EC Project 610829

A Decarbonisation Platform for Citizen Empowerment and Translating

Collective Awareness into Behavioural Change

D4.4: Final Toolset and Results of Behavioural Change Techniques

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Executive Summary

Engaging people with climate change by using technology as a medium not only requires the understanding of how different types of technology can drive engagement and behaviour change, but also requires the understanding of the needs and situations of the users so that more targeted strategies or interventions can be selected to drive such change.

Following the Decarbonisation methodology presented in D1.1.2 we list the primary interventions identified by this methodology to increase user engagement and to encourage behaviour change and we show how these interventions were: (i) monitored and assessed during the EH and COP21 social media campaigns and (ii) incorporated and assessed in the DecarboNet tools, particularly in Climate Challenge. To do so we make use of the behaviour analysis methodology developed within DecarboNet. This methodology combines theories of behaviour and computational models to identify and categorise the behaviour of users towards the environment.

We present in this deliverable the results of our analyses and our observations on the impact of these interventions in user engagement and behaviour.

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1. Introduction

Changing people's behaviour with regards to energy consumption is often regarded as key to mