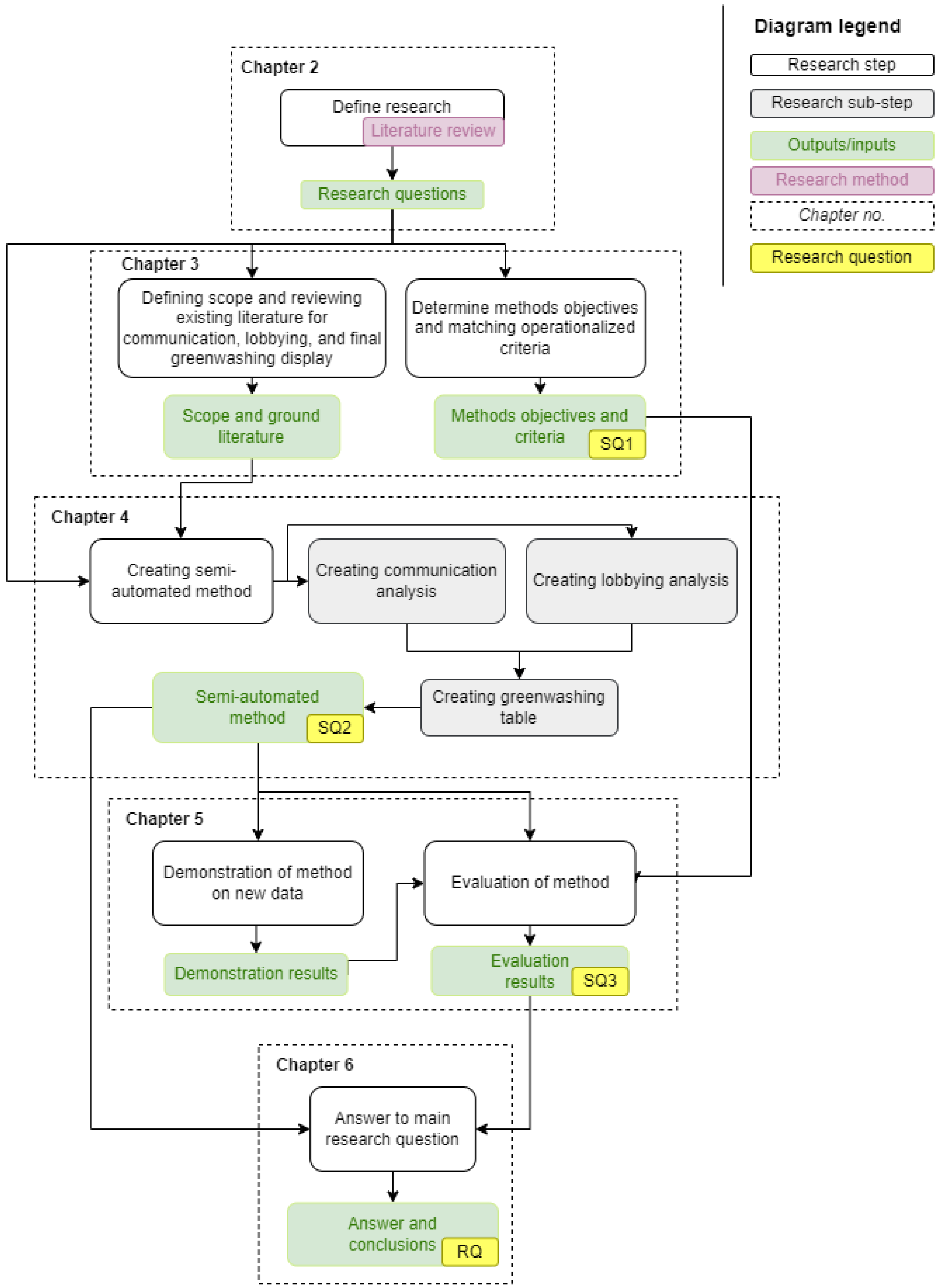


Figure 1. Research flow diagram and corresponding legends. The flow represents the research from the step carried out in the previous chapter, defining the research via a literature review to get to the research questions, till the final step, the answer to the main research question which is in the last chapter of this report. Note that "SQX" stands for "Sub-Question X" and "RQ" for the main research question.

3.2 Scope of analysis

In this section I will discuss the scope for this research. As already shown in the literature review conducted in Chapter 2, greenwashing is an extensive phenomenon that can be seen at different levels of a company (e.g., Jones, 2019). Therefore, it is unfeasible (because, for example, time limitations) to design an approach that would work on all the possible ways that greenwashing can happen. Therefore, the scope of research is limited but, at the same time, the resulting research is still novel.

3.2.1 Why online communication?

As discussed in the literature review described in Chapter 2, there are different forms of communication that can be used by companies with greenwashing intentions.

The use of misleading marketing, both ads and the packaging of products, can lead to the accusation of greenwashing (e.g., Jones, 2019). The issue with this data is its collection: there is a lack of easy and accessible ways to gather online ads of companies[1] and potentially not all the packaging of companies' products can be seen on online websites.

Another important form of corporate communication is sustainability or ESG reports which can then be the source of misleading communication (e.g., Contreras-Pacheco and Claasen, 2017). This is not chosen as the primary focus for the communication analysis because, as Contreras-Pacheco and Claasen (2017) discuss, reports are not accessible to the conventional stakeholders, which are the focus of this research.

Connecting to the previous point, the study of social media posts and corporate websites could be more digestible to the conventional stakeholders if analyzed from a discursive and linguistic perspective (Contreras-Pacheco and Claasen, 2017). Both forms of communication can be used with greenwashing intents (e.g., Lyon and Montgomery, 2015, and Contreras-Pacheco and Claasen, 2017, respectively). Indeed, because of the increased use of the Internet and social media by scientists, politicians, corporations, and NGOs for providing information and mobilizing support, online communication has become relevant for climate change and climate politics (Schäfer, 2012).

It is decided for social media communication not to be the focus of this research because it would lack novelty as there is already a paper, Oppong-Tawiah and Webster (2023), that discusses the automation of the social media analysis to detect greenwashing. Therefore, official corporate communication from websites is picked as the analysis's focal point.

Moreover, of all the environmental claims that companies can make, the focus of the analysis will be what companies say regarding climate change which then can represent their stance on climate change and/or the need for actions. This is chosen to limit the scope of analysis because of time constraints. Finally, for similar reasons, these environmental claims will be considered at the sentence level (sentence will be the unit of analysis) if the needs of the final method of analysis for communication is to allow for this.

3.2.2 Why lobbying?

The actions of a company that can be analyzed to come to a greenwashing accusation can be multiple and as discussed in Jones (2019), these can take at the product, firm, or industry level, as already discussed in Chapter 2.

At the product level, the environmental impact of products and services (e.g., Sensharma, Sinha, and Sharma, 2022) could be analyzed; in general, the environmental practices of companies could be the focus of study (Contreras-Pacheco and Claasen, 2017). A way to approach this analysis

[1] Examples of third-party tools: https://sensortower.com/pathmatics, https://adbeat.com/.

would be a products' lifecycles analysis (Jones, 2019) which I would lack the knowledge and skills to carry out (nor it is within the scope of the master's program this research is carried out for).

At the firm level, the actions to be analyzed could be multiple: organizational practices (Nemes et al., 2022); lobbying activities and ties to other organizations (e.g., Nemes et al., 2022); the legal history of the firms (Jones, 2019); economic ties to other companies (Jones, 2019); and the sustainability practices (Jones, 2019). Of these actions, the lobbying activities are chosen as the focus of this research because of the availability of a dataset in the EU, the Transparency Register, which by being mandatory for firms is the most complete dataset for these kinds of activities; thus, lobbying activities could be easily analyzed. Moreover, the data lend itself for the purposes of this research because both the quantitative and qualitative data (in the form of simple texts) can be easily processed in an automated way (see Section 3.3.4 for a more thorough description of the Transparency Register). The lack of data for the other actions (except for the environmental practices) prevents me from studying them in the automatic way that is at the center of this thesis. Moreover, the environmental practices are avoided to ensure novelty of this research: literature has extensively used them in their studies thanks to the availability of databases such as the Bloomberg ESG database (e.g., Zhang, 2022a) and the Asset4 ESG performance score from Thomson Reuters ESG rating (e.g., Zhang, 2022a). The same can't be said for lobbying since there is a lack of studies that aim to analyze it for greenwashing purposes.

Moreover, lobbying practices are of special interest because they "undermine sustainable actions and progress by creating a public image that misleads the public into believing that without major structural changes to their businesses and their holdings the company can be sustainable" (Parafiniuk and Smith, 2019)

Finally, at the industry level, according to Jones (2019), all the actions from the previous levels of all the companies in a sector should be analyzed and aggregated to get a general picture of the industry; moreover, the trade organizations' lobbying activities should be analyzed as well. Thus, this level of action should be analyzed once the previous two are done.

In this section, it is important to highlight why the the specific focus on lobbying in the European Union is chosen. Other than because of its political relevance due to the Qatargate scandal as discussed above, as it will be highlighted in Section 3.4.2, the studying of climate lobbying in the EU is still a limited field compared to the studies that study the same in the US. On the downside, the data source for lobbying data, the EU Transparency Register, has its own data limitations that create some challenges for the intent that the goal of this thesis (see Section 3.3.4 for a more thorough discussion of the Register). Because this thesis is being written in a European university, this geographical focus is, in the end, chosen.

To summarize, lobbying is chosen as the focus of this analysis because of feasibility reasons (both from a skill and data-availability points of view) and because of its novelty in the field of greenwashing. The EU focus is chosen because of the relevance of lobbying there and to the author. Therefore, the EU Transparency Register is chosen as data source for this thesis.

3.3 Requirements and data selection

In this section, I will discuss the objectives that my approach should meet and their corresponding criteria for evaluation, which is the answer to SQ1 ("What operationalizable criteria can be used to determine the success of the approach?"), and the data and its selection process for the communication and lobbying parts of this approach that stem from the research scope described above.

The objectives will be presented in Section 3.3.1. These have been retrieved from the literature that discusses objectives for scientific methods, specifically data science and AI ones, the fields of this research. Moreover, since the evaluation of my approach will be based on a small-case evaluation, the criteria for selecting such a case will also be discussed in Section 3.3.2 and evaluation case picked that satisfies these requirements will also be presented there.

Section 3.3.3 and 3.3.4 contain the procedure to select the data needed to create the communication and lobbying parts of the final approach, respectively.

3.3.1 Criteria for approach evaluation

The objectives that my approach should meet are accuracy, transparency, reproducibility, and reusability. Accuracy is a “central tenet” of science (Ma et al., 2021) and along with transparency are at the heart of FACT (fairness, accuracy, confidentiality, and transparency) principles of responsible data science (Van Der Aalst et al., 2017). Reproducibility is also a “central concept in science” (Gundersen, 2021) and reusability stems from the FAIR (findable, accessible, interoperable, and reusable) of open science (Wolf et al., 2021). The FACT and FAIR principles have been taken into consideration because these are leading principles in the data science field in which this approach has its roots. From these two principles, only accuracy, transparency, and reusability have been chosen as objective for the approach created in this thesis because of time constraints.

Since my approach consists of studying communication and lobbying, to then combine these results to form a greenwashing inspection, the objectives discussed here will be operationalized for each of these three parts to account for the differences in the analyses. In Table 1, the criteria for the identified objectives are summarized.

First, accuracy is a “foundational scientific challenge” of data science analysis (Van Der Aalst et al., 2017). As defined by Ma et al. (2021), accuracy is “the quality or state of being correct or precise”. It can also be defined as the ratio of the number of correctly predicted observations over the total number of observations (Ma et al., 2021). This latter definition is what will be used to check for the accuracy of the communication method in Chapter 4 because in that situation data whose true value is known will be used. This may not be the case for the evaluation of the overall approach because such data may not be available: for example, the data used for the analysis of the case may not be accessible to the public or may have been analyzed with a method or approach that differs from what will be created in this research. Thus, the operationalized definition discussed by Mai et al. (2021) is not applicable here.

Another way to test for the accuracy of the overall approach is discussed in Oppong-Tawiah and Webster (2023). This paper was discussed in the literature review presented in Chapter 2: it presents an automatic method that detects greenwashing claims of firms on Tweets. Their accuracy criterion is whether the method that the authors create can distinguish between the communication of companies in the oil and gas sector and those in the environmental management industry. The reason why this exercise tests accuracy is due to the assumption that the authors have that oil and gas companies are greenwashing and the others don’t (that is, the industrial sector determines the greenwashing activities). For the evaluation conducted in this thesis, I could overcome this assumption by testing whether my approach is able to detect the greenwashing of companies that have been documented to do so, without the need to make assumptions. In this way, the demonstrations case will be used to test for accuracy. Therefore, all three parts, communication, lobbying, and greenwashing part should be able to identify what the sources of the evaluation cases point to respectively to what these parts analyze.

As for accuracy, transparency is another "foundational scientific challenge" of data science because it enables users to trust and interpret the results thus making data science effective (Van Der Aalst et al., 2017). This is especially relevant because the output of this research is aimed to be used by the public. Transparency is part of the openness of data science, a trend that has developed over recent years (Brunsdon & Comber, 2020). Transparency is defined by Moravcsik (2019) as the "obligation to make data, analysis, methods, and interpretive choices underlying their claims visible in a way that allows others to evaluate them". The whole pipeline of data science projects from the initial raw data to the final interferences involves multiple steps should be comprehensively accounted for when discussing the transparency of methods (Van Der Aalst et al., 2017). Moreover, transparency has three dimensions as discussed in Moravcsik (2019): *data* transparency entails researchers making the data that they use and produce available; *analytic* transparency obliges researchers to disclose how they analyze data; finally, *production* transparency requires scientists to share the "broader set of research design and method choices" that they make. Therefore, for each of the three main steps of my approach – communication, lobbying, and greenwashing – each of these three dimensions will be discussed if possible. Note that for the final greenwashing part the transparency of the data is not applicable since the input data here is the output of the two previous steps.

The third objective is reproducibility. As described by Gundersen (2021), it is the "ability of independent investigators to draw the same conclusions from an experiment by following the documentation shared by the original investigators". As the definition hints, reproducibility is related to transparency because it deals with what researchers share. Moreover, Gundersen (2021) says that there are three degrees of reproducibility:

- *Outcome*: the final results are the same as the ones produced originally;
- *Analysis*: the same analysis on the outcome (such as statistics) is applied to the outcomes but the outcomes do not have to be the same as the originally produced;
- *Interpretation*: the outcomes and the analysis can be different but the same interpretations (that is, conclusions) can be drawn.

Therefore, these three different levels will be analyzed for each part of my approach.

Finally, the last objective that the approach should pursue is reusability. It is a principle of open science (Wolf et al., 2021) and it mainly regards the data that is used for the analysis (Wilkinson et al., 2016). Reusability is defined as the "ease of using data for legitimate scientific research by one or more communities of research (consumer communities) that is produced by other communities of research (producer communities)" as described by Thanos (2017). While the easiness of re-using the data that will be produced by this research can't be tested because this data won't be used by anyone else but the author of this research by the time this report will be published, Wilkinson et al. (2016) prescribes a main principle that should be applied to ensure reusability: "meta(data) are richly described with a plurality of accurate and relevant attributes". Thus, in the evaluation phase, I will check whether the data that will be created during the research phase meets this criterion. Note that this criterion can be applied to the greenwashing part because no data is generated there.

Objective	Communication criteria	Lobbying criteria	Greenwashing criteria
Accuracy	Is the method able to identify the problematic communication the sources talk about?	Lobbying: is the method able to identify the lobbying activities the sources talk about?	With the results of the communication and lobbying analysis, can we draw a greenwashing accusation as discussed in the sources?
Transparency	*Data* : is data used and produced publicly available? *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?	*Data* : is data used and produced publicly available? *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?	*Data* : N/A *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?
Rreproducbility	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?
Reusability	Is the data richly described?	Is the data richly described?	N/A

Table 1. The criteria to test each objective are described for each part of the approach, communication, lobbying, and greenwashing. Note that "N/A" means "not applicable" and it is used when a dimension of analysis for an objective doesn't apply for the corresponding part.

3.3.2 Selection of evaluation case

A case to be analyzed via my approach is needed for multiple reasons: the demonstration of my approach is the fourth step of the design research approach discussed in Peffers et al. (2007); the demonstration results can be used to test the accuracy of my approach as described above; finally, there is need for new data to properly test each part of the approach because, for example, the data that will be collected for the communication part of the approach will be used to test its accuracy..

The case I will use to evaluate my approach should meet the following criteria:

1. The case should concern companies, not governments or NGOs since this is the focus of the research.
2. Since my approach needs to analyze communication and lobbying to analyze greenwashing, the case selected should contain all of these elements. Thus, if the companies are accused of greenwashing because of a mismatch between what they communicate online and new polluting projects that they plan to implement, that is not suitable for evaluating this approach since the lobbying part is missing. Moreover, the lobbying of the case should be carried out at the European Union level because that is the scope chosen for this research. Possibly, the case should be about companies greenwashing to fully test the accuracy of the approach. If all these elements are present, then the case can be considered representative of the phenomenon and in this way typical (Seawright & Gerring, 2008).
3. Since greenwashing can rest in the "eye of the beholder" (Seele and Gatti, 2015), the source of the greenwashing analysis should be trustworthy, such as well-regarded newspapers, researchers, or NGOs. If possible, multiple sources of information should be included.

The case that meets these criteria and, therefore, it is selected to be used for the demonstration of the approach (Chapter 5) is about the world's five biggest oil and gas companies, BP, Chevron, ExxonMobil, Shell, and TotalEnergies, as discussed in Corporate Europe Observatory et al. (2019) and InfluenceMap (2019). These companies declared spending more than a quarter of a billion euros between 2010 and 2018 on lobbying the EU against climate regulations (Corporate Europe Observatory et al., 2019) while at the same time running branding campaigns that "position them as on board with an ambitious climate change agenda" after the signing of the Paris Agreement (InfluenceMap, 2019). This then leads to a mismatch between these companies' efforts in green communication and their actual lobbying decisions (InfluenceMap, 2019) which can be called greenwashing per the definitions discussed in Chapter 2 (such as Gatti et al., 2021) (note that in the report the companies' actions are not explicitly labeled as greenwashing but only the mismatch between their actions and deeds is highlighted. This mismatch is what is seen by the author of this research as proof to accuse these companies of greenwashing). And, at least for ExxonMobil and Chevron, InfluenceMap (2023) shows that there is still evidence of both such behaviors now.

It is important to mention that the InfluenceMap (2019) report discusses the mismatch between words and the lobbying activities in a US setting but with the proof of their negative lobbying activities at the EU level brought by Corporate Europe Observatory et al. (2019), then the greenwashing conclusions drawn by InfluenceMap (2019) are applicable and these companies can be accused of greenwashing also for what they did in Europe.

This case meets the 3 criteria discussed above for case selection:

1. The case does concern companies since these are businesses operating in the oil and gas sector.
2. All three elements of interest for my approach are present in the case: InfluenceMap (2019) discusses the companies' green communication activities; Corporate Europe Observatory et al. (2019) report on their lobbying spending on green regulations in the EU; finally, InfluenceMap (2019) draws the conclusions that can lead to a greenwashing accusation.
3. The sources cited are created by important and well-regarded NGOs: one of the NGOs behind the Corporate Europe Observatory et al. (2019) is Greenpeace and InfluenceMap is a leader in monitoring lobbying activities. Moreover, both of these reports have been shared and discussed in well-regarded newspapers: for example, articles on them have been published in The Guardian, respectively, Laville (2019) and Laville (2021).

3.3.3 Selection criteria for communication data

As discussed in Section 3.2.1, the focus of the approach for the communication part should be on what companies publish online on their official websites regarding climate change. To create the communication part of the approach, samples of communications at a sentence level from official websites of companies will be needed from few companies. Here, I will discuss the procedure to select such companies and their online communications.

3.3.3.1 Selection of sample companies

The goal of the selection of companies will be to pick those that have potentially enough communication around the issues of climate change, the focus of analysis. A good place to find such companies will be the Fortune 500: this is aligned with what has been done in past literature (e.g., Thaker, 2019; Ihlen, 2009) and their large economic activities make these companies powerful actors capable of shaping public discourse around the issue of climate change (Thaker, 2019), and, therefore, most likely to present online communication about climate change, as desired.

To select a meaningful sample of companies, a few rules should be applied. First, the companies the final approach will be evaluated on need to be excluded from the pool because that could introduce bias in the sample (these are ExxonMobil and Shell, as discussed above). Moreover, the sample of companies should display variety in the information contained: variety in terms of industrial sector and location (so not to create an approach that is context specific), lobbying activities in the EU (since the approach will also study lobbying: if only companies that lobby in the EU were included, then the approach would potentially be biased toward such companies and not those that do not lobby), and potential position on the environmental transition (since the approach will analyze what companies say on climate change, it is important to include companies that potentially have different positions on it). To create the sample, the companies that can give the greatest variety should be picked: that is, the companies that give the greatest coverage of most categories (the companies whose information will be "dominated" by other companies will be removed). If in doubt between companies, a practical rule to pick companies will be to select those that can be seen as more likely to be communicating more about climate change because of the sector they operate in (e.g., oil and gas and energy). Therefore, the categories to use are:

- *Sector and location*. The data will come from Fortune (2023).
- *Lobbying activities*. This category is included because the approach researched here also analyzes lobbying. Their lobbying activities can be found by looking at the Transparency Registry as the created approach will do (European Parliament et al., n.d. See Section 4.2. for a thorough discussion of the lobbying analysis and the use of the Transparency Register): the companies can be searched on the Registry (directly on the online portal); the resulting company's entry in the database (or other trade associations or foundation that represent the company) can be analyzed and it can be determined whether the company (or its trade associations or foundation) are lobbying on climate issues (by looking at the "Specific activities covered by the Register" section on the Register). This will be a simpler version of how the created approach, in the end, analyzes the Register.
- *Stance on climate issues*. To quickly understand the stance of the companies on climate issues (e.g., whether they support climate measures or not), data from the Net Zero Tracker (Energy & Climate Intelligence Unit et al., n.d.b), a database covering the net zero targets of companies and nations, can be used. For each company, the "End target status" variable can be seen as a proxy for their climate change commitments: this variable expresses how strongly the net zero targets are internalized in the companies' operations, and it can be assumed that these commitments to net zero targets can more broadly describe the stance of the companies on climate change issues.

3.3.3.2 Selection of webpages

To gather the selected companies' online communications data on climate change, a restricted Google search can yield relevant webpages which then can be easily filtered. The goal will be to collect the companies' sentences from these resulting webpages that discuss climate change.

First, since the goal of the communication analysis will be to study the companies' positions on climate change, the word "climate" should be searched on Google because it is a keyword in climate change debates (Ihlen, 2009). Moreover, the results should be restricted to what is contained on the companies' corporate websites (by using "site:" search operator) so to only gather their official statements. Therefore, the Google query should look like this "climate site:company-website.com".

The second step will be to select those results that potentially contain the stance of the company on the topic. For example, the article called "In China, climate action is a matter for the country's leaders" (Uniper, 2021) on the news section of Uniper's website should in this way be excluded because the focus is not Uniper's activities and opinions, but a descriptive discussion of China's climate policies that doesn't highlight Uniper's opinions on climate change nor on China's climate policies. A variety of data sources such as companies' webpages, companies' websites' news sections, and reports, should be included to guarantee diversity in the sample dataset.

If the data collected needed to be enriched, the previous two steps could be repeated with different keywords. For each company, a climate change-related topic that the sector of the company is associated with can be picked and its keyword can be searched on Google as previously described. This idea lays on the assumption that companies would present multiple results on such ad-hoc topics that are relevant for them.

3.3.4 Lobbying data: the EU Transparency Register

In this section, I will present the EU Transparency Register (TR) that is going to be at the center of the lobbying part of the approach. The TR is chosen as the source of the analysis because it contains the mandatory disclosure of companies regarding their lobbying activities in the EU as discussed in Section 3.2.2. This makes it a suitable data source for the literature that studies lobbying in the EU as will be discussed in Section 3.4.2.

The Transparency Register was created in 2008 as a voluntary disclosure platform (European Commission, 2008). In 2021, with the Interinstitutional Agreement on a mandatory transparency register (2021), the TR became mandatory for all the parties "with the objective of influencing the formulation or implementation of policy or legislation, or the decision-making processes of" the EU institutions. As seen in the text of the agreement (Interinstitutional Agreement on a mandatory transparency register, 2021), these activities include:

- "organising or participating in meetings, conferences or events, as well as engaging in any similar contacts with Union institutions;
- contributing to or participating in consultations, hearings or other similar initiatives;
- organising communication campaigns, platforms, networks and grassroots initiatives;
- preparing or commissioning policy and position papers, amendments, opinion polls and surveys, open letters and other communication or information material, and commissioning and carrying out research."

Therefore, the activities reported include both elements of direct and indirect lobbying. Note that direct lobbying happens when companies are, among others, directly engaging with government officials or making political contributions, whereas indirect lobbying involves PR campaigns, contributions to NGOs, research institutes, academia, among other activities (Principles for Responsible Investment et al., 2018). The parties registered in the TR must comply with a code of conduct which includes that the information they provide must be accurate and up to date (*Lobbying Regulation — the EU Mandatory Transparency Register*, n.d.). The TR has a public webpage where companies can register and update their information, which can be freely examined by the public (*What is the Transparency Register?* n.d.). It is worth mentioning that, in this data, historical data is not available on the TR website since the information there is up to date. Historical information of the TR can be retrieved from the official portal for European data run by the European Commission in an Excel format (Secretariat-General, n.d.). The same data can also be retrieved from the LobbyFacts website, which tracks the information of the TR over time and is run by two NGOs (Corporate Europe Observatory & Lobby Control, n.d.). In the Register, the information published includes general details (e.g., address of the head office), descriptions of the interests they cover, specific activities that are covered in the register, financial information such as the total expenditures for the activities covered by the Register and the full-time equivalent of the persons involved in the activities, and a list of meetings with the European Commissioners, Members of their Cabinet or Director-Generals (*Lobbying Regulation — the EU Mandatory Transparency Register*, n.d.).

Of all the information provided on the Transparency Register, there are two main variables that can be of interest for this research. The first one is the total expenditures that the registrants undergo for their activities since this has been widely studied in past literature (e.g., Brulle, 2018, as it will be more thoroughly discussed in Section 3.4.2). The issue with this data is that it accounts for all the lobbying efforts of the companies without differentiating between the different activities covered by the Register or the different fields of interest that the companies focus on (which they declare on the Register). To overcome this issue, the use of the second variable, the list of meetings with Commissioners and their staff, can be used. These lists contain, other than practical elements such as when the meeting was held and who participated, a brief description of the meetings. The lists contain all the meetings since the company in question since December 1, 2014.[2] By analyzing such information, it would be possible to determine the share of meetings that are relevant to a specific sector or, as far as this thesis is concerned, to climate change regulations. This share could be a proxy of the lobbying intensity of the companies on climate change issues.

It is important to mention that it won't be possible to understand from what the TR contains whether companies are lobbying against or for certain regulations because, for example, the description of their interests or of the meetings is just simple keywords that do not give away the company's intentions. This issue is present and shared in the literature that studies lobbying (as, for example, in the leading papers that discuss climate lobbying in the US described in Section 3.4.2).

To practically carry out the analysis, the full Transparency Register data can be downloaded from the European Commission data portal (Secretariat-General, n.d.): the data is an Excel file which contains the information present on the portal as of January 2023 and each row contains the data for a company. In this file, the companies' meetings are not listed: this can be downloaded from the LobbyFacts website (Corporate Europe Observatory & Lobby Control, n.d.) in a convenient Excel file (note that these lists are also present in the Transparency Register website, but in a PDF format).

3.4 Review of existing literature for building the approach

In this section, I will describe the literature and other relevant sources that will inform the creation of the approach (the details of the approach can be found in Chapter 4). Academic literature is reviewed to understand current ways in which communication and lobbying are analyzed. Furthermore, I will review existing indexes and reports to find ways in which companies' ESG performances are displayed to inform the presentation of the final results that the approach will produce.

3.4.1 Communication

In this section, I will describe possible ways discussed in the literature to analyze companies' communication and discuss their applicability to this research.

3.4.1.1 Overview of literature

To get an overview of how communication is analyzed in literature, different methods, techniques, analytical framework were reviewed: the review of literature starts with the study of frames because this method was already suggested in the literature regarding greenwashing (e.g., Jones, 2019, and Plec and Pettenger, 2012) discussed in Chapter 2. Then, in a snowball kind of manner, other methods, techniques, and framework are encountered because these are either mentioned in the papers or gray literature (e.g., Medium articles) that are analyzed, are priorly known or suggested by supervisors. To limit the search, only methods, techniques, and frameworks that analyze companies' communication from a linguistic perspective are studied because these can be more easily accessible

[2] This information comes from the web version of the Transparency Register: on any company's page, you can see it when hovering over the "info" symbol next to the "List of meetings with the European Commission" section.

to the “conventional” stakeholder this approach is aimed for as Contreras-Pacheco and Claasen (2017) point to.

The first branch of research investigated is discourse analysis (frame studies belong here) because these methods and framework all aim to analyze the general discourse in the communication of entities since language is not a “neutral means of reflecting or describing the world” (Tannen, n.d.; Gill, 2000). Table 2 describes the methods and framework within discourse analysis that are analyzed.

The second branch studied is content analysis because it enables researchers to quantify the presence of themes, concepts, and words and their relations and meanings in qualitative data such as written text and interviews (*Content Analysis*, 2023). Moreover, content analysis has gained popularity in studying corporate communications (Lischka, 2022) which makes these techniques of interest for this research. Table 3 describes the methods and techniques that fall within this branch that are analyzed.

It is important to highlight the difference between the two branches of research methods. This is clearly explained by Herrera and Braumoeller (2004):

While discourse analysis and content analysis are both interested in exploring social reality, the two methods differ fundamentally in their assumptions about the nature of that reality and of the role of language in particular. Where discourse analysis highlights the precarious nature of meaning and focuses on exploring its shifting and contested nature, content analysis assumes a consistency of meaning that allows for occurrences of words (or other, larger units of text) to be assumed equivalent and counted. Where discourse analysis focuses on the relation between text and context, content analysis focuses on the text abstracted from its contexts. […] While discourse analysis is concerned with the development of meaning and in how it changes over time, content analysis assumes a consistency of meaning that allows counting and coding. Where discourse analysts see change and flux, content analysts look for consistency and stability.

From literature	Description	Relevance to this thesis	Pros of applying here	Cons of applying here
Qualitative Frame Analysis	Framing is "the process of culling a few elements of perceived reality and assembling a narrative that highlights the connections among them to promote a particular interpretation" (Entman, 2007).	Some several frames or narratives are identified from communication of companies around climate change issues: commitments (Parafiniuk & Smith, 2019); consumer power, philanthropy, scientific innovation (Jones, 2019); energy supply/security, capitalist marketplace, "eco-sell" ("positioning a top-level executive as an 'environmental visionary'") (Plec & Pettenger, 2012); techno-optimism, necessitarianism, and countermeasures (Megura & Gunderson, 2022); fossil fuels as "saviors" and scientific uncertainty (Supran & Орескес, 2021).	Qualitative frame analysis has given many insights into how corporations communicate around climate change, and this could be applied with the goal of identifying greenwashing.	The main issue is that there is a lack of studies that aim to automate the frame analysis. The highest level of automation in frame analysis in general is achieved via quantitative frame analysis. Focusing on automating this would be a thesis of its own which is not aligned with the research question of this thesis since it also deals with corporates' actions and, then, greenwashing.
Quantitative Frame Analysis	Another way to do frame analysis is a quantitative approach which the goal is to examine overall trends in the data (e.g., counting the frequency of words) (Linström & Marais, 2012).	An example of this technique in corporate communication can be found in Schnurr et al. (2016): they compare the most frequent keywords to a standard English corpus to determine how unique these keywords are. But then, to make sense of the frames that are in the text they do a qualitative analysis.	The analysis of the most frequent words and keywords can be easily carried out with the use of any programming language.	However, this quantitative analysis would not create substantial insights because it can't give insights in how people perceive and understand communication (Linström & Marais, 2012).
Narrative Policy Framework (NPF)	It advances the studying of frames to how policies are created because of how policies are discussed on narratives terrains (e.g., on media) (Shanahan et al., 2018). The NPF has core elements that should be analyzed: setting, characters, plot, and moral of the story (Shanahan et al., 2018).	The focus on the policy could be relevant to the study of greenwashing done in this thesis because it would match the lobbying analysis that these companies do on policies. Moreover, Wolton et al. (2021) describe a semi-automated way to run an NPF analysis: with self-made dictionaries and the help of topic modeling, they select segments of text that represent each of the elements of NPF; then, they use sentiment analysis to categorize the core elements (e.g., the characters categorized as villains, victims, or heroes).	The above also applies here since the NPF also studies frames. Moreover, Wolton et al. (2021)'s research is a potentially good starting point for creating the automated analysis needed for this research.	The NPF has several core elements that should all be analyzed to have a complete understanding of the process: trying to automate this full analysis would be a thesis of its own and, therefore, the thesis would lose sight of my goal of studying greenwashing.

Table 2. Discourse analysis methods and framework. Each of these is briefly described, the reason why it is relevant for this research is presented, the pros and cons of applying it for this research are discussed.

From literature	Description	Relevance to this thesis	Pros of applying here	Cons of applying here
Coding Qualitative Data	This is a general technique to analyze qualitative data in order to gain a deeper understanding of the data by continually refining the interpretation of the data (Basit, 2003). Inductive coding entails the researchers assigning categorical labels (codes) to parts of the text and refining the labels with a deeper understanding of the text (Thomas, 2006). In deductive coding, the codes are pre-determined and then applied to a dataset (Haug et al., 2021).	Coding can be considered as the conventional qualitative content analysis (Zhang & Wildemuth, 2005). Examples of studies that employ coding for studying corporate communication can be found in Talbot and Boiral (2014) (inductive coding) and Thaker (2019) (deductive coding).	It is a widely used technique for content analysis purposes and would help in better understanding the content the approach will deal with.	These methods are manual methods that lack automation (there are computer programs that can assist in the coding as described in Chandra and Shang, 2017, or automation of coding as got as far as semi-automation as described, for example, in Rietz and Maedche, 2021)). Moreover, the output of this analysis is labeled data which would then need to be used for further steps.
Topic Modeling	It refers to generative probabilistic models that find topics in the texts as lists of words with a high probability of co-occurrence (Jaworska & Nanda, 2016). Other than for the number of topics in the topic which must be specified by the user, these models are unsupervised (Jaworska & Nanda, 2016).	This technique could be used to understand semantic frames, thematic patterns, and discourses (Jaworska & Nanda, 2016). Topic modeling is used in studying corporate communication (Jaworska & Nanda, 2016; Lischka, 2022).	The fact that it is an unsupervised technique makes it easily applicable because there is no need to pre-label the code.	The main limitation of this technique is that its outputs must then be interpreted qualitatively by the researchers because the lists of keywords need to be made sense of to understand what the topic they represent is about (Jaworska & Nanda, 2016).
Opinion Mining	Also known as sentiment analysis, it classifies the data based on the polarity (positive or negative connotation) of the language used (Sánchez-Núñez et al., 2020). Opinion mining is a fully automated task: it ranges from lexicon-based approaches (with widely available libraries that have these dictionaries) to more complex supervised and	Opinion mining is widely used in studying corporate marketing communication (Sánchez-Núñez et al., 2020). Mućko (2021) uses this to study the sentiment in CSR disclosures of EU companies.	The existence of a variety of already pre-trained models (as seen, for example, on Bits, 2023) that are publicly available makes this technique easy to use	The main issue with this technique is that it can be used as a step in a larger method rather than as the only method of analysis: for example, as seen in Wolton et al. (2021), the selection of sentences that the researchers are interested in studying with opinion mining techniques is done previously with other techniques. In this example, the method of selection of the sentences becomes more important

	unsupervised ML algorithms (Medhat et al., 2014).			because the results of opinion mining depend on that.
Relationship Extraction	The goal of this method is to be able to extract the relations between entities mentioned in a text, thus giving structure to unstructured data (Bach & Badaskar, 2007). Different algorithms implement relationship extraction, from rules-based approaches to more complex deep learning methods, from fully supervised methods to distant supervision methods and unsupervised ones (clustering) (Detroja et al., 2023). The general steps of this analysis are first identifying the entities and then determining their relations.	These techniques could be used to determine the self-declared relations of companies with climate change, climate change regulations, and so on.	It is a field of study that is widely analyzed, and multiple automated techniques could be implemented (Detroja et al., 2023)	The issue is that determining at this point the kinds of entities whose relations I am interested in analyzing (the first step of the analysis) may be limiting the scope of the research and, thus, preventing it from finding unthought elements. Moreover, most of the automated techniques are supervised ones (Detroja et al., 2023) and the more advanced ones such as deep learning would require large quantities of labeled data.

Table 3. Content analysis methods and techniques. The structure of this table is the same as the one above.

3.4.1.2 Discussion

Of what described above, the ones that can be immediately used for research purposes are topic modeling, opinion mining, and some relation extraction methods. The first technique is an unsupervised one, whereas the latter two already present pre-trained models. While they are already fully automated which is aligned with the goal of this thesis, they present some issues: as explained above, the results of topic modeling still need to be manually interpreted by the researcher to be then properly used for following tasks (this is because the lists of words produced need to be made sense of in order to understand what topic they represent, and, therefore, further manipulations of the topic modeling's results is required), while for the other two techniques, the pre-trained models may not be the right fit for the data that this approach will use (for example, the sentiment analysis tool VADER is designed specifically for social media content - Bits, 2023 – which is then not suited to analyze communication on corporate websites, the focus of the analysis as discussed in Section 3.2.1). Moreover, for opinion mining and relationship extraction, there could be the possibility of creating models with datasets that have been labeled by the researchers that represent the issue at hand (therefore, these models would be *ad-hoc* models for what is being researched): while the accuracy of applying these models to the problem that the researchers want to study could be better than when using pre-trained models, the time needed to create all the labeled data could stop researchers to go down this path.

The other methods, the discourse analysis ones, and qualitative data coding, if used inductively, that is, by inductively finding frames and codes in the text, the different narratives and shades of the texts would be captured: thus, the analysis produced would be richer. But the issue is that these methods are far less automated and more work on this aspect would be required. If these methods were to be carried out deductively, with pre-determined codebooks and dictionaries, then automation would be more easily pursued. At the same time, a lot of effort should be used in creating such codes since the whole analysis would be dependent on them.

All these reflections highlight the general trade-offs between automation and the quality of research that is well explained in Wolton et al. (2021):

"As researchers consider using semi-automated methods, they must also consider the tradeoffs. Automated textual analysis, even with the use of iteratively refined dictionaries, may not detect some nuances of language. In some cases, researchers may consider this an acceptable compromise with the increased generalizability of the findings from having a larger dataset and the gains in reliability from automation. Additionally, while these methods appear to be faster because they are automated, they take a similarly deep consideration of research design as do hand-coding studies. Significant time must be invested in conceptualizing, populating, checking the validity of, and refining dictionaries for this process. And if one is a novice programmer, time must be spent in understanding terminology, data structures, and available software."

From these discussions the creation of the communication part of the approach comes to be: this part will be an automated content analysis which automatically will find codes that will be previously inductively and manually created. The reason behind choosing content analysis was because it is a widely used technique when it comes to the analysis of qualitative text such as the communication of corporations that are to be studied by the approach. Moreover, between content and discourse analysis, content analysis presents more studies that focus on automation, another goal of this research, which then would facilitate the implementation of this method in the research. From what was analyzed of content analysis, inductively coding came as a natural method because it helps in first better understanding the data to analyze and it is a widely used method in this field. And it is chosen over topic modeling because inductive coding can be easily matched with deductive coding: the codes that would be created with inductive coding could be then found on new data with deductive coding. This could be formulated as a classification task because the codes can be seen as labels to be assigned to the new data.

It is important to mention that the choice of using content analysis as a method finds validity in the literature on greenwashing discussed in Chapter 2. Content analysis should be preferred over discourse analysis because, as discussed in Jones (2019), narratives can be "too malleable" to studied with accuracy. Content analysis approaches to corporates' communication are used by Contreras-Pacheco and Claasen (2017), and Blanco et al. (2021). Li et al. (2022) code the companies' reports with previously determined codebooks (this is an instance of deductive coding), whereas Jones (2019) has an inductive approach when analyzing companies' green advertising.

3.4.2 Lobbying

In this section I will present different papers that study lobbying to understand why this phenomenon is relevant for studying greenwashing and how to approach its analysis.

First, it is important to discuss why lobbying is specifically relevant in the context of climate regulation and greenwashing. According to Delmas et al. (2016), the saliency of the political issue is what motivates a company to lobby: in the context of climate policy, this then translates to the companies with the worst and best track records spending the most on lobbying the policy-making process. In turn, this validates the perception that the general public has of dirty industries driving the policy process at the expense of the greater good (Delmas et al., 2016). In this context, though, there can't be found any direct correspondence between the sectors of the economy and the lobbying positions (Brulle, 2018): indeed, Kim et al. (2015) found that the differences among the utility sector lobbying activities in the US in the years 2009-2010 around key climate regulations is due to the difference level of pollution that these companies emitted, with the "expected winners from climate policy" (e.g., companies which used renewable energy) and the "expected losers" (coal users) having different positions.

In terms of greenwashing, it is worth mentioning that, if companies have a mismatch between their declared intentions of support for environmental protection and their spending on lobbying to weaken or decrease environmental regulations, Parafiniuk and Smith (2019) call these companies "green gilded" since "they are coated in a thin layer of environmentalism as a means to deceive the public".

Literature is also interested in quantifying these lobbying efforts. The leading studies that I found analyzed the US situation are Brulle (2018), Delmas et al. (2016), and Kim et al. (2016). The main commonality between these studies is the use of companies' quarterly lobbying reports on direct lobbying which are mandatory in the US thanks to the Lobbying Disclosure Act of 1995 for companies lobbying at the federal level and can be downloaded online, for example, from the Center for Responsive Politics (Brulle, 2018). Then, all these papers proceed to filter these reports based on different keywords which could represent an interest in climate change in general (Brulle, 2018), in some specific bills of interest (Delmas et al., 2016) and could have a specific focus on the sector (Kim et al., 2016). Then these studies carry out different statistical analyses: Brulle (2018) looks into total expenditures per sector and into the relations between the timeline of bills introduced to the US Congress and the variation of lobbying expenditures; Delmas et al. (2016) analyzes how the level of pollution relates to the lobbying activities; Kim et al. (2015) carries a similar analysis as the previous paper but on the utility sector and uses some qualitative case studies analysis to better understand the lobbying positions of companies. All these previous studies are not interested in studying the “direction of lobbying”, that is whether companies are lobbying for or against certain regulations but rather they focus on similar behavior (in terms of expenditures) in sectors.

Since the focus of this analysis is the European Union, it is worth discussing research that studies lobbying on climate change issues there. To do so, I conduct a small literature review using the queries that can be found in the following table.

No.	Query	Results number	Goal of the query
1	(TITLE-ABS-KEY (lobby*) AND TITLE-ABS-KEY ("European Union" OR "EU") AND TITLE-ABS-KEY ("climate change"))	37	To find papers that explicitly studied lobbying on climate change issues.
2	(TITLE-ABS-KEY (lobby*) AND TITLE-ABS-KEY ("European Union" OR "EU") AND TITLE-ABS-KEY ("transparency register"))	24	To study how the Transparency Register is used in studying lobbying activities

Table 4. Description of queries for literature review on climate change lobbying in the EU: query, number of results generated, and intended goal for the query are described.

First, query no. 1 searches for the specific studies on lobbying on climate change in the EU but only a few relevant articles are found: the irrelevant ones, for example, don’t focus on lobbying or study single countries. Of those that are deemed of interest, how they approached the analysis of the lobbying is studied: Wagner et al. (2023) look at the network ties of lobbying activities via surveys; De Bruycker and Colli (2023) use surveys and content analysis of media statements to analyze interest groups’ lobbying efforts; Thomas (2021) runs a qualitative analysis on semi-structured interviews, policy papers, strategy documents, and media sources to understand the steel trade unions’ activities in lobbying the EU; similarly to the previous paper, Gullberg (2013) uses written sources such as commission communications and EP resolutions, along with semi-structured interviews to understand the lobbying efforts of the renewable energy sector.

None of the previous papers use the EU Transparency Register (TR), which contains the corresponding data to what the US papers used and is the data source that is chosen for this thesis (Section 3.2.2). Therefore, the literature review is continued to search for papers that use such a dataset to study lobbying without a specific focus on climate change (query no. 2). The relevant articles are summarized in the following table. These are deemed of interest because they used the TR to quantify lobbying activities.

Article	Fields of interest in the TR	Main method
Dellis (2023). Lobbying and innovation in the European Union.	Total amount of spending, number of employees, meetings with EC members, Persons with EP Pass	The TR data is used to draw a relation between lobbying and aspects of innovation by also using other datasets.
Мамонтова et al. (2021). The Modern Experience of Lobbying Interests in Europe.	Composition of registrants, percentage of Registrants, headquarters within the EU, EU lobbying costs, lobbying costs of large technology companies in Brussels	Statistical analysis of the registrants.

Almansa-Martínez and Ostio (2020). Spanish lobbies listed in the European transparency register	Date of registration; lobbies with headquarters in Brussels, Belgium; data of the individuals who make up the lobbies to know their profiles and their composition; objectives pursued by the lobbies; information on annual costs, to learn about the lobbies, as well as the sectors that allocate more economic resources to the activity; the areas of greater interest to registered pressure groups.	Content analysis models to study the composition of the Spanish lobbying groups in the TR.
Sluban et al. (2018). Profiling the EU lobby organizations in Banking and Finance.	Formal categorization of the Transparency Register and the goals and activities that companies report on the Register	They run a textual clustering on the companies' declared goals on the TR to profile the lobbying companies in the area of banking of finance. In support of this, they use public consultations to identify companies with similar interests.
Hollman and Murdoch (2018). Lobbying cycles in Brussels: Evidence from the rotating presidency of the Council of the European Union.	Registration and de-registration dates. They got historical data on the TR from the Joint Transparency Register Secretariat	Regression analysis to predict when companies would exit based on the Presidency of the Council.
Bloodgood and Tremblay-Boire (2017). Does government funding depoliticize non-governmental organizations? Examining evidence from Europe.	Total lobbying expenditures	Statistical models to analyze the relationship between NGO's political activities and the share of NGO's funding from governments.
Zeng and Battiston (2016). The Multiplex Network of EU Lobby Organizations.	Affiliation data (clients of lobbying firms); declared expenditures; number of lobbying employees	They run a network analysis of the lobbying relations to study the influence of firms

Table 5. Summary of relevant papers concerning the use of the Transparency Register. The "Fields of interest in the TR" are the fields of the TR that are used in the research, "main method" is the description of the analysis that the paper does.

To summarize this discussion of literature, the papers on US lobbying show that lobbying related to climate change can be studied quantitatively in a simple way. This quantification is useful because it makes the understanding of lobbying activities more immediate. The papers that studied lobbying in the EU around climate regulations don't have the goal of quantifying the lobbying activities because they use more qualitative analysis. However, the Transparency Register could be used for this purpose since it contains a variety of data that has been already used quantitatively for studies on lobbying in general or in other sectors. Therefore, the Register is a suitable data source for this thesis given its focus and scope as previously described. Since the goal of my thesis is to use automation for an overall greenwashing analysis, automating existing qualitative ways to analyze lobbying activities as discussed in the results of the first query would necessitate more time than the time span of my thesis permits.

3.4.3 Greenwashing table

To understand how to portray the results of the approach, existing indexes and reports that deal display companies' ESG (environmental, social, and corporate governance) data are researched to see how they portray such data. The ESG focus is chosen because that's broader field of greenwashing. It is important to highlight here what the approach is intended to achieve with the final presentation of results: the users should be let free of coming to their own conclusions regarding whether the companies under analysis are greenwashing or not; therefore, the results produced should be able to inform a greenwashing appraisal (see Section 2.2.2).

Three main ways that such data gets displayed are found: simple scores, categorical variables with a scale built within, and diagrams.

The first group of displays is simple scores. Two examples belong to this category: *Shop ethical!* is a website that provides information regarding the environmental and social records of companies whose products are available in Australia (Ethical Consumer Group, n.d.); *CDP* creates surveys asking companies to disclose their climate impact, and then collects and analyzes their answers (Carbon Disclosure Project, n.d.). For each company analyzed, both websites present their analysis results in the form of a final score on an A-F scale and *Shop ethical!* also shows the sources that they have analyzed to come to that conclusion.

The main issue with this kind of display is the score itself because this doesn't allow much room for interpretation for the user, which is the intent of this research. *Shop ethical!* overcomes this issue by also showing the sources to enable users to verify their scores and (partially) form their own opinions.

The second group entails displaying a variable that has categorical values that have been ordered on a scale. This is better described with an example: the Net Zero Tracker, which analyzes data on companies' and countries' (and other government bodies') net zero targets, displays the status of the companies' net zero targets on a categorical scale which lowest value is "no target" (when a company doesn't have a target at all) to "achieved (validated)" (when a company has achieved their target and this result has been validated by third parties) with in between, among others, "in corporate strategy" (when the target has been added to their strategies documents) (Energy & Climate Intelligence Unit et al., n.d.a). Other examples of these variables are present in CarbonTracker's (Carbon Tracker, 2023), Climate Action 100+'s (Asia Investor Group on Climate Change et al., n.d.), and Science Based Targets Initiative's (CDP et al., n.d.) analyses: CarbonTracker, which studies the impact of supply and demand changes on fossil fuel-exposed companies, categorizes the remuneration alignment with climate performance as "Good", "Neutral", or "Poor"; Climate Action 100+, which also assess the companies' progress on their net-zero transitions, classifies the companies' decarbonization strategies based on how many criteria they meet ("Yes, meets all criteria", "Partial, meets some criteria", or "No, does not meet any criteria"); the Science Based Targets, which measures the progress on scientifically validated climate targets of companies, classifies the net zero targets as (from a more positive to a less positive value) "Targets set", "Committed", or "Commitment removed".

While these are still scores that do limit how much users can interpret the results, the use of meaningful categorical variables makes the results more intelligible than more general A-F scales. Moreover, all these indexes present the companies' analysis with multiple variables of interest which then present categorical variables: thus, the analyses immediately appear multi-faceted, not onesided as in the group discussed previously where only one score is presented, and in this way, users can use all this information to draw their own conclusions.

The final group of displays is represented by two-dimensional diagrams. InfluenceMap (2023) compares the companies' support for policies to the companies' green communication levels (Figure 2) with a similar goal to what this research is intended to achieve, the analysis of their potential greenwashing activities. This display seems fairly open to interpretation because there are no hard coded areas where companies are seen as being more at risk or not: this analysis is done in the text of the report. There are some boundaries or hard coded information that can already shape how the picture is processed: the companies' support for policies ("performance band" on the picture) is depicted as a color-coded scale (from the lowest red "F" to the highest green "A-"); there are hard vertical lines that show (mis)alignment with the Paris agreement which can then influence how a company is perceived (e.g., it is a "good" company because it is aligned with the Paris Agreement); moreover, there are two dotted horizontal lines 1k and 10k pages. However, the scale and the vertical lines are not arbitrarily created because the performance band is computed via a methodology that has been created by InfluenceMap and on which InfluenceMap has complete control over. Not the same can be said for the horizontal lines because on the vertical axis the number of pages containing net zero terms: these lines could influence the observer by saying, for example, companies have low levels of green communication if the number of their webpages containing net zero terms is less than 1k; moreover, these are arbitrarily drawn because there exists no upper boundary (theoretically since not all companies that have a webpage have been tested). But, since these lines are dotted, these are less strict boundaries and can be seen as visualization aids to facilitate understanding the magnitude represented in the picture.

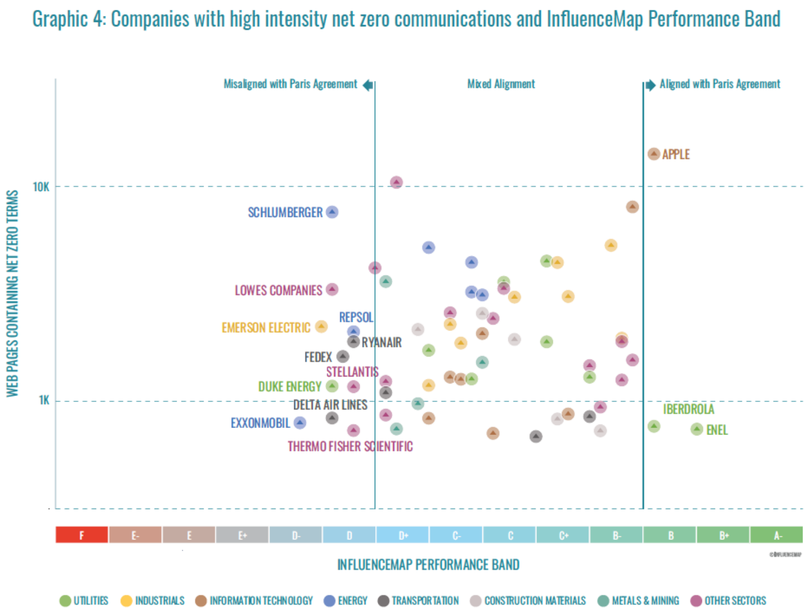


Figure 2. InfluenceMap (2023) displays of policy engagement vs green communication levels. The policy engagement is computed via the InfluenceMap's own performance band (x axis) while the green communication levels are represented by the number of pages containing net zero terms (y axis).

3.5 Limitations

The research approach and scope chosen and discussed in this chapter present some limitations.

First, an overall limitation is that, because of time constraints, only some of the steps of the design research approach discussed in Peffers et al. (2007) are included in the research design: this research will focus only on the "design development", "demonstration", and "evaluation" steps, but it doesn't properly address the problem identification and motivation phase and objectives identification steps. In the report the problem of greenwashing and why it is important to study are discussed in Chapters 1 & 2, and the objectives that are found relevant for this approach are presented in Section 3.3.1. But, since this approach's ultimate goal is to produce an output that can be used by the "conventional stakeholders" mentioned in Contreras-Pacheco and Claasen (2017) such as citizens-consumers, a more thorough way to address these two design research steps would have been to interview a sample of these stakeholders to gather a better understanding of how they perceive the problem at hand and what requirements they would see as relevant in order to better tailor the approach to their needs.

A second overarching limitation of my approach has to deal with the scope that was described above. Because of novelty issues and time limitations, the scope of the analysis of the communication is limited to the study of what companies publish on their online websites and the approach will only analyze one kind of action that companies can take, lobbying: this scope covers only a fraction of what companies can say and do that can then lead to a greenwashing accusation. For example, companies can also use other means of communication such as advertisements of their own products, and these products should be analyzed for their environmental footprints (Jones, 2019). The broader the understanding of the full spectrum of companies' activities, the more chances to find all the ways that companies can do greenwashing since it can happen at multiple levels of the companies' workings (Jones, 2019). Therefore, because of this scope, the created approach could lead to conclusions of the lack of greenwashing from companies because there is no proof of it with the online communication and the lobbying activities whereas the companies under scrutiny are greenwashing with their misleading advertisements on polluting items: because of the scope, the proposed approach could lead to "false negatives". This limitation is intrinsic to the chosen research design and scope and, therefore, users of such an approach should take it into consideration when results that don't show greenwashing evidence are produced.

Regarding the lobbying part of this research, it is worth mentioning as a limitation that the approach won't be able to understand whether companies are lobbying for or against regulations because of the data that it will use, the Transparency Register as discussed in Section 3.3.4. Thus, the numbers from the Register cannot fully represent the companies' lobbying activities for greenwashing purposes. If for example, a company were to support some regulations and oppose others, this would require having two different lobbying expenditures, one for when the company supports regulations and one for when it doesn't: then, the latter numbers should be used for a greenwashing appraisal. This is because it would represent when the company is opposing climate regulations which, if matched with positive climate communications, could, in turn, lead to a mismatch between actions and words and, therefore, greenwashing. But, if the company has predominantly polluting operations, then it can be assumed as lobbying against climate regulations (Kim et al. (2015) as discussed in Section 3.4.2), and, therefore, the Transparency Register's data can be used for a greenwashing appraisal.

For the last part of the approach, the greenwashing table, the collection of the resources didn't follow a rigorous method of research. This was due to time constraints. And it can also connect to the first limitation discussed in the section: if potential users had been interviewed to understand their problem formulation, needs and desires, their opinions could have also informed the creation of this table.

4. Design development

In this chapter, I will present the development of the approach that will be the answer to, specifically, SQ2 ("What semi-automated approach can be created to potentially allow for a holistic study of companies' communication and lobbying efforts?") and the overarching main research question. The approach is created according to the chosen scope discussed in Section 3.2 (and according to the data selection criteria discussed in Sections 3.3.3 and 3.3.4) and its development is informed by the literature reviewed in Section 3.4.

In brief, the approach first analyzes the communication of companies and their lobbying activities, to then combine the results in a table to allow the viewer to come to their own conclusions on whether the data shown is enough to call for greenwashing. The approach itself won't come to a greenwashing *appraisal* because, as the abundance of greenwashing definitions discussed in Chapter 2 suggests, greenwashing can be understood in different ways and the beholder is the final judge. Other than producing a holistic analysis of communication and lobbying efforts, the approach should also pursue semi-automation.

In the first section of this chapter, I will present the communication analysis of this approach. Remembering the lessons learned from the communication literature discussed in Section 3.4.1, I will propose an approach, create it, test it for accuracy, and reflect on its limitations.

In the second section, similarly, from the research reviewed in Section 3.4.2, I will propose and thoroughly discuss an approach that studies direct lobbying of companies at the EU level.

The final step of the approach, the combination of the results of the previous two steps to allow for a reflection on greenwashing, will be presented in the third section: I will propose a way to present the data that learns from the examples discussed in Section 3.4.3 and that improves them. Moreover, a way to interpret the results of the research under a greenwashing lens inspired by the literature discussed in Chapter 2 will also be discussed.

The last two sections of this chapter contain a discussion of the created approach's limitations and a summary of the approach, respectively. This summary will be the answer to SQ2.

An overview of the created approach can be found in the following picture. This figure can be used as an aid when reading the rest of this chapter to see where each part discussed in the text fits in the overall approach created.

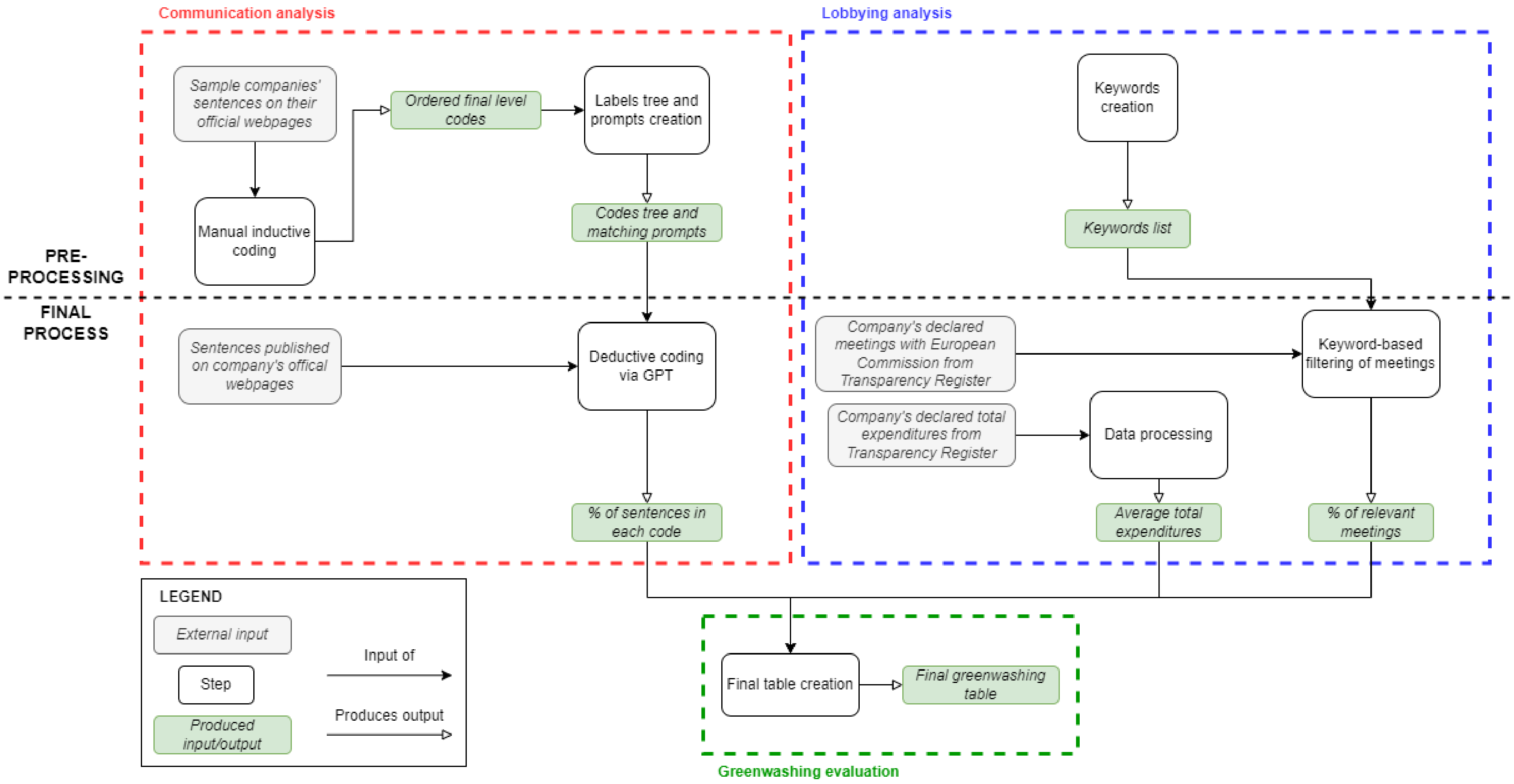


Figure 1. Overview of the overall approach created. The approach is divided in two phases: the final automated process (below the dotted black line) and the pre-processing phase that sets the details of the final automated process (above the line). Moreover, the approach is divided in the communication (within the red dotted box), lobbying (blue), and greenwashing (green) part.

The overall approach can be summarized in the following way. Each of the steps discussed here will be thoroughly discussed in the rest of this chapter.

- The approach has three main parts: one that analyzes the communication of companies, one that scrutinizes their lobbying activities, and the last part combines the results from the two previous ones to understand the greenwashing of companies. This division is informed by the literature discussed in Chapter 2 and the chosen scope shown in Section 3.2.
- The approach is divided into the final automated process that, given a company's communication and lobbying data, produces the final greenwashing table, and the pre-processing phase where the details of such process are created.
- For the communication analysis (see Section 4.1), the final approach consists of using GPT to deductively coding codes that describe companies' communication on climate change. Therefore, in the pre-processing phase the communication that some sample companies have on their official webpages is coded in an inductive manner and, therefore, codes that describe how companies discuss climate change online are produced: these codes show different ranges of intensity of companies' stances on climate change, from companies declaring targets and policies to tackle climate change to companies supporting governments' climate policies to companies making general statements regarding the relevance of climate change. Then, a tree of the codes that facilitate the deductive coding of GPT in a cascade manner is created and, at the same time, the sample companies' coded data is exploited to create prompts to be used for GPT's coding and to maximize for accuracy of the coding tasks. In the final process, a company's sentences are deductively coded using the labels tree and the prompts created and this produces the percentage of sentences that fall within each label at the lower level of the tree.
- Regarding the lobbying analysis (Section 4.2), the final process analyzes both the declared total lobbying expenditures and meetings with European Commission members and their staff of the given company, data that is present on the Transparency Register. For the expenditures, the analysis consists of simply taking the average of the declared range of total expenditures. The analysis of the meetings aims at producing the percentage of meetings that discuss climate change regulations: to do so, in the pre-processing phase, a list of keywords that relate to climate change in general or climate change EU regulations is generated so that in the final process the meetings' descriptions are filtered using them.
- Finally, in the last step (Section 4.3), a table that shows the results of the communication (the percentage of sentences on each code) and lobbying (the average total expenditures and the percentage of relevant meetings) analyses is created for the company analyzed. The data in the table is color-coded according to its position on the values scale of their corresponding variable.

4.1 Communication

The goal of the communication analysis is to analyze corporations' online communications. The scope of this analysis was limited the focus of the analysis will be the stance that companies take around climate change topics and it will be done at the sentence level (Section 3.2.1). As already discussed in Section 3.4.1.2, The approach consists first in inductively creating codes that describe the companies' communication on climate change and, then, in creating a GPT-based method to deductively code these codes.

This section is divided into:

- *Data collection*: the collection of the data needed to understand how companies communicate about climate change is shown. This is carried out according to the data collection procedure discussed in Section 3.3.3.
- *Content analysis*: this section will contain the description of the inductive coding part that is needed to create the codes that will be automatically coded by the final method. This part will belong to the pre-processing phase of the overall approach.
- *Model building*: here the model creation that runs the deductive coding of the previously identified codes will be presented. This deductive coding is part of the final approach that will find potential evidence of greenwashing.

4.1.1 Data collection

In this section, I will discuss the data collection process that is conducted to get the input information for creating the approach. The principles listed in Section 3.3.3 are followed.

4.1.1.1 Selection of sample companies

The first step consists of selecting some companies whose communication is to be analyzed. As discussed in Section 3.3.3.1, the sample companies are selected from the Fortune 500 since their large economic activities make these companies more likely to present communication on the topic of climate change. For time limitations, the selection process is limited to the first 20 companies of the Fortune 500 for the year 2023 (Fortune, 2023) and the sample is limited to six companies. Moreover, to conduct the selection process described in Section 3.3.3.1, those companies that didn't have much relevant data for the four categories that the selection process is based on (see Appendix A – Figure 1 for the companies that were further considered for the picking process) are excluded from this selection process. The selection process follows closely what is discussed in Section 3.3.3.1 and it consists in picking the companies that give the greatest coverage in the four categories: sector, location, lobbying activities in the EU, and potential position on the environmental transition. See Appendix A Figures 2-4 for the companies' values over these categories. At the end of this process, I am left with the following companies: Saudi Aramco, Amazon, Sinopec Group, Volkswagen, Uniper, and McKesson.

4.1.1.2 Selection of webpages

To gather the selected companies' sample communication from their online websites, the steps described in Section 3.3.3.2 are executed: the goal is to select relevant webpages whose sentences are then collected. See Appendix A – Figure 5 for the companies' official websites that are used. Note that for Volkswagen "climate change" was searched for instead of "climate" because by searching with the latter on Google many results related to specific models of cars are returned. For time limitations,

Company	Sector	Other topic	Source
Saudi Aramco, Sinopec Group	Oil	Oil spill	Scott and Pickard (n.d.)
Amazon	Internet service and online retail	waste	Pratt (2020)
Volkswagen	Car manufacturing	greenhouse gas emissions	Leggett (2021); Mamalis et al. (2013)
Uniper	Energy	greenhouse gas emissions	Walton (2020)
McKesson	Health	Energy efficiency	Silverstein (2023)

Table 1. For each company and sector, the other topic I select and the sources backing this decision.

the selection of articles is stopped once further Google results are less significant and/or a similar number of sentences compared to the rest of the companies is analyzed.

To enrich the dataset because it is deemed not to be varied enough of sentences that describe companies' opinions and stances, this research and analysis with a different keyword is repeated. As described in Section 3.3.3.2, a climate change-related topic based on the sector of the company is picked. Table 1 contains the topics that are searched for each company (the structure used for the query is the following: "topic keyword site: company-website.com")

The results of the data collection are the following:

Company	No. of sources analyzed	No. of general webpages	No. of news	No. of reports	No. of total sentences analyzed
Aramco	7	3	1	3	183
Amazon	7	5	1	1	156
Sinopec	4	3	0	1	145
Uniper	7	3	4	0	156
McKesson	4	1	3	0	40
Volkswagen	6	2	4	0	179
TOTAL:	**35**	**17**	**13**	**5**	**859**

Table 2. Descriptions of the sources that are collected per company and kind of resource.

Table 2 shows that my initial assumption that the top Fortune 20 companies would have lots of online data about climate change is true for all companies but for McKesson. This could be because McKesson is a business-to-business company which may then communicate with potential clients over climate issues in a different way.

4.1.2 Content analysis

The goal of this step of the analysis is to better understand what companies are saying around the issue of climate change and what the similarities between companies are. Thus, coding of this qualitative data was chosen as the method of analysis because it involves subsidizing and categorizing the data (Basit, 2003), other than for the reason explained in Section 3.4.1.2. This part is the pre-processing phase of the final approach.

Having gathered all the sentences of analysis, the first round of analysis is deductive coding because the coded categories are inspired by literature (Chandra and Shang, 2017). Each sentence is analyzed and separated between "relevant" and "not relevant". "Relevant" sentences contain a "clear" claim from the company. That is, there should be a topic on which the company says something, and what they say is their position (so they are making a statement regarding themselves). Thus, these sentences contain the company's stance on the issue. The topic is mainly related to climate change because that's what the Google query used to gather this data was about, but there are a couple of sentences that showed some kind of opinion on some other topic (e.g., workers' safety). The "not relevant" sentences are all the rest of the sentences. After having read some articles, all the sentences collected are re-read and all the labels are re-checked. This process is iterative: for example, understanding the categories is iterative in the sense that the process starts with a way to classify the sentences, and by reading more and more sentences the details of the initial classifications are fine-tuned because it is better understood how the companies are communicating. And therefore, all the sentences need to be re-checked.

It is a case of deductive coding because I set out to search for those “relevant” sentences that the literature is suggesting. As already mentioned in the literature review (Chapter 2), looking at the political actions that a company can take, there is greenwashing if a company pledges to environmentalism while this organization or other organizations such as think tanks, trade organizations, or other groups that the company is affiliated to lobby against environmental legislation (Nemes et al., 2022; Lyon and Montgomery, 2015) or to influence policymakers to obtain benefits from sustainability regulations (Contreras-Pacheco and Claasen, 2017). Thus, it could be argued that their claims are lies (TerraChoice, 2010; Wei et al., 2023) or, at least, a form of disinformation/malinformation (Oppong-Tawiah and Webster 2023; also, in Nemes et al., 2022, and Seele and Gatti, 2017).

In this first round of analysis, I also see that companies made general statements regarding a climate change topic which express some general stance or call to action. Since there was quite a relevant number of such kinds of sentences, a new category for them is created, “relevant_general” (thus, this category is achieved via inductive coding). While these sentences do not necessarily imply a company pledging environmentalism, it is decided to keep these sentences in the analysis because of their numbers and because they show at least some kind of awareness from the companies regarding the issue.

In the second round of coding, I analyze the sentences in the two categories that are deemed relevant (“relevant” and “relevant_general”). In this round inductive coding is used to analyze the sentences by looking for similarities without being guided by literature (Thomas, 2006): this inductive approach is chosen because the goal here is to first understand better the data to find codes that are relevant to the data at hand and to then deductively and automatically coding them on new data as described in Section 3.4.1.2. I follow the steps discussed in Thomas (2006) to carry out the analysis: I create the sentences in a hierarchical approach by first creating more general labels and then specializing them in the following rounds of analysis. The following rules to decide when to stop with label creations are used:

- To avoid overfitting the labels to the sample data, labels that are too specific to the data could become irrelevant when applying the method in the evaluation of the whole pipeline and, therefore, should be avoided. For example, I am not making the category "declaration_of_net_zero_target" vs "declaration_of_scope_1_reduction" but instead keeping a more general "declaration_of_target"
- I stop when the sub-class sizes are becoming so small that adding another subclass would lead to such small groups (e.g., just a couple of sentences). This, in turn, would also lead to overfitting.
- Due to time limitations, I limit the tree of hierarchical categories to a depth of four.

Note that I analyze the “relevant” and “relevant_general” sentences separately and, in this way, created two branches of inductive coding trees.

4.1.2.1 Final codes

Table 3 represents the 11 final codes that are created. See Appendix B – Figure 1 for the tree of labels that is created to come to these final labels.

Label name	Definition	Examples
support_for_policy	The company is stating the support for a piece of legilslation.	"The Volkswagen Group is committed to the goals of the Paris Agreement." (Volkswagen)
support_for_government	The company is stating the support for governments' action.	"The Company also supports the Government's efforts to achieve its contributions as a signatory of the Paris Agreement as well as other climate change mitigation and adaptation efforts by the Kingdom." (Aramco)
declaration_of_target	The company is stating to have a target for the topic. For it to be a target claim, there should be a deadline for the company to achieve it (e.g. "by 2040" as in the example).	"We remain committed to reaching net-zero carbon emissions across our operations by 2040." (Amazon)
declaration_of_policy	The company is stating that they have a certain program in place that addresses the topic.	"This investment is one piece of a $10 million commitment Volkswagen has announced to support the electric vehicle charging infrastructure. " (Volkswagen)
beliefs_company_role	The company is stating a belief it has about what the company can do.	"As an organization serving global communities, we have a broad responsibility to mitigate the impacts of our business, while helping to address the environmental and social challenges we collectively face. " (Amazon)
company_beliefs	The company is stating a belief it has about the topic in general.	"We see hydrogen — alongside gas, renewables, and hydroelectricity — as an essential ingredient in tomorrow's low-emission energy mix." (Uniper)
company_priorities	The company is stating what it perceives as their priority and what the company can do.	"Methane emissions remain a focus area for Saudi Aramco, given the greater warming potential of methane, compared to carbon dioxide." (Aramco)
stating_general_goal	The company just states a general goal without details. It is similar to "declaration_of_target" because they may be stating their "commitments" but there are no details to it (for example, there is no deadline as for the "declaration_of_target").	"'Our SBTi targets serve as another example of our commitment to sustainability and our response to climate change.'" (McKesson)
stating_more_detailed_goal	Similar to "stating_general_goal" but the company somewhat hints at how they plan to achieve the goal. But, at the same time, there is no specific deadline as for the "declaration_of_target" label.	"Meanwhile, Volkswagen also plans to reduce the carbon output of its traditional gas vehicles, through greater efficiency gains or hybridization." (Volkswagen)
universal_beliefs	The company makes a general statement that implies some kind of "belief". This category differs from "general_beliefs" because here the company is not explecitly saying that they are the one expressing that belief (e.g., they don't say "we believe that....")	"Climate change is one of the most important global issues impacting business and society." (Aramco)
call_for_action	The company says that actions or policies are needed without claiming that they are going to do it.	"At the same time, carbon emissions must be permanently reduced." (Uniper)

Table 3. Description of final labels. Each label is briefly explained and then an example is given.

This variety of labels shows that the companies can take a variety of stances and positions around the issue of climate change, going from general statements about the impact of climate change ("Climate change is a major global issue for all humankind"[3] from Sinopec) to more specific statements that commit the company to a specific target ("We remain committed to reaching net-zero carbon emissions across our operations by 2040."[4] from Amazon). Table 4 shows that each label indeed has examples of sentences, but as better shown in Table 5, the distribution of sentences over the labels does vary with the two categories that describe goals ("stating_general_goal" and "stating_more_detailed_goal") having the highest number of examples, whereas "support_for_policy" and "support_for_government" have the least number.

Company	support_for_policy	support_for_government	declaration_of_target	declaration_of_policy	beliefs_company_role	company_beliefs	company_priorities	stating_general_goal	stating_more_detailed_goal	call_for_action	universal_beliefs	Relevant	Not relevant	Total. no. sentences:
Aramco	3	1	5	1	3	4	3	11	7	3	5	46	137	183
Sinopec	0	1	1	1	1	1	0	4	5	1	1	16	129	145
Volkswagen	2	0	2	2	1	6	2	11	2	5	3	36	143	179
Amazon	0	0	5	3	2	1	2	7	7	4	1	32	124	156
Uniper	0	0	11	2	1	1	5	5	6	2	1	34	122	156
McKesson	0	0	2	0	1	1	1	5	1	0	0	11	29	40
TOTAL	**5**	**2**	**26**	**9**	**9**	**14**	**13**	**43**	**28**	**15**	**11**	**175**	**684**	**859**

Table 4. Number of sentences per company per final label.

Company	support_for_policy %	support_for_government %	declaration_of_target %	declaration_of_policy %	beliefs_company_role %	company_beliefs %	company_priorities %	stating_general_goal %	stating_more_detailed_goal %	call_for_action %	universal_beliefs %
Aramco	6.52	2.17	10.87	2.17	6.52	8.70	6.52	23.91	15.22	6.52	10.87
Sinopec	0.00	6.25	6.25	6.25	6.25	6.25	0.00	25.00	31.25	6.25	6.25
Volkswagen	5.56	0.00	5.56	5.56	2.78	16.67	5.56	30.56	5.56	13.89	8.33
Amazon	0.00	0.00	15.63	9.38	6.25	3.13	6.25	21.88	21.88	12.50	3.13
Uniper	0.00	0.00	32.35	5.88	2.94	2.94	14.71	14.71	17.65	5.88	2.94
McKesson	0.00	0.00	18.18	0.00	9.09	9.09	9.09	45.45	9.09	0.00	0.00
TOTAL	**2.86**	**1.14**	**14.86**	**5.14**	**5.14**	**8.00**	**7.43**	**24.57**	**16.00**	**8.57**	**6.29**

Table 5. Percentage of sentences per company per final label.

4.1.2.2 Re-ordering of the tree

To better make sense of these final labels, I decide to re-arrange them according to the focus that these sentences: some discuss *actions* that the company takes or has intentions to take, some discuss the *stance* that the companies have on specific *policies* or government's actions, and the others contain the *stance* that companies have on *climate change* in general. This re-ordering also facilitates the comparison of the labels within each of these three categories since they discuss similar focuses. These comparisons will be then needed for the final greenwashing appraisal (see Section 4.3 to see

[3] http://www.sinopecgroup.com/group/en/socialresponsibility/Green/facc.shtml

[4] https://sustainability.aboutamazon.com/climate-solutions

how these comparisons are used). The re-ordered tree is in Figure 2. Table 6 contains a description of the reasons behind the new classification for each label.

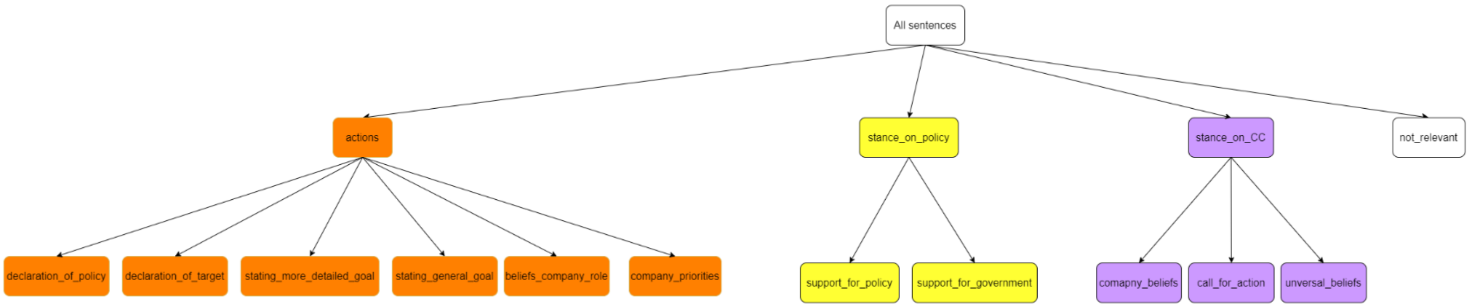


Figure 2. Re-order ed tree according to actions, stance on policy, and stance on climate change focuses. Note that "CC" means "climate change".

Main category	Label	Reason
Actions	declaration_of_policy	The company is declaring a policy that has in place or that will have in place to tackle climate change
	declaration_of_target	The company has a specific target in place (e.g., to be net zero by 2030). This implies that they will have to implement actions to reach that target.
	stating_more_detailed_goal	They state a goal. This implies that they will have to implement actions to reach it.
	stating_general_goal	As above.
	beliefs_company_role	This is a belief that the company has on what it can or should do to tackle climate change. Therefore, it implies that there are actions that the company can or should do.
	company_priorities	The company is stating priorities that the company can act on regarding climate change.
Stance on policy	support_for_policy	The company states its support for a policy that tackles climate change.
	support_for_government	The company states the support for government's actions regarding climate change.
Stance on climate change	company_beliefs	The company states a belief that they have regarding climate change.
	call_for_action	These sentences express beliefs are about what it should be done but it is not clear who is expressing the belief.
	universal_beliefs	These sentences exprese general beliefs around climate change but it is not clear who is expressing the belief.

Table 6. For each final label, I describe why it belongs to the three categories of actions, stance on policy and stance on climate change.

4.1.3 Model building

In this section, a method that can automatically code the codes found in the previous section is built. This method is what the approach will use to analyze new companies (e.g., in the demonstration step of this research shown in Section 5.1).

4.1.3.1 Model choice

I approach this challenge as a classification task because each of the codes can be considered as labels to be associated with sentences. Moreover, by already having labeled data since I inductively created the codes, I could use supervised methods. As discussed by Kowsari et al. (2019), there are multiple existing algorithms that can do this task of classification: these range from machine learning techniques such as Naïve Bayes and decision trees to more complex and more accurate deep learning algorithms such as Convolutional Neural Networks. While accuracy of this classification step should be pursued because that would lead to better results in the final greenwashing analysis which is one of the objectives listed in the main research questions (RQ), deep learning methods require far larger datasets than machine learning ones (Taye, 2023). However, the labeled data that I have is not wide enough for a machine learning algorithm because, as shown in Table 4 some labels such as "support_for_government" contain very few examples. Because of time limitations, it is not deemed feasible to increase the size of the labeled dataset by adding more sentences in the initial sample of sentences because it would entail re-coding all text since new labels could be found because of the added new sentences. Thus, machine learning models are not further examined.

To overcome such data limitations, I decide to use Large Language Models (LLMs), "artificial intelligence systems that can process and generate text with coherent communication, and generalize to multiple tasks" (Naveed et al., 2023), for deductive coding of these classes on new data. This is because using an LLM requires far less labeled data (Hu et al., 2023) and because there are examples of using LLM for general text classification such as Hu et al. (2023), Loukas et al. (2023) and Zhao et al. (2023), for content analysis methods such as relationship extraction as done in Wadhwa et al. (2023), and deductive coding as described in Tai et al. (2023). Note that all these papers are recent and, therefore, it can be concluded that the use of LLM for these purposes is an emerging one. It is worth mentioning that Gilardi et al. (2023) find that ChatGPT, an LLM, outperforms crowd-workers for several annotation tasks of texts including topic, stance, and frame detection. Therefore, LLM can be a helpful tool for both content and discourse analysis and, in this way, can be useful for this thesis. But such models do come with their own issues, for example, their not-deterministic nature as discussed in Reiss (2023) (these models are not deterministic which means that identical inputs can lead to different results. This is what also can happen with human coders) and, similar to deep learning models, LLMs lack transparency in their decision-making, thus turning them into uninterpretable black boxes (Shi et al., 2023).

For my method, I decide to use ChatGPT, an LLM built by OpenAI which has an online interface (*ChatGPT*, n.d. Note that the GPT 3.5 version was used). This model has further issues of its own that are mainly due to its "closed source" nature: as discussed in Shi et al. (2023), the model can't be finetuned to specific datasets or tasks (which could increase accuracy of their analysis) because its parameters are not accessible to the users; Trajanov et al. (2023) show that for NLP tasks that involve climate-related text, ClimateBERT which has been trained on climate-related research performs better than Chat-GPT which is a general purpose LLM. Because of its easiness of use thanks to its online interface, I decide to use GPT for this research.

4.1.3.2 Model creation

In this method, GPT is used to deductively code the previously identified codes to the sentences that can be found in the online communication of a company. The method entails creating prompts that directs GPT into coding the given sentences as one of the codes presented in the prompt (therefore, in the prompt there is a list of codes that GPT needs to use to classify the sentences that follows in the prompt). All the final codes are deductively coded in a cascading manner according to a tree structure that has been created to maximize for the accuracy of the single coding rounds.

For creating the model, how to write prompts to effectively use LLMs and to optimize for the accuracy of the classification tasks are taken into consideration. Moreover, the labeled data created in the previous step (Section 4.1.2) is leveraged to both create more accurate prompts via few-shot learning and to test the accuracy of the coding. Note that I use the ChatGPT web interface to run this model creation phase because it has easy-to-use interactive features.

To use ChatGPT efficiently, the prompts that are used to run the coding tasks need to be carefully thought in order to interact effectively with it: thus, prompt engineering should be pursued to write proper prompts (White, 2023). LLMs can perform tasks from prompts that describe these tasks that need to be executed (zero-shot learning) or with a few examples of these tasks (few-shot learning), that is, with an example input and the corresponding desired output (Touvron et al., 2023). It has been shown that few-shot learning (also called in-context learning) outperforms the zero-shot range on different tasks (Min et al., 2022). For this reason, I use few-shot learning to create my prompts. Another technique from prompt engineering that can be used is explaining the reasoning behind the examples provided: Wei et al. (2022), show how generating a "chain of thought", that is a series of intermediate reasoning steps – improves the ability of LLMs to perform their tasks that involve complex reasonings. When creating the classification method, to increase accuracy I increase the number of examples in the prompts. If that isn't enough, I then proceed to give small explanations of the coding decision behind the provided examples (inspired by chain-of-thoughts prompting) but this happens only in a few situations. Therefore, to increase accuracy I just increase the number of examples, pick better examples for the few-shot learning prompts, and/or add explanations to the examples. See an example in Appendix C – Figure 3 of how increasing the number of examples and giving brief explanations increases accuracies. The resulting structure of prompts can be found in Figure 3.

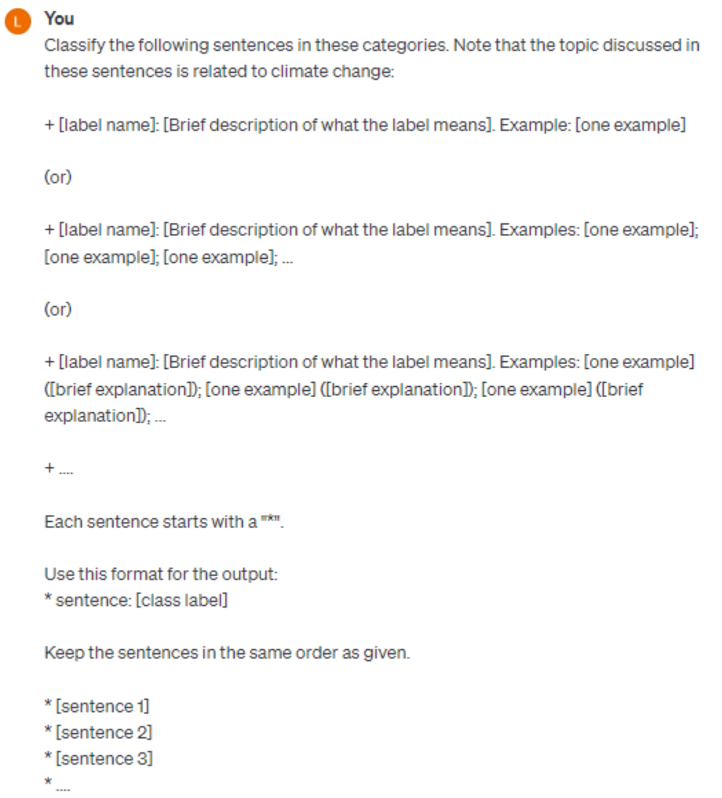


Figure 3. Structure of what the prompt look like on ChatGPT.

To test for the accuracy of the GPT coding, for each round of coding that I do (a coding round consists of a set of codes whose classification I am testing that have the same parent label), I randomly pick 30 sentences (or, if the batch of sentences to pick from is smaller than 30, then as many sentences as possible are used as the testing sample) from the labeled data the classification of its codes I am testing and that are not in the prompt I was using. I ask GPT to code these sentences and then check the accuracy of the labels by comparing the GPT-produced and the original labels. Note that this data is only used for testing purposes since this data doesn't inform the model creation: the testing sentences and the sentences used in the prompts are different.

Another principle that I apply when creating my method is that GPT performed better when the number of codes that I am asking it to code are small in number compared to when I ask to classify

No. of codes used	No. of classification tasks	Average accuracy
2	5	0.865
3	2	0.79
11	1	0.435

Table 7. Accuracy per number of labels to code. In each line the average accuracy obtained when coding the specified number of codes ("No. of codes used") is displayed; the average accuracy is computed on the different examples of classifying that number of codes ("No. of classification tasks"). The average accuracy is the average of the best accuracy achieved for each classification task. For example, the first line says that 5 times it happens that 2 codes are classified at the same time and the resulting average accuracy is 86.5%. Note that while for the first two lines of the table the average is computed over different instances of coding tasks, I only code all the labels via GPT one time (but that is indeed the best accuracy achieved).

larger amounts of labels. I experience this firsthand: when coding all 11 original labels, the highest accuracy achieved is 43% whereas the average accuracy achieved when classifying two or three codes at the same time is much higher as shown in Table 7 (86.5% and 79%, respectively). Note that these accuracies are with few-shot learning prompts.

While applying the considerations above in creating the prompts, I approach the coding of the final labels that I found in a cascade manner: starting with the tree depicted in Figure 2, GPT first codes the upper labels (for example, "actions", "stance_on_policy", and "stance_on_CC") and then, based on these upper classifications, GPT is used to code the lower labels: that is if a sentence is coded as "actions", then GPT is used to code it as one of the "actions" labels in the figure. This is done in order to limit the number of labels that GPT has to code in one round which can be beneficial to the accuracy as described above. Moreover, intermediate labels are created between the labels that are present in Figure 2 in order to maximize the accuracy of the coding. An actual example can better explain the technique. When all three labels are classified under the "stance_of_CC" category, I get an accuracy of 68% and I see that this lower accuracy is due to sentences whose true code is "call_for_action" being misclassified as "universal_beleifs". To me, this makes sense because these two labels come from the same branch of the classification tree that I created when I was inductively coding the sentences (as depicted in Appendix B – Figure 1). Thus, I create a new intermediate label called "common_beleifs"

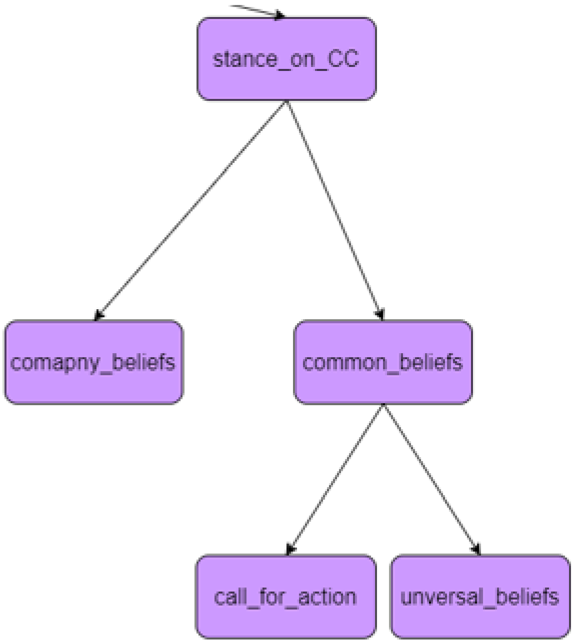


Figure 4. New "stance_on_CC" branch structure after maximizing for accuracy (that is, after introducing the "common_beliefs" mid-level label).

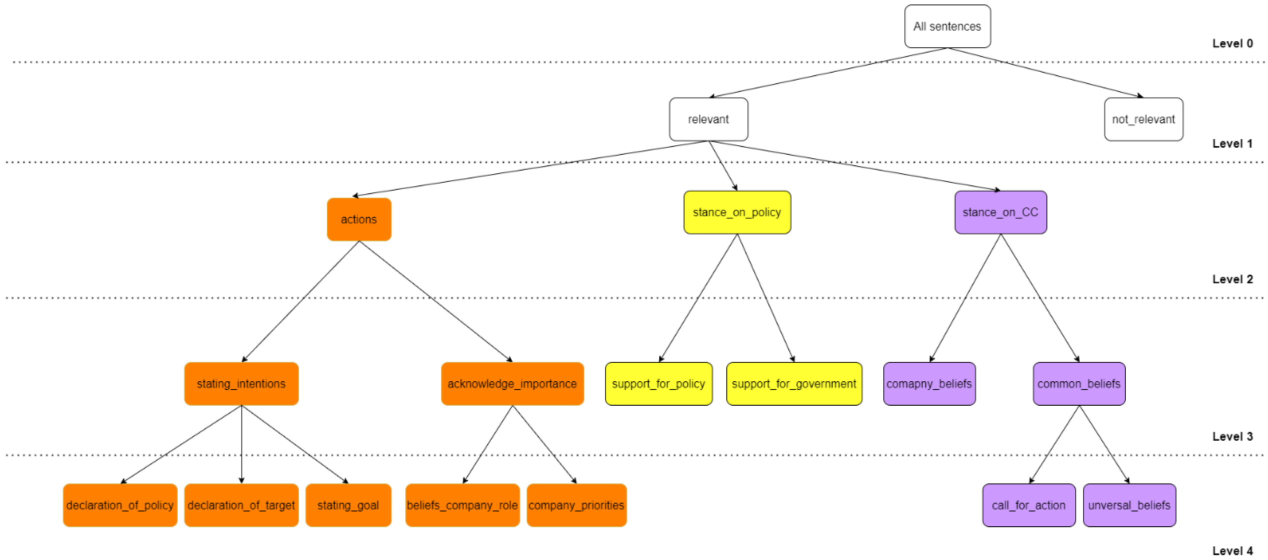


Figure 5. Final classification tree that resulted from the accuracy maximization process described in this section.

that groups these two labels and this branch is transformed to what is shown in Figure 4. This is a good decision because the accuracy of the coding between "company_beliefs" and "common_beliefs" becomes 96% and the coding between "call_for_action" and "universal_beliefs" is 81%. I apply this kind of approach to the "actions" branch while the "stance_on_policy" branch doesn't need so because of the limited number of labels there. Therefore, the final classification tree can be seen in Figure 5. Finally, it is important to mention that the two original labels of "stating_general_goal" and "stating_more_detailed_goal" are merged and not further coded because it is seen that further dividing them would not increase the accuracy of the tree. This is not a loss in terms of the quality of the final coding since these two labels are, in the end, very similar.

Two practical considerations that are also applied. First, to overcome the limitations of non-determinism discussed previously, to test each prompt I run two rounds of coding with GPT and take the average of the accuracy to represent the overall accuracy of the prompts. Secondly, due to time limitations reasons, I decide to stop improving the accuracy of the prompts when I reach an accuracy of around 80%.

4.1.4 Final model and results

The final tree resulting from the process described in Section 4.1.3.2 can be found in Figure 5. This is the tree that is to be used when running the coding of the analysis, from top to bottom. For example, in the first round of coding a sentence is coded between "relevant" and "not_relevant"; then, if it is a "relevant" sentence, the next round of classification is between "actions", "stance_on_policy", and "stance_on_CC"; if it is coded as "stance_on_CC", then in the third round of coding it will coded between "company_beliefs" and "common_beliefs"; if it is coded as "common_beliefs", then the final coding round would be between "call_for_actions" and "universal_beliefs". All these coding rounds are done by submitting to GPT the matching prompt and the sentences to be coded.

Regarding the accuracy of the method, first the accuracy of GPT as a coder needs to be discussed and then the accuracy of *this* coding tree can be analyzed. The average accuracy of all the coding tasks was 0.84. Each coding task is a task that, given the sentences that fall within a higher category (such as "actions"), classifies them between the lower categories ("stating_intentions" or "acknowledge_importance"). In Appendix C – Figure 1, the accuracy for each coding task is reported.

Regarding the accuracy of the created coding tree, the accuracy of the final labels is computed differently because to get to these labels, the method first codes the upper labels in the branch in a cascade manner: thus, the accuracy of the final labels is the multiplication of all the accuracy on the path that starts from the root of the tree (“all sentences”) till the final label. For example, to get to “company_beliefs” on the “stance_on_CC”, first the sentences need to be classified as “relevant”, then as “stance_on_CC”, and, finally, as “company_beliefs”. Therefore, the final accuracy is

$$accuracy(all\ sentences) * accuracy(relevant) * accuracy(stance\_on\_CC) == 0.79 * 0.85 * 0.97 = 0.65$$

Where, for example, $accuracy(relevant)$ is the accuracy achieved when coding all the sentences that were coded as “relevant” between “actions”, “stance_on_policy”, and “stance_on_CC”. By applying this principle to all the final labels, the resulting accuracies for all the final labels are presented in Table 8.

<table>
<tr><th>Label</th><th>declaration_of_policy</th><th>declaration_of_target</th><th>stating_goal</th><th>beliefs_company_role</th><th>company_priorities</th><th>Average accuracy:</th><th>Standard deviation:</th></tr>
<tr><td>Accuracy</td><td>0.385</td><td>0.385</td><td>0.385</td><td>0.407</td><td>0.407</td><td rowspan="3">0.501</td><td rowspan="3">0.124</td></tr>
<tr><td>Label</td><td>support_for_policy</td><td>support_for_governement</td><td>company_beliefs</td><td>call_for_action</td><td>universal_beliefs</td></tr>
<tr><td>Accuracy</td><td>0.670</td><td>0.670</td><td>0.647</td><td>0.526</td><td>0.526</td></tr>
</table>

Table 8. Accuracy per final label., average accuracy and standard deviation of final labels. These are computed for when using the tree depicted in Figure 5.

The accuracy is quite low (50.1%), considering that is comparable to a toss of a coin. This lower average accuracy than the accuracy of GPT as a coder is due to the several numbers of intermediate levels that require to be coded and, thus, that bring their own inaccuracies to the final labels, in a trickle-down effect. Therefore, to increase the accuracy of the overall coding tree, I decide to prune it, that is, to remove some of the lower-level labels. But, at the same time, the tree should have enough lower labels that can be then meaningful for evaluating the greenwashing of companies because that is the ultimate goal of this approach: for example, while keeping only the “actions”, “stance_on_policy”, and “stance_on_CC” would have a much higher accuracy, it would not be meaningful for the overall approach because the nuance of the analysis of the companies’ communication is in the lower levels (for example, in the difference between stating a specific policy to tackle climate change – “declaration_of_policy” – compared to just saying that tackling climate change is one of the companies’ priorities – “company_priorities”). Therefore, to have a good trade-off between the accuracy (number of levels) and the meaningfulness of the tree, I decide to remove the fourth level. The pruned tree can be found in Figure 6. The accuracy, thus, increases to 0.614 (see Appendix C – Figure 2 for the values of all the lower label accuracies) when using the pruned tree and the final level of this tree contains different labels that enable to analyze different shades of companies’ communications. The prompts that achieve this accuracy and that are to be used for running the approach can be seen in Appendix D, along with a brief summary of how to run the deductive coding method up until now discussed. A description of the lower labels and their root labels can be found in Table 9.

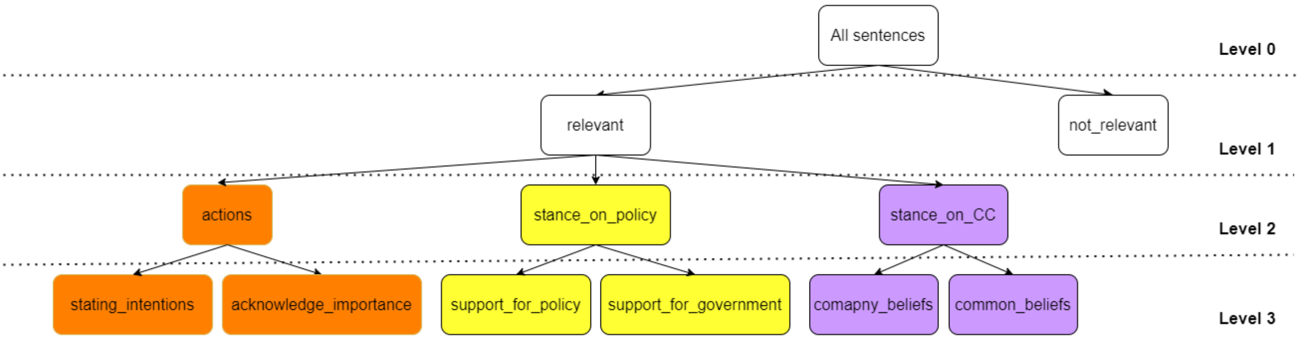


Figure 6. Pruned tree. This is the tree that is to be used to deductively code the sentences on new data.

Main category	Description	Label	Description
Actions	Sentences that involve or imply actions that companies take or will take to tackle climate change.	stating_intentions	The company is stating what they (will) do (policy) or want to achieve (target or goal).
		acknowledge_importance	The company are acknowledging the importance of them taking some actions regarding climate change.
Stance on policy	Sentences that contain the stance tha companies take around (government's) to tackle climate change.	support_for_policy	The company is stating the support for a piece of legilslation that tackles climate change.
		support_for_government	The company is stating the support for governments' action that tackle climate change.
Stance on climate change	Sentences that contain the stance of companies on climate change in general.	company_beliefs	The company is stating a belief the company itself has about the topic in general.
		common_beliefs	These sentences express beleifs about climate change or what it should be done about climate change but it is not clear who is expressig the beliefs.

Table 9. A description of the labels of the pruned tree (level 2 and level 3 labels, that is all the labels that in Figure 6 are colored).

4.1.5 Reflections

Different considerations at this point must be made regarding the usability of this method in general and as part of a bigger greenwashing analysis.

First, the overall accuracy of GPT as a decoder is promising and is aligned with the results in the literature discussed above. It is important to mention that, because of time limitations, sometimes a higher percentage of accuracy was not pursued once an accuracy around 80% was achieved, even at the first prompt that was tried. Thus, more examples and explanations of classifications could have been implemented to get even higher accuracy values. Therefore, more research on this and more research on prompt engineering could be pursued to show the full potential of using GPT for deductive coding.

Secondly, the use of a tree of labels to do coding presents an important trade-off between the number of levels and the accuracy of the lower labels. If on one side creating intermediate labels was chosen as a strategy to increase the accuracy of the single coding task, the increase in the number of levels entailed more intermediate coding tasks that drew the accuracy of the final labels down. Due to time limitations, this trade-off wasn't further explored. A way to find the best equilibrium between these two needs could be to analyze different trees or branch structures and then pick the one with the best accuracy.

While the previous considerations deal with the automation part of this method, a more structural consideration regarding the feasibility of qualitative data coding for the greenwashing analysis must be made because this analysis is to be used in a larger approach that finds evidence for greenwashing. And this lies with the labels that I was able to create and code into the data (labels are depicted in Tables 3 and 9). The labels do show a variety of positions that a company can take regarding climate change: there are specific policies and targets that they can set to tackle climate change (all the labels that fall within the "actions" branch), they can state their support for policies or governments' actions ("stance_on_policy") and, finally, there are general opinions that they can have or, at least, can show on their website around the issue of climate change ("stance_on_CC"). These three categories also have different levels of specificity or details regarding what companies do or say they do, that is, their commitment in general to tackling climate change: whereas the sentences classified as "actions" have specific policies or goals, the "stance_on_CC" sentences show the least commitment to the challenge of climate change since these are general positions that are unclear who they belong to, with the "stance_on_policy" showing some mid-level commitment because they do state the support for actions but these actions are carried out by someone else. Moreover, these differences in scales can also be found within the single branches: for example, on the "stance_on_CC" branch as seen in Figure 2, the "company_beliefs" label contains a more detailed stance than the other two because in these sentences the company explicitly say that they are the ones expressing that belief (for example, Amazon's "We believe we have an obligation to stop climate change, and reducing carbon emission to zero will have a big impact"[5]) whereas the other kinds of sentences it is not clear who is expressing these beliefs; moreover, the "call_for_action" sentences (e.g., "At the same time, carbon emissions must be permanently reduced"[6] by Uniper) are more specific than the "universal_beleifs" (Sinopec's "Climate change is a major global issue for all humankind"[7]) because the former acknowledge that some kind of actions is needed while the latter kind is just general opinions. Figures 2, 5, and 6 do already contain this order as on the left there are the labels that represent the more specific sentences and on the right the ones of the least specific sentences.

Therefore, these labels show similar scales to the greenwashing definitions of Li et al. (2022) and Contreras-Pacheco and Claasen (2017) as discussed in Chapter 2 where high levels of positive green communications could translate to higher usage of sentences that belong to the "actions" branch and low levels could translate to the presence of mainly "stance_on_CC" sentences. In this sense, with these different labels, this method provides a nuanced analysis of a companies' communication that can be later used for the intended greenwashing analysis.

4.2 Lobbying

The goal of this analysis is to quantify the lobbying data in order to compare it with the communication analysis results as already discussed in Section 3.4.2: this comparison will let the user see the presence or lack of a mismatch between words and deeds which then can inform a greenwashing appraisal.

As discussed in Section 3.3.4, two variables can be of interest to study: the declared total lobbying expenditures and the list of meetings between companies and European Commission members and their staff.

[5] https://www.aboutamazon.com/planet/climate-pledge
[6] https://www.uniper.energy/news/the-most-important-sustainability-issues-at-uniper
[7] http://www.sinopecgroup.com/group/en/socialresponsibility/Green/facc.shtml

It is important to highlight again that these analyses cannot determine whether the lobbying activities of the companies under scrutiny are for or against climate regulations: as discussed in Section 3.3.4, this is due to the data that comes from the Transparency Register because it doesn't contain such information to begin with. As Kim et al. (2015) suggest, the level of pollution of the companies can inform the "direction" of lobbying: polluting companies are deemed as likely to oppose climate regulations. This assumption is also made in this research.

4.2.1 Declared total expenditures

The use of total expenditures has been informed by the literature discussed in Section 3.4.2 (e.g., Brulle, 2018). As discussed in Section 3.3.4, the expenditures can be found on the online version of the Register under the "The estimated annual costs attributable to activities covered by the Register" entry in the "Financial data" section; on the downloadable Excel version (Secretariat-General, n.d.) the expenditures can be found in the "Annual costs for registers activity or total budget" column. The total expenditures are provided as value brackets (e.g., 400 000 – 499 999) (Interinstitutional Agreement on a mandatory transparency register, 2021): the lowest bracket is "< 10 000" and the highest is "≥ 10 000 000"; the bracket sizes differ. To process this, the average of the upper and lower brackets is taken.

4.2.2 Meetings between companies and European Commission

Since the total expenditures can't properly depict the lobbying efforts of companies on climate related issues because it summarizes all the activities conducted by companies (Section 3.3.4), the list of meetings between companies' representatives and with Commissioners, Cabinet Members, and Director-General can be used. As discussed in Section 3.3.4, the data can be downloaded from the web version of the Register in the "List of meetings with the European Commission" entry under the "Specific activities covered by the Register" section. This list can't be downloaded from the Secretariat-General (n.d.) but can be retrieved from the LobbyFacts website in Excel format. The list contains the meetings with a short description of what was discussed. Therefore, a textual analysis is needed to process them.

Since the goal of this analysis is to quantify the lobbying activities, a way to do so with these lists is to get the number of meetings that are relevant to climate change regulations. This share could be a proxy of the lobbying intensity of the companies on climate change issues. To filter the meetings, a keywords-based filtering similar to what Brulle (2018), Delmas et al. (2016), and Kim et al. (2016) do in their research could be used. The filtering can be done on the "Subject" field of the data downloaded from LobbyFacts (on the PDF downloadable from the online version of the TR the field is called "Subject(s)"). A keyword analysis is deemed to be enough to make an informed filtering decision because of the simplicity of the text that describes such meetings: these are just small sentences without verbs that tell the key topics discussed during the meetings. This filtering will be the lobbying part of the approach.

The main part of this process is the keywords that are to be used for the filtering. The compiling of the keywords used to run the filtering is part of the pre-processing phase of the approach. Informed by the literature discussed above, these keywords can be divided into two main categories:

- *Specific legislation*. Following Kim et al. (2016), the most prominent climate regulations that have been discussed throughout the years are to be included in the keywords list. Examples of these policies are the "European Green Deal", "Paris Agreement", and the "ReFuelEU Aviation Regulation". Some of the less recent regulations (such as the Green Deal) are included because these lists include meetings since the end of 2014. To get the names of such legislation I search on Google for “key eu climate legislation” and stop the search when no new results are encountered. Moreover, my own knowledge of important legislation informed such list.

- *General climate change words*. These are keywords that I are taken from Brulle (2018), Delmas et al. (2016) and words that the Net Zero Tracker uses for its data collection (J. Zhang, personal communication, November 2, 2023): these words represent the main keywords and buzzwords around climate change. Examples of these are “climate change”, “renewable energy”, and “decarbonization”. Moreover, from the keywords retrieved from these sources, I remove those words that are more likely to create false positives in the filtering because such words could be used in different contexts that are not related to climate change. These words are “carbon” because it could be discussed as an element on its own for some products, and “climate” and “environment” because they could be used to describe the mood of something (e.g., “political climate”).

These keywords want to capture all the meetings that are more likely to be lobbying on specific regulations or that discuss climate change in general. I include in the keywords list also related words, synonyms, and acronyms of the original keywords for more accurate filtering. Different spellings and all the plurals of the words can be included for an easier filtering process. A list of these keywords can be found in Appendix E – Figure 1.

Since this analysis deals with textual data, the principles learned from the review of techniques discussed for the communication part of the approach (Section 3.4.1.2) are also relevant for this analysis. As prescribed by Wolton et al. (2021), deep care is taken for the creation of these keywords lists: significant time is spent in conceptualizing and populating these dictionaries of keywords by searching in the literature discussed in Section 3.4.2 for the lists of keywords used and understanding the motivations behind them, by searching for legislations’ names, and by thinking of different spellings or related words.

To conduct the filtering, Python and the library “re - Regular expression operations” (*Re — Regular Expression Operations*, n.d.) can be used to find the exact matches of keywords. The capitalization of words can be considered as irrelevant (therefore, all descriptions and keywords should be transformed into lowercase) because it can be assumed that mistakes in capitalization could easily happen. For the actual filtering, a meeting is deemed relevant to climate change if any of the keywords are found in the description. Finally, the share of the relevant meeting is computed as the number of relevant meetings over the total meetings recorded.

4.3 Greenwashing table

This is the final step of the approach: with the companies’ communication and lobbying efforts analyzed, the user of the approach should be able to come to their own conclusion regarding whether these companies are greenwashing or not. The goal of this step is to enable the user to form their own judgment, not coming to a direct greenwashing accusation (or to an absence of one) as discussed when forming the main research question (Section 2.2.2) because, as discussed in Chapter 2, there is a variety of definitions that different users may agree with differently: in the end, as Seele and Gatti (2015) point out, greenwashing exists in the “eye of the beholder”. Indeed, the table that will be created by the approach allows the user to come to their own conclusions, but a greenwashing interpretation that stems from Li et al. (2022) and Contreras-Pacheco and Claasen (2017) will be discussed.

The lessons learned from the visualizations presented in Section 3.4.3 teach the following principles to create a display that can let the observer come to their own greenwashing conclusions:

- All the variety of data that is produced should be shown. The more data shown, the less it can be summarized and the less it introduces further bias (which are already present in the created approach), and the more the data is open for interpretation.
- The hard coding of boundaries or colors should only be possible if I have overall control over the scale that the variables can take.

Therefore, it is decided to create a table with all the communication and lobbying data displayed with each cell color-coded according to their position on the values scale of their corresponding variable (darker color represents higher values).

Color coding is possible for all the variables (note that each variable has its own color-coding rule). For communication, I use the percentage of sentences that fall within the final labels which has an inherent scale of 0 to 100 and the same applies for the percentage of relevant meetings for the lobbying analysis. Finally, the total expenditures variable's scale comes from the Transparency Register itself: as described in Section 4.2.1, companies do not declare absolute values but brackets within which their expenditures fall, and in Transparency Register the lowest bracket they can declare is "< 10 000" and the highest is "≥ 10 000 000". Therefore, I use 0 as the lower bound and 10,000,000 as the upper bound. To create the color coding, I used Excel conditional formatting where the colors with the highest (lowest) possible number on the scale are matched with the darkest (lightest) color, and all the numbers in between are spread uniformly on the scale.

In this way, sharing all the data allows for the reader to see the results of the analyses carried out without immediately adding an interpretation of the results via, for example, summary statistics or via an overall greenwashing score. This color coding is not to be seen as interpretation of the data, but as a facilitator of the reading of the data by displaying where the data is in its natural scale.

In Table 10 a mockup of such a table is represented. Note that for the communication data, I only present the labels that are the lowest ones in the pruned tree (Figure 6). If the whole tree were to be used, then the same tables could be used by displaying the values for the leaves of the tree (Figure 5) which are the codes that were inductively created as for the first step of the communication part of the approach (as described in Table 5).

Company	***stating_intention %***	***acknowledge_importance %***	***support_for_policy %***	***support_for_government %***	***company_beliefs %***	***common_beliefs %***	***Declared expenditures***	***% relevant meetings***
Volkswagen	47.22	8.33	5.56	0.00	16.67	22.22	3249999.50	11.96
Amazon	68.75	12.50	0.00	0.00	3.13	15.63	3249999.50	7.27
Uniper	70.59	17.65	0.00	0.00	2.94	8.82	549999.50	10.00

Table 10. Mock-up of the final display with the companies that I used to create the codes inductively in Section 4.1.2. Note that only the companies that have an entry in the Transparency Register are kept. Moreover, since all but the yellow codes and "company_beliefs" are created by me when creating the GPT deductive coding method (and, therefore, are not in the tree created when I was doing the inductive coding), to create the values in the table for these labels (orange and "common_beliefs"), I sum the number of sentences that fall in the labels that belong to their corresponding branch as shown in Figure 5 of this chapter (e.g., to get the values of "common_beleifs" I sum the labels that belonged to "call_for_action" and "universal_beleifs".

To create the data depicted in the table, I use the data from the companies I created the codes with (see Sections 4.1.1 and 4.1.2) and I run the analysis on their lobbying activities (as described in Section 4.2). Note that the companies depicted in the figure are the ones that had an entry on the Transparency Register, for the others no lobbying data was available and, therefore, they are not included.

Moreover, while this table lets the user come to their own conclusions regarding how companies are communicating around climate change, how companies lobbying around climate regulations in the EU, and how these two elements can be used to come to a greenwashing appraisal because it shows all the data with limited further bias introduced, with the analysis carried out in this research and the greenwashing definitions discussed in Chapter 2, it is possible to already point out to when this table can suggest that greenwashing is happening.

In Chapter 2, Li et al. (2022) and Contreras-Pacheco and Claasen (2017) show 4 different categories that companies can fall into based on their level of green communication and their green practices. To adjust that table to this case, it is first needed to discuss the scale of the two variables studied in this research:

- For the communication, the codes that were created are already ordered for the specificity of their stances on climate change, with the "actions" category being the one with the highest intense stances, followed by "stance_on_policy" and "stance_on_CC". Figures 2, 5, and 6 in this chapter present the codes ordered accordingly, with the more specific codes on the left. Therefore, the more positive communication discussed in Li et al. (2022) and Contreras-Pacheco and Claasen (2017) can be defined as presenting more sentences that are more specific, that is, that fall more in the "actions" codes ("high communication") whereas the less least positive communication is when the sentences are concentrated in the "stance_on_CC" category ("low communication").
- Regarding lobbying, the translation is easier since it follows the numerical scale of the lobbying data: the higher the declared expenditures and the higher the percentage of meetings, the more intense their lobbying activities. If the focus of the analysis is polluting companies, the translation from the table discussed in Li et al. (2022) and Contreras-Pacheco and Claasen (2017) can happen: as discussed at the beginning of Section 4.2, polluting companies can be assumed as lobbying against climate regulations, and, therefore, the higher levels of lobbying activities translate to the higher levels of negative green practice ("high lobbying"). If the company is not polluting, then the assumption can't properly hold, and the translation can't take place: the lobbying numbers can be interpreted as indication of the lobbying activities regarding climate change, but they can't give the full picture.

Therefore, the four categories can be defined in the following way for the analysis conducted in this research:

		Lobbying	
		High	**Low**
Green communication	High comm.	Greenwashing	Vocal green
	Low comm.	Silent brown	Silent green

Figure 7. The greenwashing table discussed in Li et al. (2022) and Contreras-Pacheco and Claasen (2017) adjusted to the analysis done in this research: "High comm." Is when companies' sentences are coded more in the "actions" branch and "Low comm." when they fall more in the "stance_on_CC" group; "High lobbying" happens when there are higher levels of expenditures and percentage of relevant meetings. Note this table can be used if the company being analyzed can be assumed as lobbying against climate regulations (as in the case of polluting companies).

It must be highlighted that this table can be used to interpret the results of this analysis as depicted for example in Table 10, but there are no "hard lines" that separate what "high" and "low" mean for the communication and lobbying variables: that is, determining in which specific category the companies analyzed fall is still up to the user.

4.4 Limitations of the created approach

In this section I will present the limitations of the created approach in its parts.

4.4.1 Limitations of communication part

The communication part of the approach and the way that I took to get to it present limitations.

Regarding the data collection, due to time constraints, the dataset that was used is limited. More companies, more sentences, and more time would have increased the quality of results. But also, this data would have been too much for a single human coder to process. Thus, a future potential avenue of research could be looking into AI-based system to semi-automate this coding (an example of this can be found in Rietz and Maedche, 2021): by using such a system, the analysis of the data and the creation of ways to identify the sentences would be incorporated and require less time for the researcher.

In terms of inductive coding, while I only analyzed sentences for the simplicity of this analysis (this is part of the scope as discussed in Section 3.2.1), paragraphs could have been analyzed. I believe that this was not strictly necessary: the sentences I analyzed were very simple and straightforward and the stance of the company were contained in a single sentence. I only found a couple of examples where analyzing two contiguous sentences would have given me a company's stance (thus, analyzing the single sentences didn't result in them being considered as relevant). An example of this is Saudi Aramaco's "For some, the idea of an oil and gas company positively contributing to the climate challenge is a contradiction. We don't think so."[8]. While this is true for sentences that turned out to be in the "relevant" category, it was less valid for the general statements that make up the "call_to_action" and "universal_beliefs" labels (the initial "relevant_general" category): in this case, a more general stance was expressed over a couple of sentences. But, regardless of this, I was able to find single sentences that still expressed a meaningful statement.

Moreover, to simplify my analysis, I only assigned one label per sentence even if some sentences could be classified under multiple labels. An example is Amazon's "At Amazon, we care deeply about our packaging achieving both of these goals, and we have teams of scientists and other experts who are constantly working to reinvent how products are shipped for the good of customers and the planet"[9]: the first part could be classified as "company_priorities" whereas the second part as "stating_more_detailed_goal". For this case, I decided to pick the label that seemed more valid, also considering the context of the rest of the document where the sentence was taken (in the example, the sentence was classified as "stating_more_detailed_goal").

Lastly, regarding the automated deductive coding, the low accuracy is the most obvious limitation. Further research is needed to bring this method to higher accuracy levels as discussed above: for example, fine-tuning of LLMs could be used to create a better-suited LLM for these coding tasks. For the evaluation phase of my research, this low accuracy will be taken into account and some quick fixes will be implemented (see Chapter 5).

4.4.2 Limitations of lobbying part

Regarding my specific approach to the lobbying analysis, I see as an important limitation the fact that the indirect lobbying of companies is not further examined, but I am mainly focusing on direct lobbying (which is directly lobbying the policymaking process by, for example, engaging with government officials) (Principles for Responsible Investment et al., 2018) via the analysis of the meetings lists. The total expenditures field in the Transparency Register does also include the amount spent for indirect

[8] https://www.aramco.com/en/sustainability/climate-change

[9] https://www.aboutamazon.com/news/sustainability/how-amazon-is-reducing-packaging

lobbying activities such as communication campaigns and position papers as previously discussed in Section 3.3.4. But this number doesn't differentiate between the different activities. Moreover, this number does not include other indirect lobbying efforts which are: contributions to NGOs, research institutes, think tanks, and academia; membership to trade associations (Principles for Responsible Investment et al., 2018; Beder, 2011). Analyzing all the indirect lobbying activities of a company was deemed unfeasible from a time perspective. Moreover, the study of PR campaigns would overlap with the study of the communication of companies discussed previously because the data to be analyzed would be the communication of companies. Thus, my proposed method for studying the online communication of companies could inspire research that wants to automatically study indirect lobbying in the form of PR campaigns.

Another limitation is using the share of meetings that are relevant to climate change as a proxy for the lobbying intensity on climate change issues since it is not known how much of the total expenditures declared by the companies are due to the organizations of the meetings. This is a limitation that is intrinsic to the data of the Transparency Register since this number includes all the activities run by the companies.

4.4.3 Limitations of greenwashing table

The main issue with the design process that created the greenwashing table, the last part of the created approach, is determining whether the goal of creating a table that enables people to come to their own conclusions regarding the data displayed in the table has been met or not. The doubt stems from the fact that the greenwashing table discussed in Li et al. (2022) and Contreras-Pacheco and Claasen (2017) could *easily* overlap the greenwashing table of the approach as depicted in Figure 7. Therefore, it can be questioned whether the greenwashing table allows different interpretations or only what is present in Figure 7. This can't be answered with this research design because it didn't entail interviews with potential users of the approach to receive feedback on how the table is interpreted.

4.5 Conclusions

The approach whose development and details were thoroughly discussed in this chapter can be summarized here in this way:

- The approach analyzes both communication and lobbying activities according to the scope of this research discussed in Section 3.2.
- First, a company's online communication (in the form of what they publish on their websites) is analyzed. The approach here is to automatically do deductive coding. The codes used are first created by inductively coding the communication around climate change of six sample companies and are at a sentence level. These codes highlight the difference in the specificity of the communication of companies: some sentences may lay out specific policies to achieve certain targets, and others may just state a general acknowledgment that climate change is a real phenomenon. The automatic deductive coding part, which is the key part of the communication step of the final approach, is achieved by using GPT to deductively code the sentences in a cascade manner according to a label tree (prompts have been tested and optimized for the accuracy of the coding tasks). The final output of this step is the percentage of sentences that fall within each code.
- Secondly, the lobbying activities of the companies at the EU level are scrutinized. The data comes from the EU Transparency Register. First, the total expenditures that companies declare for their lobbying activities at the EU level are gathered. Then, the declared meetings between the company's representatives and European Commissioners and their staff are studied by

determining the percentage of meetings that are relevant to climate change regulations. To do so, first a list of keywords that contain both general keywords that relate to climate change and the names of key European legislation needs to be developed; then this list is used to filter the meetings based on their brief descriptions. This could be considered as a proxy of the intensity with which the company lobby efforts are concentrated on climate change regulations.

- Lastly, the final output of the approach is produced, a table where the values from the previous two steps are displayed. To aid the comparison the data is color-coded (the higher the values, the darker the color) in a way that is true to the values that are presented and not so that further biases are introduced: the viewer is left to come to their own conclusions regarding the presence, or the lack thereof, of mismatch between words and deeds which is key to come to a greenwashing accusation. This final table does not tell whether the values represented can be proof of greenwashing: that task is the job of the user. This judgment can be aided by using the literature discussed in Chapter 2: higher levels of communication are represented by presenting more sentences in the "actions" codes and when compared to higher levels of lobbying (higher expenditures and higher percentage of relevant meetings), they can lead to considering the company under analysis as greenwashing (if this company is a polluting one).

This approach is the answer to SQ2 ("What semi-automated approach can be created to potentially allow for a holistic study of companies' communication and lobbying efforts?") since it is an approach that studies both communication and lobbying efforts of companies, the two elements that the research question contained, and does that in a way that is holistic because the analysis results of these two elements are compared in the final step of the approach. Moreover, the approach is semi-automated at the moment: while the lobbying step is fully automated because I already developed code that analyzes the data automatically, the communication analysis still involves manual steps in the form of copying and pasting the prompts and the sentences to classify on the ChatGPT web interface; moreover, the final tables are created using Excel. But these last two steps could be fully automated by using the (paid) GPT API and Python to create such a table, respectively, and, with the use of some code that connects all the steps, a fully automated pipeline could be created.

It is important to mention that this is *an* approach that runs such an analysis, and it has its own limitations: for example, the deductive coding for the communication part has low accuracy, and the lobbying analysis is not able to determine whether the companies are lobby for or against climate regulations. Some of these limitations are also due to the limited time available for the development of the research: thus, future research could investigate improving the approach that is presented in this chapter.

5. Demonstration and Evaluation

In this section, I will demonstrate the use of the approach developed in the past chapter on a new case, and with the results, I will evaluate my approach according to the criteria that are discussed in Chapter 3. Respectively, these are steps 4 and 5 of the design research approach (Peffers et al., 2007). As already discussed in Section 3.1, since the evaluation is using a single case, in this chapter I am conducting a small-scale evaluation (Wohlin & Rainer, 2022). In Chapter 3, I also described the criteria to select a case that is suitable for this evaluation and picked a case accordingly (Section 3.3.2).

5.1 Demonstration

To demonstrate the approach, the communication and the lobbying analysis are run for 2 of the companies discussed in the case described in Section 3.3.2, ExxonMobil and Shell. This limited number was due to time limitations. Moreover, these two particular companies are chosen because they are the first two companies of the five listed above for total revenue according to the Fortune 500 list (Fortune, 2023): similar to what was discussed in Section 3.3.3.1 when selecting companies to study via inductive coding, the bigger the companies, the more powerful they are in shaping the discourse around climate change (Thaker, 2019), the more likely they are to present communication on climate change. Another reason behind this could be the higher pressure from shareholders in publicly traded companies to tackle environmental, social, and corporate governance issues as reported by Copley (2023) (note that both ExxonMobil and Shell are publicly traded companies).

5.1.1 Communication analysis

The analysis is executed according to steps described in Appendix D – Table 1. To run this analysis, the sentences of interest are selected in the same way as it was den when creating the codes inductively as discussed in Section 4.1.1.2: I search for the term "climate" on Google and restrict the results to the companies' corporate websites (for ExxonMobil the website is https://corporate.exxonmobil.com and for Shell is https://www.shell.com).

Since the overall low accuracy of the communication method is an important limitation of the approach (Section 4.4.1), I decide to manually carry out the first step of the deductive coding, that is the classification between "relevant" and "not relevant" sentences: this ensure a higher quality of the "relevant" classification while still showcasing the applicability of the GPT method and the nuanced results it can produce with the two following classification. The resulting average accuracy of the classifications is 77.9% if the accuracy of the classification between "relevant" and "not_relevant" can be seen as equal to 100% because it is manually executed by the author of this thesis who is the creator of the whole approach and, therefore, knows best what these two categories mean (see Appendix C – Figure 4 for the accuracy values of the different labels). The results of the data collection and the first coding phase are shown in Table 1.

Company	No. of sources analyzed	No. of general webpages	No. of news	No. of reports	No. of total sentences analyzed	No. "relevant" sentences	No. "not_relevant" sentences
ExxonMobil	6	4	1	1	167	96	71
Shell	6	2	0	4	136	65	71

Table 1. The results of the data collection are in the white cells. The results of the coding phase are highlighted in green. Note that for Shell, all the reports that I analyze are actually displayed on a webpage (and not, for example, a PDF): they are classified as reports because the webpage they are on clearly states that they are a report.

With the sentences that are manually coded as "relevant", I then proceed to use GPT for further coding. The sentences are coded hierarchically according to the final labels pruned tree portrayed in Figure 6 of Chapter 4: first, GPT codes sentences according to "actions", "stance_on_policy", and "stance_on_CC" labels; then, based on this coding, GPT is used to classify the corresponding lower labels. To run the deductive coding, I use the prompts that had the best accuracy from the various testing runs discussed in Section 4.1.3.2 (see in Appendix D the Prompts Section for the text of these prompts). Note that I only run the coding tasks only once (and not twice as it was done when I was testing the GPT classification accuracy) because of time limitations: thus, the labels that are returned from GPT are assigned to the sentence for further classifications or as its final label. It happens a couple of times that two labels are returned per sentence: in this case, I re-send the prompt with "only give one label!" added to it along with the sentence in question: the returned label is assigned to the sentence. I use Excel to record the sentences and their classifications; I manually paste on ChatGPT the prompts and the sentences to classify. Table 2 contains the results of the first round of coding (level 2 of the tree) and Table 3 contains the results for the final labels of the pruned tree (level 3).

Company	actions	stance_on_policy	stance_on_CC
ExxonMobil	51	34	11
Shell	38	17	10

Table 2. Coding results for the level 2 of the tree

Company	stating_intention	acknowledge_importance	support_for_policy	support_for_government	company_beliefs	common_beliefs
ExxonMobil	49	2	30	4	7	4
Shell	34	4	12	5	5	5
Tot. ExxonMobil:	51		34		11	
Tot. Shell:	38		17		10	

Table 3. Coding results for the level 3 of the tree. Note that the last two rows contain the sum of the labels per company per branch (which match the corresponding level 2 label in Table 2): each branch is a different color ("actions" is orange, "stance_on_policy" is yellow, "stance_on_CC" is purple) and these colors match the ones in Table 2 and on the trees depicted in Chapter 4.

It is important to highlight that the choice of doing one step of the classification by hand is forced by the low accuracy of the classification tree: as discussed in Section 4.1.4, the accuracy for the final tree is 50.1% whereas the accuracy for the pruned tree is 61.4%. Because of these values, it doesn't seem advisable for future research to use the fully automated version of this part of the approach (even by using the pruned tree) in order to increase the scale of analysis by studying more companies. First, the method should be improved for its classification accuracies.

5.1.2 Lobbying analysis

For the lobbying analysis, no adjustment of the method's steps is needed since all the data was easily available. The steps described in Section 4.2 are closely followed.

The total expenditures are retrieved from the Transparency Register Excel version (Secretariat-General, n.d.) and the meetings of the companies with European Commission members and staff are downloaded from the LobbyFacts website (Corporate Europe Observatory & Lobby Control, n.d.). Then, the average of the total expenditures is computed, and the meetings are filtered based on their descriptions as discussed in Section 4.2. The results of these two analyses can be found in Table 4.

Company	Decleared total exepnditures range	Total expenditures average	TOT. meetings	TOT. relevant meetings	% relevant meetings
ExxonMobil	3500000-3999999	3749999.5	52	15	28.85
Shell	4000000-4499999	4249999.5	116	41	35.34

Table 4. Results of lobbying analysis. In green the averaged total expenditures and the percent of relevant meetings which are relevant for the rest of the analysis.

5.1.3 Greenwashing table

Here the final table is created according to what is described in Section 4.3. The results are shown in Table 5. There is no issue in creating this table because all the results to portray are available and in the format required.

Company	*stating_intention %*	*acknowledge_importance %*	*support_for_policy %*	*support_for_government %*	*company_beliefs %*	*common_beliefs %*	*Declared expenditures*	*% relevant meetings*
ExxonMobil	51.04	2.08	31.25	4.17	7.29	4.17	3749999.50	28.85
Shell	52.31	6.15	18.46	7.69	7.69	7.69	4249999.50	35.34

Table 5. Comparison of communication and lobbying efforts for ExxonMobil and Shell. This is the greenwashing table that is the output of the approach created in this thesis.

5.1.4 Discussion

There are several aspects of the results shown above that need to be unpacked.

Looking at the communication results shown in Table 5, both companies present similar patterns in their communication: most of the sentences that they have fall within the "stating_intention" category which means that they have set targets, goals, and/or policies that want to tackle climate change. The second label with the highest number of sentences is "support_for_policy" where companies state their support for climate regulations. From these results, it could be concluded that these companies seem to support climate actions, at least in their words.

It is worth mentioning that when reading the sentences to separate them into "relevant" and "not_relevant", I could already think of which of the final labels could be applied to these sentences: that is, the same patterns were seen in what ExxonMobil and Shell said and how they phrased their sentences as what the companies that were analyzed to inductively create the codes did (Section 4.1.2). This could also be because in the pool of companies used to create the codes, there were two businesses that were from the oil and gas industry, Aramco and Sinopec. In Table 6 the communication of ExxonMobil, Shell, and these latter two companies are presented: it can be seen that all the companies present a high amount of sentences in the "stating_intention" category, but then ExxonMobil and Shell present the second highest amount of sentences in the "support_for_policy" category, whereas for Aramco and Sinopec it is in "common_beliefs". Therefore, it can be concluded that the codes that were created are not just valid because I am testing on companies whose sector is represented in the pool of companies I created the codes with, but because the codes do describe a variety of positions that is valid to different companies (for example, if I only had considered in the analysis Sinopec, then the "support_for_policy" code would have not been created since there is no record of Sinopec having such kind of sentence).

Company	*stating_intention %*	*acknowledge_importance %*	*support_for_policy %*	*support_for_government %*	*company_beliefs %*	*common_beliefs %*
ExxonMobil	51.04	2.08	31.25	4.17	7.29	4.17
Shell	52.31	6.15	18.46	7.69	7.69	7.69
Aramco	52.17	13.04	6.52	2.17	8.70	17.39
Sinopec	68.75	6.25	0.00	6.25	6.25	12.50

Table 6. Comparison of the two case study companies, ExxonMobil and Shell, with Aramco and Sinopec, which have been used to create the codes.

Regarding the lobbying results, the declared expenditures of the companies are in the middle of the lobbying scale (0-10,000,000) and this is reflected in the medium dark blue color. The percentage of meetings is around 30% and that's why they have a lighter color. It is hard to draw conclusions with this data because it is hard to say if just 30% of meetings on climate change regulations is a low or high value: these companies are massive, and their activities span across different continents and different operations. The issue is that there is a lack of benchmarking that enables me or the user to properly judge this information. But, at the same time, the goal of the approach was to provide information, not to purely judge it. This issue is less present in the communication analysis since all the green communication of the companies gets classified within these codes, and, therefore, drawing conclusions becomes easier.

Regarding the comparison of the communication and the lobbying results, from Table 5 the high level of communication for the more specific category, "stating_Intention", and the higher mid-high levels of lobbying expenditures pop out. Is this greenwashing? The table doesn't say this, it only points the viewer to look at these more closely without claiming whether it is greenwashing or not. Therefore, it seems to me that the goal of the visualizations discussed in Section 4.3 has been achieved (but an external judge is better suited to evaluate this as already mentioned in Section 4.4.3). As discussed in Section 4.3, because both companies are polluting since they operate in the oil and gas sector, the greenwashing table discussed by Li et al. (2022) and Contreras-Pacheco and Claasen (2017) and adjusted to this specific research as depicted in Figure 7 in Section 4.3 can be used: based on it, it is possible to call the data shown as evidence of potential greenwashing because both companies present high levels of green communication since the majority of their sentences fall in the “stating_intention” code, the more specific code, and the lobbying expenditures and percentage of relevant meetings are significant.

5.2 Evaluation

In this section, I will evaluate the overall approach based on the criteria discussed in Section 3.3.1 and the results of the demonstration described and discussed above: this task is the answer to SQ3 (“To what extent is the created approach successful to the previously defined criteria when evaluated on a selected case?”). Each of the previously identified criteria will be reviewed and then the results will be summarized in Table 7.

5.2.1 Accuracy

The accuracy criteria aim at determining whether the approach was correct in identifying all the problematic communication and lobbying elements of the case that was picked so that the final results that the approach produces can be used to form a greenwashing accusation.

For communication, InfluenceMap (2019) reported how these companies are “on board” with climate actions: this is also reflected in the fact that the majority of their green communications have been coded as “stating_intentions”, the more specific of the codes that show how they have targets and/or plans to tackle their negative climate impacts. Therefore, it can be concluded that my method was able to come to similar conclusions on communication as the source did.

The lobbying analysis that was conducted is slightly different than the one discussed by Corporate Europe Observatory et al. (2019) because in this report the authors looked at the cumulative spending of the companies and their trade associations groups whereas the lobbying part of the approach only focused on the single companies' spending. But, I can also come to some sort of conclusion that highlights potential negative lobbying behavior of the companies: the numbers that ExxonMobil and Shell spent on lobbying are not insignificant (they are on at a mid-level of the scale of spending that the Transparency Register allows showing) and the percentage of meetings that deal with climate change cannot be ignored (around 30%): thus, it can be concluded that these companies are actively lobbying in the EU and that some of their focus is on climate regulations. This could be considered by users as a reason to worry.

Finally, all the sources discussed above point towards a mismatch between the words and deeds of the companies: this mismatch can also be hinted at with the results that I have concluded as discussed above. The difference between the sources analysis and my approach is that the former does conclude that there is a mismatch whereas the latter’s goal was never the same, but it was about enabling the users to draw their own conclusions (which can be used to form a greenwashing appraisal as discussed above).

To summarize, my approach is somewhat accurate when compared to the case study sources. My approach results are not an exact match to what the sources show because the focus of the analyses (as for the lobbying analysis) and the goal of the analyses were different (mismatch discussion).

5.2.2 Transparency

Transparency is about sharing data, analysis, and choices so that they can be evaluated by others. The main object of evaluation here is this report itself because it contains all this information.

The communication data that used to create the codes and the accuracy testing for the GPT method are available on a GitHub repository at the following link:

https://github.com/LudovicaBindi/collecting_greenwashing_evidence.git. On the same repository, the demonstration results are present. Thus, all the data used and produced is publicly available.

I believe that all my analyses and choices have been thoroughly discussed and motivated. I analyzed published literature to form the basis of my method, I discussed all the steps that created the final GPT method, and I presented data to support my choices. Therefore, I consider that what I did has been communicated properly and, therefore, is transparent.

But what is not being disclosed are the assumptions that lie behind how GPT works since this is a proprietary model that can be publicly used but not modified. This is an intrinsic issue with using GPT as discussed in Section 4.1.3.1, and it is the main limitation to the transparency of my overall approach. I did, however, thoroughly discuss why it was decided to use it, and future research could investigate using open-source large language models.

For the lobbying answer, the transparency discussion is more straightforward. The data used is already publicly available because it comes from the Transparency Register which is free and easy to use for any online user; this data has also been shared on the GitHub repository. As for the communication analysis, I believe I did my best in documenting my analysis and interpretive choices. Moreover, in this case, the algorithm is based on keywords that are discussed and displayed in this report (other than on the GitHub repository), and the code that runs the filtering is on the repository as well. So, all the analyses should be considered as transparent.

For the final step of the analysis, the comparison of the communication and lobbying efforts, I introduced very little extra analysis and choices because I simply combined the results of the previous two steps and color-coded them according to their values, but all these choices have been explained and justified in Section 4.3. Moreover, the greenwashing table has been shared on the GitHub repository in order to disclose the Excel settings that were used for the color coding.

Overall, I believe that the parts of my approach I had control over are transparent because I shared data and discussed the steps in my analyses and my interpretive choices. On the other hand, the use of a non-transparent model, GPT, hinders my overall transparency.

Evaluating the transparency on my own is the hardest of the evaluation analyses because only external readers can fully judge whether, for example, all the assumptions have been made clear: I might have written my assumptions in a way that is clear to me but not for others because the time spent on this research has made the concepts cemented in me and, therefore, the description in the text can be very obvious for me whereas an external reader only has the space of this report to fully grasp what my research is about.

5.2.3 Reproducibility

The goal of the reproducibility criteria is to test whether my analysis can be recreated in a different context. The discussion is based on the approach itself and the demonstration results.

First, the communication method relies on a model, GPT, that is non-deterministic in nature as discussed in Section 4.1.3.1, therefore, the same input can lead to different outputs: therefore, the first level of reproducibility, outcome, is not guaranteed. This was taken into account when choosing GPT to run the deductive coding because of the lack of large quantities of labeled data. Future research can create deterministic machine learning or deep learning models that overcome this issue if more labeled data is available. Note that these methods are deterministic once they are trained, the training process itself can also be not deterministic (e.g., different choices in the training dataset can lead to different model parameters).

Regarding the second degree of reproducibility, analysis, as shown in the demonstration step above, the same analysis is applied to the outcomes of the deductive coding because I simply computed the percentage of the sentences that fall within the codes: the ability to run this step is independent of the actual numbers of sentences.

Not much can be said about the reproducibility of the interpretations, the third degree of reproducibility, because I didn't run my demonstration analysis twice. This is yet to be determined.

Regarding the lobbying analysis, since the method of analysis (taking the average for the total expenditures and keyword-based filtering) is fully deterministic, the same outcomes are obtained with the same inputs. The reproducibility of analysis is not applicable here because I didn't further analyze the outcomes I obtained, but since there is outcome reproducibility, the analysis and interpretation reproducibility are implied (for example, if further analyses on the outcomes were to be carried out, these would be automatically reproducible) (Gundersen, 2021).

Finally, for the comparison of the communication and lobbying analyses, outcome reproducibility is achieved since all that this final step entails is copying and pasting the results of the previous two steps on a table and then color-coding according to their values which are all deterministic steps. Therefore, as for the lobbying step, the analysis and interpretation reproducibility are implied.

The main issue with the reproducibility of my approach is the use of a non-deterministic method. This is an issue with the approach design choices. The rest of my approach, though, is fully reproducible because it involves deterministic methods.

5.2.4 Reusability

These last criteria involve the easiness of use for other purposes of the data that was employed, produced, and then shared in this thesis. Since my data hasn't been used by others yet, what can be assessed is the quality of the meta-data that accompanies the shared data. Since it deals with data used and produced, these criteria only apply to the communication and lobbying analyses.

For both, the data that is on the GitHub repository presents a general description of how the data has been collected, and how it has been processed. For the communication analysis, in particular, the descriptions of all labels are present.

Therefore, I can conclude that the data that I shared is richly described and this, in turn, can facilitate the re-usability of the data for other studies. But, as for transparency, external judges can properly assess whether the documentation of the data is rich enough.

5.2.5 Conclusions

A summary of the evaluation can be found in Table 7. To briefly recapitulate the answer to SQ3 ("To what extent is the created approach successful to the previously defined criteria when evaluated on a selected case?"), not all the criteria have been met as the table points out: this is due to intrinsic characteristics of the developed approach. The partial accuracy of the lobbying analysis is because I didn't analyze the same as what the sources that describe the demonstration case do; the partial lack of transparency and reproducibility for the communication analysis is due to having chosen to use GPT, a proprietary and non-deterministic algorithm. While bringing some limitations, the use of GPT helped in overcoming issues that were present in the research (the lack of enough labeled data, which was also due to time limitations): therefore, when I introduced GPT, I was aware of the trade-offs. Moreover, I am also confident that with more time, future research can overcome some of these issues: by creating more labeled data, machine learning or deep learning algorithms can be created which then can produce deterministic results, and the use of open-source models could increase the transparency of this proposed approach.

It is important to highlight that the evaluation process is limited since, as already mentioned, evaluating the transparency of the approach would be better executed if an independent reader were to assess it since transparency deals with sharing the research so that it can be evaluated by others who are then the proper judges. The same can be said for the reusability objective.

Objective		Communication	Lobbying	Greenwashing
Accuracy	*Criteria*	Is the method able to identify the problematic communication the sources talk about?	is the method able to identify the lobbying activities the sources talk about?	With the results of the communication and lobbying analysis, can we draw a greenwashing accusation as discussed in the sources?
	Answer	Yes, my method identifies similar findings	Partial, different but still relevant findings are identified.	Yes, similar conclusions can be drawn.
Transpaerncy	*Criteria*	*Data* : is data used and produced publicly available? *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?	*Data* : is data used and produced publicly available? *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?	*Data* : N/A *Analysis* : are all the methods of data anlaysis discussed in the report? *Production* : are assumptions/definitions used/choices clearly stated in the report?
	Answer	Partial, what I did is communicated transparently but GPT is not a transparent model	Yes, this step is fully transparent.	Yes, this step is fully transparent.
Rreproducbility	*Criteria*	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?	*Outcome* : with same input, can we get same output? *Analysis* : can the same analysis be applied? *Interpretation* : can the same conclusions be drawn?
	Answer	Partial, because GPT is non-deterministic but analyses are reproducible. Interepretation yet to be determined.	Yes, fully reproducible because lobbying analysis is deterministic.	Yes, fully reproducible because this step is deterministic.
Reusability	*Criteria*	Is the data richly described?	Is the data richly described?	N/A
	Answer	Yes, it is.	Yes, it is.	N/A

Table 7. Summary of the evaluation of my method on previously identified criteria of accuracy, transparency, reproducibility, and reusability. In green the criteria that have been fully met, in orange the ones that have been partially met.

6. Discussions and conclusions

In this last chapter of this report, I will discuss the answers to the research questions this thesis was set out to answer and then will conclude by analyzing the limitations and scientific contributions of my research, pointing out possible avenues for future research that can build on what it was done here, and, finally, considering possible policy recommendations that stem from what it was learned in the process of this research.

6.1 Answers to research questions

Three subquestions have been answered throughout this report.

The answer to SQ1, "What operationalizable criteria can be used to determine the success of the approach?", is discussed in Section 3.3.1 where the objectives of accuracy, transparency, reproducibility, and reusability have been operationalized to assess the created approach.

Chapter 4 contains the description of the proposed approach which is the answer to SQ2, "What semi-automated approach can be created to potentially allow for a holistic study of companies' communication and lobbying efforts?". The approach was created according to the scope determined in Section 3.2 (company's communication from official websites and their lobbying activities in the EU are to be analyzed). To summarize the approach here briefly,

- first, the online communication of a company is analyzed by using GPT to deductively code its sentences into labels that highlight the difference in their specificity: some sentences may lay out specific policies to achieve certain targets, others may just state a general acknowledgment that climate change is a real phenomenon. The percentage of sentences that fall within each label is computed;
- secondly, the lobbying activities of the companies at the EU level are scrutinized by gathering declared total expenditures of companies, and by computing via keyword-based filtering the percentage of meetings that representatives of these companies have had with EU Commissioners and their staff and that are relevant to climate change regulations;
- finally, the values gathered from the previous two steps are displayed in a table that allows the viewer to compare the communication and lobbying activities of companies, thus, to compare the presence, or the lack thereof, of mismatch between words and deeds which is key to come to a greenwashing accusation. Note that the final table produced does not tell whether the values represented can be used as proof of greenwashing: that task is the job of the user. At the same time, a possible greenwashing interpretation of this table is possible and has been demonstrated.

Finally, the answer to SQ3, "To what extent is the created approach successful to the previously defined criteria when evaluated on a selected case?", is discussed in Chapter 5: according to the criteria developed, not all the criteria have been fully met. This is mainly due to the approach choices that were made (other than the different focuses of analysis between the proposed approach and the sources that describe the selected case): there are issues of transparency and reproducibility because for my communication analysis GPT was used, a proprietary and non-deterministic model. These issues could be overcome by, for example, further researching how to use open-source models that are deterministic once trained (such as machine learning models).

With all the subquestions answered, the answer to the main research question, "To what extent can a semi-automated approach effectively and holistically study companies' communication and lobbying efforts to find potential evidence of corporate greenwashing?", can be answered. To answer this question, I need to reflect on the "semi-automated", "holistic", "effective", and "greenwashing" parts of the question.

Regarding the first part, my approach is indeed at this state *semi-automated*. This is because, in the demonstration step (Section 5.1), I manually coded the sentences in "relevant" and "not_relevant" to increase the accuracy of the approach, and because I manually copied and pasted the prompts and the sentences to code onto ChatGPT web interface. All the rest of the steps were fully automated. Whereas the manual coding was needed because of issues with the accuracy of the communication method, the interaction of GPT could be fully automated by using the (paid) API of GPT and, in this way, a fully automated pipeline could be created. If the issue with the accuracy of the communication analysis were to be resolved with further research, then a fully automated and accurate approach would be available. As part of the answer to this sub-question, it is worth mentioning what was learned from the review of existing techniques that study communication (Section 3.4.1.2) which can also be applied to the study of lobbying since it also involves textual data (as discussed in Sections 3.4.2 and 4.2.2). There is an important trade-off between automation and quality of research which is significant in the case of textual analysis because automated analyses may not be able to detect nuances in the text that are visible to human coders as Wolton et al. (2021) describe. On top of this, there is the added question of whether using supervised and unsupervised learning which in turn can impact the degree of automation: while unsupervised algorithms could be more immediately used, supervised ones require more data preparation. Indeed, for this latter group of algorithms, it is key to run this step with the utmost care because the quality of the results depends on this (researchers should thoroughly conceptualize labels and precisely categorize data accordingly; the same applies for the creation of dictionaries that can be used in the analyses). For creating the approach, the answer to this questions was a combination of manual work and automated steps to both accommodate the need for good quality of results (the data preparation steps were manually and thoroughly executed: the communication labels were coded in an inductive and manual manner to guarantee that they were representative of what was analyzed; similarly, the lobbying keywords used to filter the companies' meetings were manually picked inspired from past research to guarantee their significance to this case) and the need for automation (in the communication part, the deductive coding can be used in a fully automated way; the lobbying analysis is already fully automated).

The approach that I found is indeed an example of such a semi-automated that can *holistically* study communication and lobbying efforts to then give elements of reflections for a greenwashing appraisal because of the creation of the final output: therefore, I was able to create an approach that connected all the elements that I set to analyze. Moreover, the final table that my approach produces lets the viewers come to their own conclusions regarding the greenwashing activities of companies since the data is presented without saying what the creator of the approach think can be considered greenwashing or not. This meets what I set out to do because, in the research questions, I say that the approach should look for evidence.

Regarding the *effectiveness* of the approach, the issue with this approach lies in the low accuracy of the communication analysis as discussed in Section 4.4.1: if the accuracy of the approach is low, the results can't be trusted, and so it defeats the purpose of creating results that users can use to come to their own conclusions on greenwashing efforts of companies. Moreover, the evaluation of the approach according to the criteria discussed above shows that the approach doesn't meet them all: the transparency issue could be easily overcome by using an open-source large language model (such as those available on HuggingFace.com); to increase the accuracy of the communication analysis, better performing models could be used (such as GPT-4) but there are no guarantees on the resulting accuracy values; to overcome the reproducibility issue a change of the model in charge of doing the deductive coding would be needed because large language models have a non-deterministic nature. Therefore, while some of the flaws of my approach could have been overcome if more time had been available (e.g., with more time, I would have used an open-source models which may not be as ready and easy to use as GPT), while others are intrinsic to the research that was developed (the use of a non-deterministic model). Therefore, the effectiveness with which my model runs its analysis is limited.

The last part of this question that needs to be addressed is the *greenwashing* one and the answer to this lies in how the results of my approach can inform a greenwashing appraisal as discussed in Section 4.3. If on one side the final table that the approach produces is still open to interpretation for the reader to come to their own greenwashing conclusions, the results can be easily interpreted using the greenwashing table discussed in Li et al. (2022) and Contreras-Pacheco and Claasen (2017) (Chapter 2) as shown in Figure 7 in Section 4.3: positive green communication are represented in this research by companies presenting more sentences in the "actions" categories and higher levels of lobbying in terms of higher expenditures and percentage of relevant meetings are the corresponding of negative green practices. Therefore, with this one way of interpreting the results of the approach that is backed by literature, I can conclude that my approach is able to inform a greenwashing appraisal. It is important to highlight, though, that, because of the limitations of the Transparency Register's data, this greenwashing appraisal can only be applied to companies that pollute. Polluting companies can be assumed as lobbying against climate regulations as mentioned at the beginning of Section 4.2: thus, the results of the lobbying analyses can be interpreted as negative green practices as seen in Section 4.3. If the company is not polluting, then the greenwashing appraisal can't take place: the lobbying numbers can be interpreted as indication of the lobbying activities regarding climate change, but they can't give the full picture.

To conclude, I can say that my approach has potential because it is indeed semi-automated, can holistically run the analysis as I intended to do when writing the main research question, and can be used for a greenwashing appraisal, but the issues with accuracy and the other criteria I evaluated my approach against point out to the fact that this approach doesn't fully run its analysis effectively, and, therefore, it is not the best model that could have been created since some of its validity issues are intrinsic to the method choices that were made.

While this research was not able to find an approach that met all the *desiderata*, I believe that this thesis advances research in the fields of greenwashing and ML/AI studies, or, at least, some of the limitations of the greenwashing research discussed in Chapter 2 are overcome. The most obvious one is that my approach by being semi-automated is already an addition to the very limited use of automation in greenwashing studies.

Secondly, my approach was able to study holistically both (some kind of) green communication (corporate communication from their official websites) and a specific instance of actions that a company can do (lobbying) as the most comprehensive definitions of greenwashing suggest whereas some past studies lacked this double focus (they, for example, only analyzed the communication part of the greenwashing definition). Moreover, the studies that analyzed both communication and actions together presented issues of data accessibility that I overcame by using publicly available data (online webpages and the Transparency Register) and that were easy to interpret by the conventional stakeholders (this applies to the communication part of the approach).

Specifically to the studies that analyze communication, while my approach presents reproducibility issues (because the outcomes of GPT are non-deterministic) as the manually executed analyses found in the reviewed literature, my approach with its semi-automated nature can be more easily used to run multiple analyses and save time to researchers compared to conducting these manual analyses as they did. Furthermore, some of the analyses conducted discourse analyses which can become hard to test for accuracy of analysis whereas my content analysis approach facilitated this.

6.2 Research limitations

As already discussed throughout the report, this research presents limitations that were due to time constraints and intrinsic design choices. This latter refers to both the limitations that were due to the research approach and scope that was chosen and to the limitations of the created approach. Here, I will summarize both groups of limitations. Moreover, there is one limitation that deals with the evaluation phase of the approach.

Regarding the limitations that stem from the research design (see Section 3.5 for a more detailed discussion), the most obvious limitation is the fact that not all the steps of the design research approach were properly executed. Since the focus of this research has been on producing an approach that can be used by normal citizens, these should have been interviewed to formulate the problem ("problem identification and motivation" step) and the needs that the final approach should meet ("define the objectives for a solution") according to them. This could guarantee better that the approach can be used and trusted by them.

Another important limitation of this research has to do with the scope of research that was chosen (just focusing on corporates' online communications from their official websites and on their lobbying activities). While this scope is valid, it could lead to results that are "false negatives" in the case the results of the approach were to lead to a lack of greenwashing while the studied companies could be seen as greenwashing because of other activities that they are running which are not being studied by the approach (e.g., because of polluting products that are advertised as environmentally friendly).

Regarding specifically the data choices for the lobbying part, the main issue with the use of the Transparency Register is that from what is published there, it can't be determined whether the companies are lobbying for or against a certain climate regulation. Therefore, the results of the lobbying analysis can't properly inform a greenwashing accusation (unless it can be assumed that the company is lobbying against regulations as in the case of polluting businesses).

Lastly, a more thorough review of how to properly display the communication and lobbying data to inform a greenwashing appraisal could have been carried out.

There are several limitations regarding the approach that was created during this thesis (Section 4.4).

For the communication part of the approach, the creation of the inductive codes was done manually on a limited number of companies in a limited timeframe: more companies and more time could have led to more general codes (but my limited method demonstration shown in Section 5.1.4 hints towards the possibility that these codes are general enough because they were applicable to the new ExxonMobil and Shell data). Moreover, the focus of analysis could have been extended to paragraphs instead of sentences and more codes could have been assigned to each unit of analysis. The use of GPT to run the automatic deductive coding brings issues of accuracy (and of transparency and reproducibility as discussed in Section 5.2) to the whole approach: these issues are deep-seated in the communication method itself and overcoming them would mean to change the specific large language model used or switch the kind of model used altogether.

For the lobbying analysis, the most important limitation is that I am only analyzing the direct lobbying activities reported on the Transparency Register while leaving unscrutinized the companies' indirect lobbying efforts which can include produced research and contributions to think tank. These activities are relevant because they can influence public opinion, but it was deemed unfeasible to study them thoroughly enough in the given timeframe. Another limitation is considering the share of meetings that are relevant to climate change as a proxy for the lobbying intensity on climate change issues since it is not known how much of the total expenditures declared by the companies are due to the organizations of these meetings.

For the last part of the approach, the greenwashing table, the limitation is that it is not clear whether the goal of creating a table that enables people to come to their own conclusions regarding the data displayed in the table has been met or not. While the final results table doesn't tell whether the data displayed is evidence for greenwashing or not, this research design doesn't entail, for example, the surveying of potential users of such table to understand how they interpret it.

Lastly, the evaluation for the transparency and reusability objectives presents an important limitation: evaluating these would be better executed if an independent reader were to assess it since they deal with sharing research and data so that it can be, respectively, evaluated and used by others who are then the proper judges of these objectives.

6.3 Scientific contributions

Despite the limitations listed in the previous section, this research can make relevant contributions to the scientific literature that studies greenwashing, and which was discussed in Chapter 2. First, this research was able to create an approach that detects greenwashing from a holistic perspective (because both corporates' communication and lobbying activities are analyzed, and their comparison can give elements of reflections for a greenwashing appraisal) which is lacking in the literature as most of the existing approaches that aim at detecting greenwashing seem to focus only on the communication perspective. Moreover, the created approach does this in a semi-automated way of which there is scarcity in the literature (only one paper, Oppong-Tawiah and Webster, 2023, of those reviewed detects greenwashing automatically). In this way, this research is adding to the literature that uses automation in greenwashing studies.

Regarding the part of the research that uses GPT, this thesis adds to the emerging field of using LLM for deductive coding of text (Section 4.1.3.1). As already discussed in Section 4.1.5, my research finds that GPT is a good classifier if the number of classes is limited (accuracy of all coding tasks was 84% - Section 4.1.4). Moreover, I proposed a way to do multi-label classification (that is, by coding in a cascade manner using a hierarchical tree of labels) and how to maximize for its accuracy (by re-arranging the tree): though, these still need to be furthered researched because the accuracy that was reached was quite low (50.1% for the 4-level tree and 61.4% for the 3-level tree as reported in Section 4.1.4).

The lobbying part of this research also makes scientific contributions to its field. First, this research adds to the literature that studies lobbying related to climate change in the European Union since there was a lack of such studies as highlighted in Section 3.4.2. Moreover, with the filtering of the companies' meetings, I was able to bring the quantification of lobbying activities related to climate change to European data as done in the papers that study US data: this was yet to be done as discussed Section 3.4.2.

6.4 Future research

The first place where future research could focus is trying to overcome the limitations of the research described in this report. Then, research could focus on expanding the scope of the research.

Regarding the former group of limitations, at the top of the list of improvements sits the accuracy issues of the communication step because with low accuracy, the communication method and the overall approach can't be trusted to begin with. Therefore, more time could be spent in finding a tree structure of the labels that could lead to higher levels of accuracy: since the labels are in a tree format, researchers could get inspired by random forest classification methods to find such tree partition. Also, using better-performing versions of GPT such as GPT-4 could help in increasing accuracy. Or researchers could look into LLMs that can be fine-tuned to get better-performing models tailored to the problem at hand.

Secondly, since the issue of transparency of my overall approach stems from the use of GPT which is a proprietary model, open-source models could be used to create the deductive coding. Using different models would require re-running the prompt creation process because different models may respond differently to the same prompt structures.

Solving the issue of reproducibility would involve changing how the deductive step of the proposed communication method is conducted: keeping the inductive codes the same, machine learning or deep learning models could be used instead of GPT since these models are deterministic once trained. This change would require larger amounts of labeled data to be present which could be acquired by the researchers spending more time creating such data, using crowdsourcing platforms such as Amazon Mechanical Turk, or using the communication method that was created in this research to label new data (assuming that issues of accuracy are solved or dealt with somehow – e.g., the method could be used to run the last steps of the coding as I did in the demonstration step of the analysis in Section 5.1.1) since GPT has the potential to perform better in annotating tasks than crowd-workers (Gilardi et al., 2023). Using such models, though, has its issues since the final output depends on the quality of the training data used (both in terms of the standard of the labeling and the partitions in training and testing data).

The use of GPT in this thesis could be seen as prototyping an automated solution for the analysis of communication for greenwashing purposes: now that it has been proven that an automatic solution can be used for this goal, future research can focus on improving it.

While the first group of suggestions deals with the most pressing limitations of the approach that was developed since these are the issues with the criteria the approach was evaluated against, this second group of recommendations involves overcoming those limitations that deal with the scope of the analysis.

For example, the study of indirect lobbying could be pursued to find the positions of companies on regulations and, in this way, infer whether companies are lobbying against or in favor of them and, therefore, inform the direct lobbying analysis. An example of using media articles containing statements on policies of interest groups to analyze these groups' positions on such regulations is discussed in De Bruycker and Colli (2023). In the paper, the authors use content analysis which would then need to be automated (if the automation goal is still of interest to future researchers) but, as the communication analysis that was developed shows, the (semi-)automation of content analysis can be achieved.

While one of my goals was to have a semi-automatic approach, the way to get to it didn't necessarily have to be automated, especially for the communication analysis. Future research could look into creating the codes (that I manually and inductively developed) in an automatic way, not just for the sake of automation but because with (semi-)automation more data could be processed and, in this way, better codes could be created. For example, Rietz and Maedche (2021) show an AI-based system that semi-automates coding by letting the researchers interactively (re-)define code rules and by using supervised machine learning to extend the coding to new data.

Finally, the scope of the kinds of communication and action to analyze could be extended, with or without changes to the existing methods of analysis. For example, the same communication analysis could be applied to data coming from new sources such as social media. Including more actions would mean finding also new ways to analyze them. And, at the end, a way to smartly display all this data so that the final product still allows the viewer to come to their own greenwashing conclusions should be investigated.

Another recommendation that stems from the limitations of this research is to use all the steps of the design research approach to create a final approach that is designed considering the needs of the final users so that the approach itself and the results can be trusted by them. But their input is especially needed for the "problem identification and motivation" phase because greenwashing is an issue that can be open to interpretation as the vast quantity of definitions (as seen in Chapter 2) hints to: how they perceive and interpret the issue should guide the design development. To do so, interviews could be carried out at the beginning of the process to understand how the final users formulate the problem, their needs, and their objectives for a solution and at the end of the process to evaluate such solution(s). The users of such an approach could be citizens-consumers who can be misled by the greenwashing efforts of companies and/or policymakers that are interested in regulating the phenomenon. Then, the final output of this approach could be a web tool that lets the users run the approach on the companies they are interested in.

Lastly, related to the previous point, it should be investigated how to properly guarantee that the outputs of such an AI-based approaches (as the one created in this thesis) can be trusted by decision-makers (both consumers-citizens and policymakers): in this thesis, accuracy, transparency, and reproducibility were used as objectives to meet to make the approach trustworthy. But this was not an extensive list of objectives and other requirements could come out of the literature on the role of AI in decision-making or by interviewing potential users of such approach. Moreover, the potential biases that can be introduced when using or creating an AI system that deals with decision-making should be further and thoroughly investigated. This is especially true if such AI-based systems were to be used for public decision making because this introduces a whole new set of issues: a relevant example of this is the use of AI software for risk assessment used in US courts to assist judges in deciding whether to release or detain the defendants which has been found to be biased against black offenders as reported by Mattu (2016).

6.5 Policy recommendations

From the research conducted some policy recommendations can be concluded.

What I learned with this research can be of special relevance at this point in time because the European Union has an ambitious plan to "ban" greenwashing (European Parliament, 2023): the European Parliament and Council have reached an agreement containing new rules that will ban "misleading advertisements and provide consumers with better product information".

While reading the text of the agreement[10], I saw a lot of the definitions of greenwashing that were discussed in Chapter 2 reflected in it: for example, banning the use of third-party sustainability certification schemes for labels that have not been established by public authorities can originate from the last of the "sins of greenwashing", "worshiping false labels", discussed by TerraChoice (2010).

I see two potential issues in the text of the agreement: first, it is not clear which criteria will exist to assess whether a claim can be considered as "misleading", and these claims are prohibited on a "case-by-case assessment" which could entail extra manual work by public authorities for each company (or even for each product?) which could easily pile up and slow the greenwashing ban enforcement. Note that this is still an agreement, so its actual implementation is yet to be concluded.

A way to overcome both issues could be to implement some sort of AI-based automatic controller that checks the online claims of companies (e.g., on their webpages that promote products, on online ads) against publicly available information which, in some way, can resemble in its simplest form what was created in this thesis. It could solve the issue of case-by-case assessment because such

[10] Available here:
https://www.europarl.europa.eu/meetdocs/2014_2019/plmrep/COMMITTEES/IMCO/AG/2023/11-28/1289669EN.pdf

a system could be built to flag all the problematic communication of companies and find all the information that can relate to such claims (for example, if a company claims to have third-party certifications, the system could pull up data about this claimed certification authority) in order to aid the final decision by authorities. The controller, similar to what my approach does, should just facilitate the final decision and not determine the final assessment of the claim: this is because AI-based methods and approaches are also bound to errors and an extra layer of control by knowledgeable humans could reduce the amount of errors. Another reason for not building in the controller the final greenwashing appraisal is more practical: the final rules of what is greenwashing or not could vary from country to country; thus, the final appraisal could be left to the local authorities in charge of the final decision while keeping the same structure of the controller the same in all the countries (in this way, only a controller could be built and, therefore, all the money and efforts could be concentrated there).

And, in order to implement an effective controller, the criteria that determine what a misleading (or, at least, a potentially misleading) claim should be specific because the more specific the easier it is to look for it in an automatic way. This comes from the experience that was gathered building the approach in this thesis: the clearer the boundaries between the different codes the easier it was for GPT to classify them correctly.[11] Moreover, it could be worth letting the misleading appraisal to the human controller. As the literature discussed in Chapter 2 teaches, there is greenwashing if there is a mismatch between the words of the companies and what the companies actually do: in this way, the analysis of the communication could become simpler and be more about flagging specific content (such as those sentences that discuss third-party labels) which is a far simpler and more specific task and, thus, easier to automate.

When the implementation of the agreement will come into place (regardless of how it is enforced), the consumers-citizens that have been the ideal potential users of such an approach should not hope that greenwashing will suddenly disappear but they should keep being vigil: because greenwashing can take many forms (as all the different definitions listed in Chapter 2 show) and it deals with perceptions (since communication is involved) which, if the greenwashing assessment that implementations of the agreement will provide for won't have been thoroughly thought of, could impact the decision process of the controllers (for example, if the rules of assessment are too loosely defined and, therefore, too much interpretation is left up to the human controller, some misjudgments could happen and greenwashing companies could be not sanctioned). Therefore, it is suggested that the data being used to analyze companies' claims and the decision outcome should be made open to the public in a way that is easily accessible: with this consumers-citizens would be free to come to their greenwashing conclusions (as the approach that was created in this thesis aimed to do).

The creation of an automatic system, which I tried to pursue in this thesis and suggested above as a recommendation for policy makers, is not to be pursued just for the sake of automation because using AI tools for public decision-making introduces its own issues with system biases that can impact the life of real people as highlighted above. It is because greenwashing, as discussed in Bingler et al. (2023), can undermine climate regulations and the climate transition by enabling companies to hide, for example, their climate footprints and, therefore, conceal the extent to which further actions may

[11] For example, the accuracy achieved in classifying the "stance_on_CC" is one of the highest, 97% (see Appendix C – Figure 1), because the two codes that are used to classify them are clearly separable: one, "company_beleifs", contained sentences where the company was clearly mentioned as the holder of the belief, whereas the other, "common_beleifs", had sentences where it was not mentioned who was the author of such beliefs.

or may not be required. And, as the world is not on track to reach net zero by 2050 as reported by UN Climate (2023), faster and stronger actions are indeed needed.

References

About Greenwashing. (n.d.). Greenwashing Index. Retrieved July 18, 2023, from https://www.greenwashingindex.com/about-greenwashing/.

Almansa-Martínez, A., & Ostio, E. C. (2020). Lóbis espanhóis no registo europeu de transparência. *Revista Comunicação E Sociedade*, 109–126. https://doi.org/10.17231/comsoc.0(2020).2743

Amelang, S. (2022, September 8). “Climate neutral” products are counterproductive greenwashing bluff - NGO. *Clean Energy Wire*. https://www.cleanenergywire.org/news/climate-neutral-products-are-counterproductive-greenwashing-bluff-ngo

Asia Investor Group on Climate Change, Ceres, Investor Group on Climate Change, Institutional Investors Group on Climate Change, & Principles for Responsible Investment. (n.d.). *Methodologies: Net Zero Company Benchmark*. Climate Action 100+. Retrieved December 4, 2023, from https://www.climateaction100.org/net-zero-company-benchmark/methodology/

Bach, N., & Badaskar, S. (2007). A Review of Relation Extraction. *CMU Language Technologies Institute*. https://nguyenbh.github.io/publication/bach-badaskar-2007/bach-badaskar-2007.pdf

Basit, T. N. (2003). Manual or electronic? The role of coding in qualitative data analysis. *Educational Research*, *45*(2), 143–154. https://doi.org/10.1080/0013188032000133548

Beder, S. (2011). Lobbying, greenwash and deliberate confusion: How vested interests undermine climate change regulation. *ResearchGate*. https://www.researchgate.net/publication/275276392_Lobbying_Greenwash_and_Deliberate_Confusion_How_Vested_Interests_Undermine_Climate_Change_Regulation

Bingler, J., Colesanti Senni, C., Fixler, D., & Schimanski, T. (2023, September). *Net Zero Transition Plans: Red Flag Indicators to Assess Inconsistencies and Greenwashing* [Video]. University of Zurich, Oxford Sustainable Finance Group. Retrieved December 1, 2023, from https://wwfint.awsassets.panda.org/downloads/red-flag-indicators-for-transition-plan-inconsistencies-and-greenwashing-26-sept.pdf

Bits, N. (2023, June 4). Best Python Sentiment Analysis Libraries: Unleashing the power of Text Analysis. *Medium*. https://medium.com/@nile.bits/best-python-sentiment-analysis-libraries-unleashing-the-power-of-text-analysis-ad13c272e5d4

Berrone, P., Fosfuri, A., & Gelabert, L. (2015). Does Greenwashing Pay Off? Understanding the Relationship Between Environmental Actions and Environmental Legitimacy. *Journal of Business Ethics*, *144*(2), 363–379. https://doi.org/10.1007/s10551-015-2816-9

BEUC. (2023, June 22). *Consumer groups launch EU-wide complaint against 17 airlines for greenwashing* [Press release]. https://www.beuc.eu/press-releases/consumer-groups-launch-eu-wide-complaint-against-17-airlines-greenwashing

Blanco, S. R., Romero, S., & Souto, B. F. (2021). Green, blue or black, but washing–What company characteristics determine greenwashing? *Environment, Development and Sustainability*, *24*(3), 4024–4045. https://doi.org/10.1007/s10668-021-01602-x

Bloodgood, E. A., & Tremblay-Boire, J. (2016). Does government funding depoliticize non-governmental organizations? Examining evidence from Europe. *European Political Science Review*, *9*(3), 401–424. https://doi.org/10.1017/s1755773915000430

Bricker, B., & Justice, J. (2022). Identifying and Challenging Greenwashing through *Conciliatio*. *Western Journal of Communication*, *86*(4), 521–540. https://doi.org/10.1080/10570314.2022.2087893

Brulle, R. J. (2018). The climate lobby: a sectoral analysis of lobbying spending on climate change in the USA, 2000 to 2016. *Climatic Change*, *149*(3–4), 289–303. https://doi.org/10.1007/s10584-018-2241-z

Brunsdon, C., & Comber, A. (2020). Opening practice: supporting reproducibility and critical spatial data science. *Journal of Geographical Systems*, *23*(4), 477–496. https://doi.org/10.1007/s10109-020-00334-2

Carbon Disclosure Project. (n.d.). *About us*. CDP. Retrieved December 4, 2023, from https://www.cdp.net/en/info/about-us

Carbon Tracker. (2023, February 2). *About Us*. Carbon Tracker Initiative. Retrieved December 4, 2023, from https://carbontracker.org/about/

CDP, United Nations Global Compact, World Resources Institute, & World Wide Fund for Nature. (n.d.). *Measurement, Reporting, and Verification (MRV)*. Science Based Targets Initiative. Retrieved December 4, 2023, from https://sciencebasedtargets.org/measurement-reporting-and-verification-mrv

Chandra, Y., & Shang, L. (2017). An RQDA-based constructivist methodology for qualitative research. *Qualitative Market Research: An International Journal*, *20*(1), 90–112. https://doi.org/10.1108/qmr-02-2016-0014

ChatGPT. (n.d.). OpenAI. Retrieved November 29, 2023, from https://openai.com/chatgpt

Content analysis. (2023, March 30). Columbia University Mailman School of Public Health. Retrieved November 28, 2023, from https://www.publichealth.columbia.edu/research/population-health-methods/content-analysis

Contreras-Pacheco, O. E., & Claasen, C. (2017). Fuzzy reporting as a way for a company to greenwash: perspectives from the Colombian reality. *Problems and Perspectives in Management*, *15*(2), 525–535. https://doi.org/10.21511/ppm.15(si).2017.06

Copley, M. (2023, April 9). Businesses face more and more pressure from investors to act on climate change. *NPR*. https://www.npr.org/2023/04/09/1168446621/businesses-face-more-and-more-pressure-from-investors-to-act-on-climate-change

Corporate Europe Observatory, Food & Water Europe, Friends of the Earth Europe, & Greenpeace. (2019, October 24). *Big Oil and gas buying influence in Brussels*. Greenpeace. https://www.greenpeace.org/eu-unit/issues/climate-energy/2238/big-oil-gas-buying-influence-brussels/

Corporate Europe Observatory & Lobby Control. (n.d.). *LobbyFacts*. LobbyFacts.eu. https://www.lobbyfacts.eu/

De Bruycker, I., & Colli, F. (2023). Affluence, congruence, and lobbying success in EU climate policy. *Journal of Public Policy*, 1–21. https://doi.org/10.1017/s0143814x23000120

Dellis, K. (2023). Lobbying and innovation in the European Union. *Scottish Journal of Political Economy*, *70*(4), 319–354. https://doi.org/10.1111/sjpe.12344

Delmas, M. A., Lim, J., & Nairn-Birch, N. (2016). Corporate environmental performance and lobbying. *Academy of Management Discoveries*, *2*(2), 175–197. https://doi.org/10.5465/amd.2014.0065

Demers, E., Hendrikse, J., Joos, P., & Lev, B. (2021). ESG did not immunize stocks during the COVID-19 crisis, but investments in intangible assets did. *Journal of Business Finance & Accounting*, *48*(3–4), 433–462. https://doi.org/10.1111/jbfa.12523

Detroja, K., Bhensdadia, D., & Bhatt, B. (2023). A survey on Relation Extraction. *Intelligent Systems With Applications*, *19*, 200244. https://doi.org/10.1016/j.iswa.2023.200244

Energy & Climate Intelligence Unit, Data-Driven EnviroLab, NewClimate Institute, & Oxford Net Zero. (n.d.a). *Methodology*. Net Zero Tracker. Retrieved December 4, 2023, from https://zerotracker.net/methodology

Energy & Climate Intelligence Unit, Data-Driven EnviroLab, NewClimate Institute, & Oxford Net Zero. (n.d.b). *Net Zero Tracker* [Dataset]. https://zerotracker.net/

Entman, R. M. (2007). Framing Bias: Media in the distribution of power. *Journal of Communication*, *57*(1), 163–173. https://doi.org/10.1111/j.1460-2466.2006.00336.x

Ethical Consumer Group. (n.d.). *About*. Shop Ethical! Retrieved December 4, 2023, from https://www.ethical.org.au/about/

European Commission. (2021, January 28). *Screening of websites for 'greenwashing': half of green claims lack evidence* [Press release]. https://ec.europa.eu/commission/presscorner/detail/en/ip_21_269

European Insurance and Occupational Pensions Authority. (2022, November 15). ESAs launch joint Call for Evidence on greenwashing. *European Insurance and Occupational Pensions Authority*. Retrieved December 1, 2023, from https://www.eiopa.europa.eu/esas-launch-joint-call-evidence-greenwashing-2022-11-15_en

European Parliament. (2023, September 19). *EU to ban greenwashing and improve consumer information on product durability | News | European Parliament* [Press release]. https://www.europarl.europa.eu/news/en/press-room/20230918IPR05412/eu-to-ban-greenwashing-and-improve-consumer-information-on-product-durability

European Parliament, Council of the European Union, & European Commission. (n.d.). *Transparency register* [Dataset]. https://ec.europa.eu/transparencyregister/public/consultation/search.do?locale=en&reset=

Fortune. (2023). *Fortune Global 500* (Version 2023) [Dataset]. https://fortune.com/ranking/global500/2023/search/

Futerra (2009). *Understanding and Preventing Greenwash: A Business Guide*. BSR. https://www.bsr.org/reports/Understanding%20_Preventing_Greenwash.pdf

Feng, T., Liu, S., & Zhang, Q. (2022). Linking perceived institutional force and environmental strategy: the moderating role of institutional incompleteness. *Baltic Journal of Management*, *17*(3), 392–412. https://doi.org/10.1108/bjm-06-2021-0221

Gatti, L., Pizzetti, M., & Seele, P. (2021). Green lies and their effect on intention to invest. *Journal of Business Research*, *127*, 228–240. https://doi.org/10.1016/j.jbusres.2021.01.028

Gilardi, F., Alizadeh, M., & Kubli, M. (2023). ChatGPT outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(30). https://doi.org/10.1073/pnas.2305016120

Gill, R. (2000). Discourse Analysis. In P. Atkinson, M. W. Bauer, & G. Gaskell (Eds.), *Qualitative Researching with Text, Image and Sound*. SAGE Publications Ltd. https://books.google.nl/books?hl=it&lr=&id=UQewQ4FzHowC&oi=fnd&pg=PA172&dq=discourse+analysis&ots=lcvXZbQUNL&sig=m_PUspUNhG8NRpJsaPIhBdnyOyU&redir_esc=y#v=onepage&q=discourse%20analysis&f=false

Gullberg, A. T. (2013). Pressure or information? Lobbying for binding renewable energy targets in the European Union. *Review of Policy Research*, *30*(6), 611–628. https://doi.org/10.1111/ropr.12049

Gundersen, O. E. (2021). The fundamental principles of reproducibility. *Philosophical Transactions of the Royal Society A*, *379*(2197). https://doi.org/10.1098/rsta.2020.0210

Haug, S., Rietz, T., & Maedche, A. (2021). Accelerating Deductive Coding of Qualitative Data: An Experimental Study on the Applicability of Crowdsourcing. *MuC '21: Proceedings of Mensch Und Computer 2021*. https://doi.org/10.1145/3473856.3473873

Hevner, March, Park, H., & Ram. (2004). Design science in Information Systems Research. *Management Information Systems Quarterly*, *28*(1), 75. https://doi.org/10.2307/25148625

Herrera, Y. M., & Braumoeller, B. F. (2004). *Discourse and Content Analysis*. Weatherhead - Center for International Affairs at Harvard University. https://wcfia.harvard.edu/publications/symposium-discourse-and-content-analysis

Hollman, M., & Murdoch, Z. (2018). Lobbying cycles in Brussels: Evidence from the rotating presidency of the Council of the European Union. *European Union Politics*, *19*(4), 597–616. https://doi.org/10.1177/1465116518796306

Hu, T., Chen, Z., Ge, J., Yang, Z., & Ji-Chao, X. (2023). A Chinese Few-Shot text classification method utilizing improved prompt learning and unlabeled data. *Applied Sciences*, *13*(5), 3334. https://doi.org/10.3390/app13053334

Ihlen, Ø. (2009). Business and Climate Change: The climate response of the world's 30 largest corporations. *Environmental Communication-a Journal of Nature and Culture*, *3*(2), 244–262. https://doi.org/10.1080/17524030902916632

InfluenceMap (2019). Big Oil's real agenda on climate change. In *InfluenceMap*. https://influencemap.org/report/How-Big-Oil-Continues-to-Oppose-the-Paris-Agreement-38212275958aa21196dae3b76220bddc

InfluenceMap. (2023). "Net Zero Greenwash": The Gap Between Corporate Commitments and their Policy Engagement. In *InfluenceMap*. InfluenceMap. https://influencemap.org/briefing/The-State-of-Net-Zero-Greenwash-24402

Interinstitutional Agreement on a mandatory transparency register, European Parliament - Council of the European Union - European Commission, May 20, 2021, EUR-Lex, https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=uriserv:OJ.L_.2021.207.01.0001.01.ENG

Jaworska, S., & Nanda, A. (2016). Doing Well by Talking Good: A topic Modelling-Assisted Discourse Study of Corporate Social Responsibility. *Applied Linguistics*. https://www.researchgate.net/publication/303832094_Doing_Well_by_Talking_Good_A_Topic_Modelling-Assisted_Discourse_Study_of_Corporate_Social_Responsibility

Jones, E. (2019). Rethinking Greenwashing: Corporate Discourse, Unethical Practice, and the Unmet Potential of Ethical Consumerism. *Sociological Perspectives*, *62*(5), 728–754. https://doi.org/10.1177/0731121419849095

Kim, S. E., Urpelainen, J., & Yang, J. (2015). Electric utilities and American climate policy: lobbying by expected winners and losers. *Journal of Public Policy*, *36*(2), 251–275. https://doi.org/10.1017/s0143814x15000033

Kowsari, K., Meimandi, K. J., Heidarysafa, M., Mendu, S., Barnes, L. E., & Brown, D. E. (2019). Text Classification Algorithms: A survey. *Information*, *10*(4), 150. https://doi.org/10.3390/info10040150

Kurpierz, J., & Smith, K. (2020). The greenwashing triangle: adapting tools from fraud to improve CSR reporting. *Sustainability Accounting, Management and Policy Journal*, *11*(6), 1075–1093. https://doi.org/10.1108/sampj-10-2018-0272

Laville, S. (2019, October 24). Fossil fuel big five "spent €251m lobbying EU" since 2010. *The Guardian*. https://www.theguardian.com/business/2019/oct/24/fossil-fuel-big-five-spent-251m-lobbying-european-union-2010-climate-crisis

Laville, S. (2021, August 25). Top oil firms spending millions lobbying to block climate change policies, says report. *The Guardian*. https://www.theguardian.com/business/2019/mar/22/top-oil-firms-spending-millions-lobbying-to-block-climate-change-policies-says-report

Leggett, D. (2021, September 27). COP26 – climate change and the automotive sector (1). *Just Auto*. https://www.just-auto.com/features/cop26-climate-change-and-the-automotive-sector-1/

Li, W., Li, W., Seppänen, V., & Koivumäki, T. (2022). Effects of greenwashing on financial performance: Moderation through local environmental regulation and media coverage. *Business Strategy and the Environment*, *32*(1), 820–841. https://doi.org/10.1002/bse.3177

Lischka, J. A. (2022). Content analysis in the research field of corporate communication. In *Standardized Content Analysis in Communication Research* (pp. 349–361). Springer VS. https://doi.org/10.1007/978-3-658-36179-2_30

Linström, M., & Marais, W. (2012). Qualitative News Frame Analysis: A Methodology. *Communitas*, *17*, 21–38. https://www.researchgate.net/publication/351884528_QUALITATIVE_NEWS_FRAME_ANALYSIS_A_METHODOLOGY_Communitas

Lobbying regulation — the EU mandatory transparency register. (n.d.). EUR-Lex. Retrieved November 27, 2023, from https://eur-lex.europa.eu/EN/legal-content/summary/lobbying-regulation-the-eu-mandatory-transparency-register.html

Loukas, L., Stogiannidis, I., Malakasiotis, P., & Vassos, S. (2023). Breaking the Bank with ChatGPT: Few-Shot Text Classification for Finance. In *Proceedings of the Joint Workshop of the 5th Financial Technology and Natural Language Processing (FinNLP) and 2nd Multimodal AI For Financial Forecasting (Muffin)*. https://aclanthology.org/2023.finnlp-1.7.pdf

Lyon, T. P., & Montgomery, A. W. (2015). The Means and End of Greenwash. *Organization & Environment*, *28*(2), 223–249. https://doi.org/10.1177/1086026615575332

Ma, L., Peterson, E. A., Shin, I. J., Muesse, J., Marino, K., Steliga, M. A., & Johann, D. J. (2021). NPARS—A Novel approach to address accuracy and Reproducibility in Genomic data science. *Frontiers in Big Data*, *4*. https://doi.org/10.3389/fdata.2021.725095

Мамонтова, Э. В., Buryk, Z., Strikha, L., Vonsovych, S., Voropayeva, T., & Баранова, О. В. (2021). Modern experience of lobbying interests in Europe. *Estudios De Economía Aplicada*, *39*(8). https://doi.org/10.25115/eea.v39i8.6203

Mamalis, A., Spentzas, K. N., & Mamali, A. A. (2013). The impact of automotive industry and its supply chain to climate change: Somme techno-economic aspects. *European Transport Research Review*, *5*(1), 1–10. https://doi.org/10.1007/s12544-013-0089-x

Mattu, J. a. L. K. (2016, May 23). Machine bias. *ProPublica*. https://www.propublica.org/article/machine-bias-risk-assessments-in-criminal-sentencing

Medhat, W., Hassan, A., & Korashy, H. (2014). Sentiment analysis algorithms and applications: A survey. *Ain Shams Engineering Journal*, *5*(4), 1093–1113. https://doi.org/10.1016/j.asej.2014.04.011

Megura, M., & Gunderson, R. (2022). Better poison is the cure? Critically examining fossil fuel companies, climate change framing, and corporate sustainability reports. *Energy Research & Social Science*, *85*, 102388. https://doi.org/10.1016/j.erss.2021.102388

Min, S., Lyu, X., Holtzman, A., Artetxe, M., Lewis, M., Hajishirzi, H., and Zettlemoyer, L. (2022, February 25). *Rethinking the role of demonstrations: What makes In-Context Learning work?* arXiv.org. https://arxiv.org/abs/2202.12837

Moravcsik, A. (2019). Transparency in Qualitative Research. *Foundations*. https://www.princeton.edu/~amoravcs/library/TransparencyinQualitativeResearch.pdf

Moodaley, W., & Telukdarie, A. (2023). Greenwashing, Sustainability Reporting, and Artificial Intelligence: A Systematic Literature review. *Sustainability*, *15*(2), 1481. https://doi.org/10.3390/su15021481

Mućko, P. (2021). Sentiment analysis of CSR disclosures in annual reports of EU companies. *Procedia Computer Science*, *192*, 3351–3359. https://doi.org/10.1016/j.procs.2021.09.108

Naveed, H., Khan, A. U., Qiu, S., Saqib, M., Anwar, S., Usman, M., Akhtar, N., Barnes, N., and Mian, A. (2023). A Comprehensive Overview of Large Language Models. *arXiv.org*. https://arxiv.org/abs/2307.06435

Nemes, N., Scanlan, S. J., Smith, P., Smith, T., Aronczyk, M., Hill, S., Lewis, S. L., Montgomery, A. W., Tubiello, F. N., & Stabinsky, D. (2022). An integrated framework to assess greenwashing. *Sustainability*, *14*(8), 4431. https://doi.org/10.3390/su14084431

Oppong-Tawiah, D., & Webster, J. (2023). Corporate Sustainability communication as 'Fake news': Firms' greenwashing on Twitter. *Sustainability*, *15*(8), 6683. https://doi.org/10.3390/su15086683

Parafiniuk, A., & Smith, Z. A. (2019). Green Gilded Oil: How Faux Sustainability by US Oil Companies is Undermining Neo-Sustainability. *Sustainability*, *11*(14), 3760. https://doi.org/10.3390/su11143760

Peffers, K., Tuunanen, T., Rothenberger, M. A., & Chatterjee, S. (2007). A Design Science research Methodology for Information Systems research. *Journal of Management Information Systems*, *24*(3), 45–77. https://doi.org/10.2753/mis0742-1222240302

Plec, E., & Pettenger, M. E. (2012). Greenwashing consumption: the didactic framing of ExxonMobil's energy solutions. *Environmental Communication-a Journal of Nature and Culture*, *6*(4), 459–476. https://doi.org/10.1080/17524032.2012.720270

Pratt, M. (2020, February 5). Amazon's environmental impact delivers climate change concerns | Supply Chain Transportation and Logistics Center at the University of Washington. *Tech Target*. https://depts.washington.edu/sctlctr/news-events/in-the-news/amazons-environmental-impact-delivers-climate-change-concerns

Principles for Responsible Investment, United Nations Environment Programme Finance Initiative, & United Nations Global Compact. (2018). *Converging on Climate Lobbying*. https://www.unpri.org/Uploads/g/v/q/PRI_Converging_on_climate_lobbying.pdf

Protecting consumers from greenwashing. (2022, June 24). *The Behavioural Insights Team*. https://www.bi.team/blogs/there-is-a-growing-epidemic-of-climate-anxiety/

re — Regular expression operations. (n.d.). Python Documentation. https://docs.python.org/3/library/re.html

Recent Study Reveals More Than a Third of Global Consumers Are Willing to Pay More for Sustainability as Demand Grows for Environmentally-Friendly Alternatives. (2021, October 14). *BusinessWire*. https://www.businesswire.com/news/home/20211014005090/en/Recent-Study-Reveals-More-Than-a-Third-of-Global-Consumers-Are-Willing-to-Pay-More-for-Sustainability-as-Demand-Grows-for-Environmentally-Friendly-Alternatives

Reiss, M., V. (2023, April 17). *Testing the reliability of ChatGPT for text annotation and Classification: A cautionary remark*. arXiv.org. https://arxiv.org/abs/2304.11085

Rietz, T., & Maedche, A. (2021). Cody: An AI-Based System to Semi-Automate Coding for Qualitative Research. In *CHI '21: Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445591

Sánchez-Núñez, P., De Las Heras Pedrosa, C., & Peláez, J. I. (2020). Opinion Mining and Sentiment Analysis in Marketing Communications: A science mapping analysis in Web of Science (1998–2018). *Social Sciences*, *9*(3), 23. https://doi.org/10.3390/socsci9030023

Santos, C. M. R. G. D., Coelho, A., & Marques, A. (2023). A systematic literature review on greenwashing and its relationship to stakeholders: state of art and future research agenda. *Management Review Quarterly*. https://doi.org/10.1007/s11301-023-00337-5

Scott, A., & Pickard, S. (n.d.). *FAQ 3: oil and gas, poverty, the environment and human rights*. ODI: Think Change. Retrieved October 6, 2023, from https://odi.org/en/about/our-work/climate-and-sustainability/faq-3-oil-and-gas-poverty-the-environment-and-human-rights/

Secretariat-General. (n.d.). *Transparency Register* (January 2023) [Dataset]. https://data.europa.eu/data/datasets/transparency-register?locale=en

Shanahan, E. A., Jones, M. D., McBeth, M. K., & Radaelli, C. M. (2018). The narrative policy framework. In *Routledge eBooks* (pp. 173–213). https://doi.org/10.4324/9780429494284-6

Schäfer, M. S. (2012). Online communication on climate change and climate politics: a literature review. *WIREs Climate Change*, *3*(6), 527–543. https://doi.org/10.1002/wcc.191

Schnurr, S., Wharton, S., Alansari, S., Angouri, J., Phiri, R. C., Chiriatti, T., Debray, C., Efthymiadou, C., Hah, S., Harrison, T., Kedveš, A., Khamkhien, A., Kim, K., Omar, N. a. M., Nguyễn, T. H. N., & Reissner-Roubicek, S. (2016). Not so 'innocent' after all? Exploring corporate identity construction online. *Discourse & Communication*, *10*(3), 291–313. https://doi.org/10.1177/1750481315623902

Seawright, J., & Gerring, J. (2008). Case selection techniques in case study research. *Political Research Quarterly*, *61*(2), 294–308. https://doi.org/10.1177/1065912907313077

Seele, P., & Gatti, L. (2015). Greenwashing Revisited: In Search of a Typology and Accusation-Based Definition Incorporating Legitimacy Strategies. *Business Strategy and the Environment*, *26*(2), 239–252. https://doi.org/10.1002/bse.1912

Sensharma, S., Sinha, M., & Sharma, D. (2022). Do Indian Firms Engage in Greenwashing? Evidence from Indian Firms. *Australasian Accounting, Business and Finance Journal, 16*(5). https://ro.uow.edu.au/aabfj/vol16/iss5/5/

Shi, Y., Hehuan, M., Wenliang, Z., Qiaoyu, T., Gengchen, M., Xiang, L., Tianming, L., and Huang, J. (2023, May 3). *ChatGraph: Interpretable text classification by converting ChatGPT knowledge to graphs*. arXiv.org. https://arxiv.org/abs/2305.03513

Siano, A., Vollero, A., Conte, F., & Amabile, S. (2017). "More than words": Expanding the taxonomy of greenwashing after the Volkswagen scandal. *Journal of Business Research*, *71*, 27–37. https://doi.org/10.1016/j.jbusres.2016.11.002

Silverstein, K. (2023, February 21). Environment+Energy Leader. *Environment+Energy Leader*. https://www.environmentenergyleader.com/2023/02/mckesson-corporation-tackles-climate-change-by-increasing-energy-efficiency-and-renewable-energy/

Sluban, B., Mikac, M., Novak, P. K., Battiston, S., & Mozetič, I. (2018). Profiling the EU lobby organizations in Banking and Finance. *Applied Network Science*, *3*(1). https://doi.org/10.1007/s41109-018-0099-7

The State of Consumer Spending: Gen Z Shoppers demand sustainable retail. (n.d.). FirstInsight. Retrieved August 11, 2023, from https://www.firstinsight.com/white-papers-posts/gen-z-shoppers-demand-sustainability

Supran, G., & Орескес, H. (2021). Rhetoric and frame analysis of ExxonMobil's climate change communications. *One Earth*, *4*(5), 696–719. https://doi.org/10.1016/j.oneear.2021.04.014

Tai, R. H., Bentley, L. R., Xia, X., Sitt, J., Fankhauser, S. C., Chicas-Mosier, A. M., & Monteith, B. D. (2023). Use of large language models to aid analysis of textual data. *bioRxiv (Cold Spring Harbor Laboratory)*. https://doi.org/10.1101/2023.07.17.549361

Talbot, D., & Boiral, O. (2014). Strategies for climate change and impression Management: a case study among Canada's large industrial emitters. *Journal of Business Ethics*, *132*(2), 329–346. https://doi.org/10.1007/s10551-014-2322-5

Taye, M. M. (2023). Understanding of Machine Learning with Deep Learning: Architectures, Workflow, Applications and Future Directions. *Computers*, *12*(5), 91. https://doi.org/10.3390/computers12050091

Tannen, D. (n.d.). *Discourse Analysis—What Speakers do in Conversation*. Linguistic Society of America. Retrieved November 28, 2023, from https://www.linguisticsociety.org/resource/discourse-analysis-what-speakers-do-conversation

TerraChoice (2010). *The Sins of Greenwashing*. Underwriters Laboratories. https://www.twosides.info/wp-content/uploads/2018/05/Terrachoice_The_Sins_of_Greenwashing_-_Home_and_Family_Edition_2010.pdf

Thaker, J. (2019). Corporate communication about climate science. *Journal of Communication Management*, *24*(3), 245–264. https://doi.org/10.1108/jcom-06-2019-0092

Thanos, C. (2017). Research data reusability: conceptual foundations, barriers and enabling technologies. *Publications*, *5*(1), 2. https://doi.org/10.3390/publications5010002

Thomas, D. R. (2006). A general inductive approach for analyzing qualitative evaluation data. *American Journal of Evaluation*, *27*(2), 237–246. https://doi.org/10.1177/1098214005283748

Thomas, A. (2021). 'Heart of steel': how trade unions lobby the European Union over emissions trading. *Environmental Politics*, *30*(7), 1217–1236. https://doi.org/10.1080/09644016.2021.1871812

Tidey, A. (2022, December 14). Calls for EU lobbying rules to be reformed grow as corruption scandal rocks Brussels. *Euronews*. https://www.euronews.com/my-europe/2022/12/12/calls-for-eu-lobbying-rules-to-be-reformed-grow-as-corruption-scandal-rocks-brussels

Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., Rodriguez, A., Joulin, A., Grave, É., & Lample, G. (2023). *LLAMA: Open and Efficient Foundation Language Models*. arXiv.org. https://doi.org/10.48550/arxiv.2302.13971

Trajanov, D., Лазарев, Г. И., Chitkushev, L., & Vodenska, I. (2023). Comparing the performance of ChatGPT and state-of-the-art climate NLP models on climate-related text classification tasks. *E3S Web of Conferences*, *436*, 02004. https://doi.org/10.1051/e3sconf/202343602004

Transparency register. (n.d.). Retrieved August 11, 2023, from https://ec.europa.eu/transparencyregister/public/homePage.do?redir=false&locale=en

Turing. (2022, September 16). *Which language is useful for NLP and why?* www.turing.com. https://www.turing.com/kb/which-language-is-useful-for-nlp-and-whyVollero, A., Palazzo, M., Siano, A., & Elving, W. (2016). Avoiding the greenwashing trap: between CSR communication and stakeholder engagement. *International Journal of Innovation and Sustainable Development*, *10*(2), 120. https://doi.org/10.1504/ijisd.2016.075542

UN Climate. (2023, November 14). New Analysis of National Climate Plans: Insufficient Progress Made, COP28 Must Set Stage for Immediate Action. *United Nations Climate Change*. https://unfccc.int/news/new-analysis-of-national-climate-plans-insufficient-progress-made-cop28-must-set-stage-for-immediate

Uniper. (2021, October 15). In China, climate action is a matter for the country's leaders". *Uniper News*. https://www.uniper.energy/news/debateenergy-in-china-climate-action-is-a-matter-for-the-countrys-leaders

Van Der Aalst, W. M. P., Bichler, M., & Heinzl, A. (2017). Responsible Data science. *Business & Information Systems Engineering*, *59*(5), 311–313. https://doi.org/10.1007/s12599-017-0487-z

Wadhwa, S., Amir, S., & Wallace, B. C. (2023). Revisiting Relation Extraction in the era of Large Language Models. In *Proceedings of Association for Computational Linguistics Conference*. https://doi.org/10.18653/v1/2023.acl-long.868

Wagner, P. M., Ocelík, P., Gronow, A., Ylä-Anttila, T., Schmidt, L., & Delicado, A. (2023). Network ties, institutional roles and advocacy tactics:Exploring explanations for perceptions of influence in climate change policy networks. *Social Networks*, *75*, 78–87. https://doi.org/10.1016/j.socnet.2021.11.008

Walton, M. (2020, March 23). If the energy sector is to tackle climate change, it must also think about water – Analysis - IEA. *IEA Commentary*. https://www.iea.org/commentaries/if-the-energy-sector-is-to-tackle-climate-change-it-must-also-think-about-water

Wei, W., Ma, D., Wu, F., Sun, M., Xu, S., Hua, Q., & Sun, Z. (2023). Exploring the knowledge structure and hotspot evolution of Greenwashing: A visual analysis based on bibliometrics. *Sustainability*, *15*(3), 2290. https://doi.org/10.3390/su15032290

Wei, J., Wang, X., Schuurmans, D., Bosma, M., Ichter, B., Xia, F., Chi, E., Le, Q.V., and Zhou, D. (2022). Chain-of-Thought prompting elicits reasoning in large language models. In *Advances in Neural Information Processing Systems 35 (NeurIPS 2022)*. https://proceedings.neurips.cc/paper_files/paper/2022/hash/9d5609613524ecf4f15af0f7b31abca4-Abstract-Conference.html

Weise, Z., & Coi, G. (2023, July 25). This summer is what climate change looks like, scientists say. *POLITICO*. https://www.politico.eu/article/climate-change-summer-2023-heat-wave/

What is greenwashing? (2023, February 9). NRDC. https://www.nrdc.org/stories/what-greenwashing

What is the Transparency Register? (n.d.). Transparency Register. Retrieved November 27, 2023, from https://ec.europa.eu/transparencyregister/public/staticPage/displayStaticPage.do?locale=en&reference=WHY_TRANSPARENCY_REGISTER

White, J. (2023, February 21). *A Prompt Pattern Catalog to Enhance Prompt Engineering with ChatGPT*. arXiv.org. https://arxiv.org/abs/2302.11382

Wilkinson, M. D., Dumontier, M., Aalbersberg, I. J., Appleton, G., Axton, M., Baak, A., Blomberg, N., Boiten, J., Da Silva Santos, L. O. B., Bourne, P. E., Bouwman, J., Brookes, A. J., Clark, T. W., Crosas, M., Dillo, I., Dumon, O., Edmunds, S., Evelo, C. T., Finkers, R., . . . Mons, B. (2016). The FAIR Guiding Principles for scientific data management and stewardship. *Scientific Data*, *3*(1). https://doi.org/10.1038/sdata.2016.18

Wohlin, C., & Rainer, A. (2022). Is it a case study?—A critical analysis and guidance. *Journal of Systems and Software*, *192*, 111395. https://doi.org/10.1016/j.jss.2022.111395

Wolf, M., Logan, J., Mehta, K., Jacobson, D., Cashman, M., Walker, A. M., Eisenhauer, G., Widener, P., & Cliff, A. (2021). Reusability first: toward FAIR workflows. In *2021 IEEE International Conference on Cluster Computing*. https://ieeexplore.ieee.org/document/9556094

Wolton, L. P., Crow, D. A., & Heikkila, T. (2021). Stepping Forward: Towards a More Systematic NPF with Automation. In *Narratives and the Policy Process: Applications of the Narrative Policy Framework*. PressBooks. https://oer.pressbooks.pub/scienceofstoriesv2/chapter/stepping-forward/

Wong, K. (2019, November 6). How to Be a More Conscious Consumer, Even If You're on a Budget. *The New York Times*. https://www.nytimes.com/2019/10/01/smarter-living/sustainabile-shopping-conscious-consumer.html

Wu, W., Chen, W., Fu, Y., Jiang, Y., & Huang, G. Q. (2022). Unsupervised neural network-enabled spatial-temporal analytics for data authenticity under environmental smart reporting system. *Computers in Industry*, *141*, 103700. https://doi.org/10.1016/j.compind.2022.103700

Wu, Y., Zhang, K., & Xie, J. (2020). Bad greenwashing, good greenwashing: corporate social responsibility and information transparency. *Management Science*, *66*(7), 3095–3112. https://doi.org/10.1287/mnsc.2019.3340

Yu, E. P., Van Luu, B., & Chen, C. H. (2020). Greenwashing in environmental, social and governance disclosures. *Research in International Business and Finance*, *52*, 101192. https://doi.org/10.1016/j.ribaf.2020.101192

Zeng, A., & Battiston, S. (2016). The Multiplex network of EU lobby organizations. *PLOS ONE*, *11*(10), e0158062. https://doi.org/10.1371/journal.pone.0158062

Zhang, D. (2022a). Are firms motivated to greenwash by financial constraints? Evidence from global firms' data. *Journal of International Financial Management and Accounting*, *33*(3), 459–479. https://doi.org/10.1111/jifm.12153

Zhang, D. (2022b). Environmental regulation, green innovation, and export product quality: What is the role of greenwashing? *International Review of Financial Analysis*, *83*, 102311. https://doi.org/10.1016/j.irfa.2022.102311

Zhang, D. (2023). Subsidy expiration and greenwashing decision: Is there a role of bankruptcy risk? *Energy Economics*, *118*, 106530. https://doi.org/10.1016/j.eneco.2023.106530

Zhang, Y., & Wildemuth, B. M. (2005). Qualitative Analysis of Content by. *Human Brain Mapping*, *30*(7), 2197–2206. https://philpapers.org/rec/ZHAQAO

Zhao, B., Jin, W., Del Ser, J., & Yang, G. (2023). ChatAgri: Exploring potentials of ChatGPT on cross-linguistic agricultural text classification. *Neurocomputing*, *557*, 126708. https://doi.org/10.1016/j.neucom.2023.126708

Appendix

Appendix A – Companies' details

Fotune 500 Position	Company	Included or Excluded in pool	Fotune 500 Position	Company	Included or Excluded in pool
1	Walmart	Included	11	CVS Health	Included
2	Saudi Aramco	Included	12	Trafigura Group	Included
3	State Grid	Excluded because not enough data	13	China State Construction Engineering	Excluded because not enough data
4	Amazon	Included	14	Berkshire Hathaway	Excluded because not enough data
5	China National Petroleum	Included	15	Volkswagen	Included
6	Sinopec Group	Included	16	Uniper	Included
7	Exxon Mobil	Excluded because it is one of the companies for the evaluation of the whole method.	17	Alphabet	Included
8	Apple	Included	18	McKesson	Included
9	Shell	Excluded because it is one of the companies for the evaluation of the whole method.	19	Toyota Motor	Included
10	UnitedHealth Group	Included	20	TotalEnergies	Excluded because it is one of the companies for the evaluation of the whole method.

Figure 1. List of Fortune 20 and whether they were further included or excluded from the picking process (and the reason behind the eventual exclusion).

Net Zero Position / Sector	In corporate strategy	Declaration/pledge	Proposed / in discussion	Ambigous*
Retail	Walmart			
Oil		***Saudi Aramco***	***Sinopec Group***	China National Petroleum
Internet service and online retail	***Amazon*** , Alphabet			
Computers / phones	Apple			
Health	CSV Health	UnitedHealth Group		***McKesson***
Trading				Trafigura Group
Car manufacturing	***Volkswagen*** , Toyota			
Energy				***Uniper***

Figure 2. Distributions of companies over Net Zero position and industrial sector. The companies in bold and italic are the ones that are picked in the end.

** The companies in the "Ambiguous" column are the ones that are not in the Net Zero Tracker, and, therefore, I can't say much about their Net Zero positions.*

Relevant lobby	Company
Yes	***Saudi Aramco*** , ***Amazon*** , Apple, Trafigura group, ***Volkswagen*** , ***Uniper*** , ***McKesson*** , Toyota
No	Walmart, China National Petroleum, CSV Health, United Health Group, Alpahebet, ***Sinopec Group***

Figure 3. Distributions of companies over their lobbying activities. The companies in bold and italic are the ones that are picked in the end.

Location	Company
US	Walmart, ***Amazon*** , Apple, CSV Health, United Health Group, Alphabet, ***McKesson***
Middle East	***Saudi Aramco***
East Asia	China National Petroleum, ***Sinopec Group*** , Singapore, Toyota
Europe	***Volkswagen*** , ***Uniper***

Figure 4. Distributions of companies over their locations. The companies in bold and italic are the ones that are picked in the end.

Company	Website
Saudi Aramco	aramco.com
Amazon	aboutamazon.com
Sinopec Group	sinopecgroup.com
Volkswagen	vw.com
Uniper	uniper.energy
McKesson	mckesson.com

Figure 5. Companies' official corporates websites.

Appendix B – Inductively-created codes

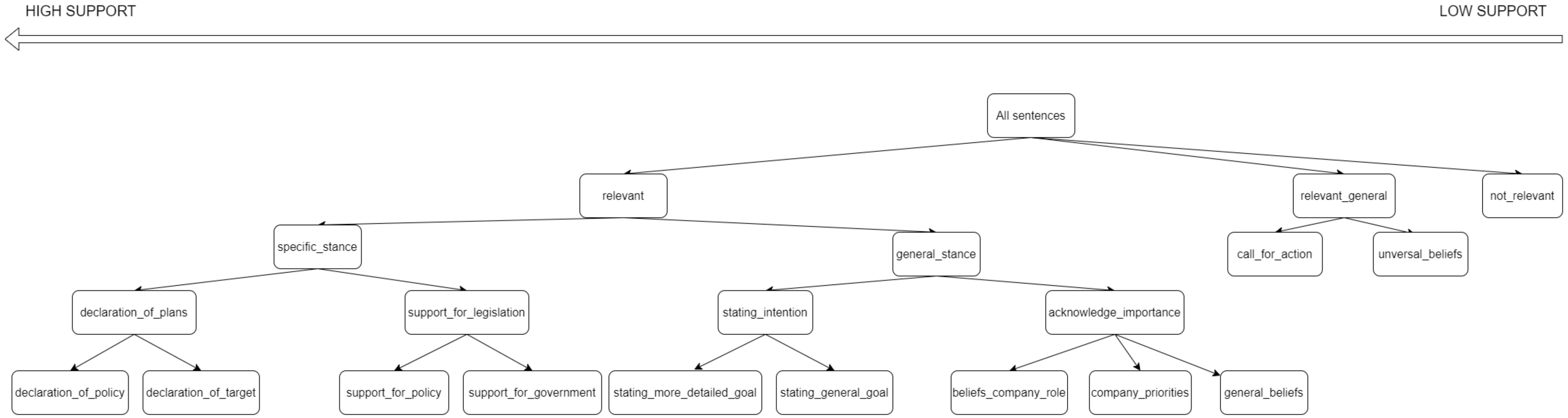


Figure 1. The tree that originated from the inductive coding of the sample companies' sentences. The inductive coding was done in an hierarchical manner and, therefore, a tree resulted from this process.

Appendix C – Deductive Coding via GPT

Root label	Highest accuracy reached
all sentences	0.79
relevant	0.85
actions	0.78
stating_intentions	0.73
acknowledge_importance	0.78
stance_on_policy	1.00
stance_on_CC	0.97
common_beliefs	0.81

Figure 1. Accuracy for each classification task. On each line the accuracy represented is the accuracy achieved on the classification task that differentiates between the sentences that have the higher label (root label) present on the line. So, the accuracy of 100% is achieved when classifying all the "stance_on_policy" sentences between the "support_for_policy" and "support_for_government" labels (see Chapter 4 – Figure 5 for the tree version of the labels).

Label	*stating_intentions*	*acknowledge_importance*	*support_for_policy*	*Average accuracy:*	*Standard deviation:*
Accuracy	0.525	0.525	0.670	0.614	0.070
Label	*support_for_government*	*company_beliefs*	*common_beliefs*		
Accuracy	0.670	0.647	0.647		

Figure 2. Average accuracy and standard deviation of pruned tree, accuracy per lower label of the pruned tree. These are computed for when using the tree depicted in Chapter 4 – Figure 6 (the pruned tree).

Prompt no.	Description	Average accuracy
1	One example from each sub-category of "relevant" ("actions", "stance_on_policy", "stance_on_CC") and one example for "not relevant"	*0.67*
2	5 more examples from "actions" since this is the biggest sub-category of "relevant". 5 more examples for "not relevant" with explanations of why they are not relevant. More examples and better prompts for "actions" and "not_relevant". One example for each of the actions classes	*0.67*
3	One more example from the "stance_on_policy" and two from "stance_on_CC" to make the number of examples more even.	*0.73*
4	Explaining the reasoning behind each examples' classification	*0.79*

Figure 3. Example of accuracy values for different prompts. This example comes from classifying "actions" vs "stance_on_policy" vs "stance_on_CC". Increasing the number of examples and explaining the reasoning helps in increasing the accuracy.

Label	*stating_intentions*	*acknowledge_importance*	*support_for_policy*	*Average accuracy:*	*Standard deviation:*
Accuracy	0.666	0.666	0.850	0.779	0.089
Label	*support_for_government*	*company_beliefs*	*common_beliefs*		
Accuracy	0.850	0.822	0.822		

*Figure 4. The accuracy of the final labels in the demonstration step of this research. This accuracy is computed as described in Section 4.1.4, but it is computed from the "relevant" label since the classification between "relevant" and "not_relevant" was done by hand. An example: accuracy(acknowledge_importance) = accuracy(relevant)*accuracy(actions) = 0.85 * 0.78 = 0.66. The accuracy values of the single classification tasks can be seen in Appendix C – Figure 1.*

Appendix D – Running deductive coding with GPT

Table 1 contains a description of the steps to use to run the deductive coding described in Section 4.1.4.

Steps	*Description*
1	Select pages by searching for "climate site:company-website.com"
1.1	Select results in the first pages that can potentially contain companies' opinions on climate change
2	Classify the sentences as "Relevant" and "Not relevant". You can use GPT and the prompt in the following sheet. If done by hand, note that "Relevant" sentences are "claims" or "general statements". "Claims": rules for a "clear" claim are: * There should be a topic on which the company says something + The topic is mainly related to climate change + And the topic is something that the company can work towards + Simply saying what they do is not enough, there should be some sign of intentions * they are making a statement regarding themselves * With these sentences the companies are taking a stance on the topic "General statements": these are sentences that express a general opinion regarding climate change without clarifying who is expressing this opinion. "Not relevant" are the rest of the sentences. Use the "All sentences" sheet to store such classification.
2.1	If step 2 is done by hand, you can have multiple sentences in a single cell for the not_relevant (since these are not needed for following classifications). But remember to separate them to have a count of the total number of not_relevant sentences for the final results.
3	Classify the "Relevant" sentences between "actions", "stance_on_policy", and "stance_on_CC" using GPT and the prompt in the following sheet. Use the "Level 2" sheet to store such classification.
4	Further classify the sentences based on the results of the classification done in step 3 using GPT with the prompts in the following sheet: * separate sentences that were classified as "actions" in "stating_intentions" and "acknowledge_importance" * separate sentences that were classified as "stance_on_policy" in "support_for_policy" and "support_for_government" * separate sentences that were classified as "stance_on_CC" in "company_beliefs" and "common_beliefs" In this way, the classification is done by following the tree structure presented below. Use the "Level 3" sheet to store such classification.
5	Count the number of sentences that fall within each category and compute the percentage over the total number of "Relevant" sentences. Use "Results statistics" to run this step of the analysis.

Table 1. Instructions to use to run the deductive coding with GPT. This table contains instructions for when coding "relevant" vs "not_relevant" both via GPT or by hand.

Prompts

Here are displayed the prompts that have been selected to perform the deductive coding tasks according to the tree depicted in Figure 6 of Chapter 4. Each prompt is preceded by a description of where this prompt is used.

- **To classify at level no.: 1**
- **To classify within label: all sentences**
- **To classify between which labels: relevant, not_relevant**
- **To use in step (as described in Appendix D – Table 1): 2**

"*Classify the following setnences in these categories. Note that the topic discussed in these sentences is related to climate change:*

+ relevant: the company is taking a stance on the issue. It could be stating an action regarding the topic like a goal, target or action/policy that they already have in place. It could be stating the support for a piece of legilslation or governments' action. Finally, it could be expressing a general statement about the topic. Examples: "We aim to reach net-zero carbon emissions across our operations by 2040 by investing in renewable energy, scaling solutions, and collaborating with partners to broaden our impact." (the company is stating a target), "This investment is one piece of a $10 million commitment Volkswagen has announced to support the electric vehicle charging infrastructure."(the company is declaring a policy to tackle climate change), "Aramco conducts business in a manner that aims to prevent incidents with the potential to impact people, damage assets, or harm the environment."(the company is stating a goal), "We aim to avoid waste altogether through innovation, design, and operational efficiencies."(the company is stating a goal), "Climate change is one of humanity's biggest challenges and one of our top priorities." (the company is stating one of their priorities), "We believe we have an obligation to stop climate change, and reducing carbon emission to zero will have a big impact."(the company is stating a beliefs about what their role should be in tackling climate change), "Earlier this year, the Volkswagen Group committed itself to the goals of the Paris Agreement, the 200-nation agreement that aims to limit global warming to 3.6 degrees Fahrenheit by cutting emissions of carbon dioxide and other pollutants.'" (the company is stating their support for a piece of legislation), "Sinopec takes it as the top political priority to study, publicize and implement the guiding principles of the 20th CPC National Congress, closely follows the instructions given by General Secretary Xi Jinping, and effectively coordinates work on all fronts to promote the implementation of the guiding principles of the 20th CPC National Congress throughout Sinopec." (the company is stating support for the government's actions), "The energy transition must balance sustainability, security of supply and affordability." (this is a general statement about climate change), "Even with aggressive decarbonization efforts, many companies will need to neutralize some emissions that cannot be eliminated to achieve net-zero carbon."(this is a general statement about actions that need to be taken regaring climate change), "Saudi Aramco understands that no single solution is sufficient to solve the climate challenge." (the company is stating a belief that they have on climate change).

+ not_relevant: the rest. For example, the company may be stating a fact or taking a stance on another topic. Examples (each example is followed by an explanation why it is not relevant): "There were 15 hydrocarbon spills in 2022 with two of the spills responsible for more than 99% of the total volume spilled" (it is a fact), "'Additionally, Volkswagen has selected ChargePoint to complete the driver experience by providing all authorized e-Golf dealerships with VW-branded charging stations and by giving e-Golf drivers access to the largest network of public EV charging stations'" (unneeded detail, it doesn't show the stance of Volkwagen on the topic), "The project initially will run for six years." (It is a

fact and it is not relevant to the topic), "Like most other retailers, we leverage a variety of packaging options for product shipping to optimize for strong durability, light weight, and optimal size, including paper-based options, such as boxes and paperboard envelopes—and plastics, such as envelopes and bags" (it is not relevant to the topic of climate change), "All business units increased the weight of energy efficiency index assessment to further conduct competitive activities, including the "follow and surpass" and "make the plant meet the standards." (while showing the stance of the company on climate change, it is in the past, so not relevant), "The package uses recycled paper, which eliminates the need for plastic liners or bubble-bag insulation." (this is a fact).

The "relevant" sentences describe a stance that the company is taking around the topic of climate change. The "not_relevant" sentences do not contain stances, but more facts.

Each sentence starts with a "".*

Use this format for the output:

** sentece: [class label]*

Keep the sentences in the same order as given."

- **To classify at level no.: 2**
- **To classify within label: relevant**
- **To classify between which labels: actions, stance_on_policy, stance_on_CC**
- **To use in step (as described in Appendix D – Table 1): 3**

"Classify the following setnences in these categories. Note that the topic discussed in these sentences is related to climate change:

+ actions: The company is stating an action regarding the topic. It could be a goal or target or an action that they already have in place. Example: "Aramco conducts business in a manner that aims to prevent incidents with the potential to impact people, damage assets, or harm the environment."

+ stance_on_policy: The company is stating the support for a piece of legilslation or governments' action. Example: "'The Volkswagen Group is committed to the goals of the Paris Agreement.'"

+ stance_on_CC: The company is expressing a general statement about the topic. Example: "'Restoring landscapes has the potential to remove billions of tons of carbon emissions while improving local livelihoods."

Each sentence starts with a "".*

Use this format for the output:

** sentece: [class label]*

Keep the sentences in the same order as given."

- **To classify at level no.: 3**
- **To classify within label: actions**
- **To classify between which labels: acknowledge_importance, stating_intentions**
- **To use in step (as described in Appendix D – Table 1): 4**

“Classify the following setnences in these categories. Note that the topic discussed in these sentences is related to climate change:

+ acknowledge_importance: The company is acknowledging the topic or something related to the topic as important. Example: "We believe we have an obligation to stop climate change, and reducing carbon emission to zero will have a big impact."

+ stating_intention: The company is stating what they will do or want to achieve. In general, the company is stating intentions for the future regarding the topic. Examples: "Target: Reduce our indirect (Scope 3) carbon emissions by 35% by 2035 (relative to 2021)", "In 2022, we developed a Corporate Waste Management Strategy with a goal to minimize and divert waste from landfill and provide short- and long-term targets.", "We make great efforts in developing coal-bed methane (CBM) and shale gas.", "Plastic packaging is also an industry-wide challenge, and we’re collaborating across the industry to help try to solve it.", "Our objective is to enhance our ability of low-carbon growth by reinforcing our mid-term and long-term strategic low-carbon technology preparation.", "'Our long-term goal is climate-neutral mobility for everyone. '"

Each sentence starts with a "".*

Use this format for the output:

** sentece: [class label]*

Keep the sentences in the same order as given.”

- **To classify at level no.: 3**
- **To classify within label: stance_on_policy**
- **To classify between which labels: support_for_policy, support_for_government**
- **To use in step (as described in Appendix D – Table 1): 4**

“Classify the following setnences in these categories. Note that the topic discussed in these sentences is related to climate change:

+ support_for_policy: The company is stating the support for a piece of legilslation.

+ support_for_government: The company is stating the support for governments' action.

Each sentence starts with a "".*

Use this format for the output:

** sentece: [class label]*

Keep the sentences in the same order as given.”

- **To classify at level no.: 3**
- **To classify within label: stance_on_CC**
- **To classify between which labels: company_beliefs, common_beliefs**
- **To use in step (as described in Appendix D – Table 1): 4**

“Classify the following setnences in these categories. Note that the topic discussed in these sentences is related to climate change:

+ company_beliefs: The company is stating a belief it has about the topic in general. Example: "To preserve and ameliorate the environment is regarded by Sinopec as an important social responsibility and a major way to improve production and living conditions for employees."

+ common_beliefs: The company makes a general statement on the topic that implies some kind of "belief". This category differs from "company_beliefs" because here the company is not explecitly saying that they are the one expressing that belief. Example: "At the same time, the impacts of climate change on ecosystems, economies, societies and businesses are already clear and are predicted to increase".

Each sentence starts with a "".*

Use this format for the output:

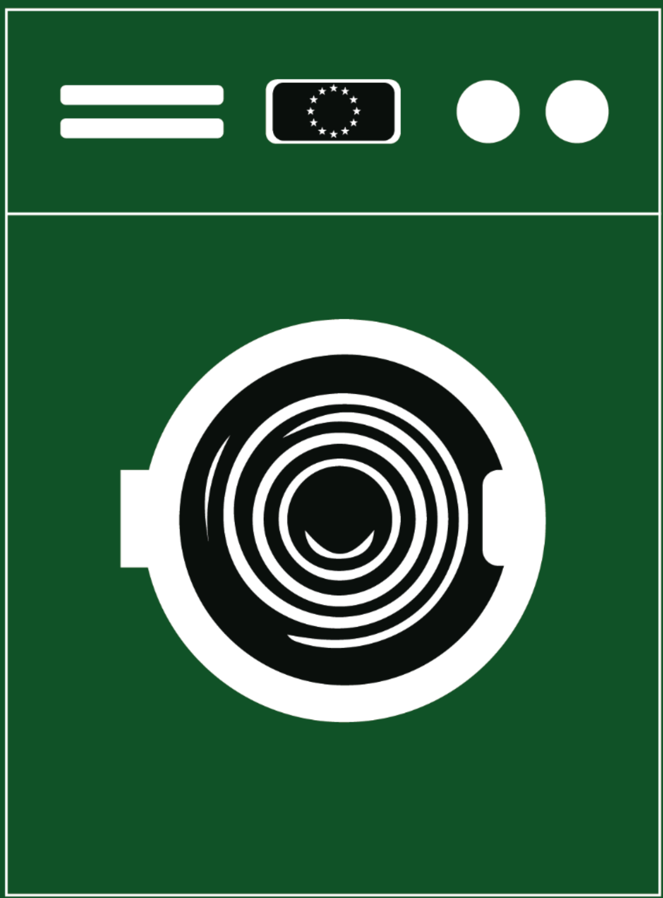
** sentece: [class label]*

Keep the sentences in the same order as given."

Appendix E – Lobbying details

Group	Keywords
General	climate change, global warming, greenhouse (GHG, GHGs, greenhouse gases), renewable energy (renewables, Renewable Energies), clean energy (clean energies, green energy, green energies), cap and trade (emissions trading), fuel economy, renewable electricity, net zero (net-zero), decarbonisation (decarbonization), pollution, clean air, sustainability, climate adaptation (climate resilience), emissions (carbon emissions, carbon footprint), co2 (carbon dioxide), circular economy (circularity, CE), climate goal (climate policy, climate action, climate target, cliamate goals, climate policies, climate actions, climate targets)
Legislation	Keystone, Kyoto, CAFE, European Climate Law (Climate Law), European Green Deal (Green Deal), Fit for 55, Renewable Energy Directive, ReFuelEU Aviation Regulation (RefuelEU aviation initiative, RefuelEU), Carbon Border Adjustment Mechanism (CBAM), EU Circular Economy Action Plan (Circular Economy Action Plan, CEAP), Farm to Fork strategy (EU Farm to Fork, Farm to Fork), EU Biodiversity Strategy (Biodiversity Strategy), Sustainable Europe Investment Plan, Just Transition Mechanism (Just Transition Fund, JTF), Paris Agreement, COP2 (COP 2), COP1 (COP 1), EU Emissions Trading System (EU ETS, ETS, Emissions Trading System, emission trading), Clean energy for all Europeans package (Clean energy for all, Clean energy package), Plastics strategy, EU taxonomy for sustainable activities (EU Taxonomy), European Clean Hydrogen Alliance (Clean Hydrogen Alliance)

Figure 1. The keywords used for the filtering. The parentheses contain related words, synonyms, acronyms, different spellings, and plurals of the corresponding words outside the parenthesis.



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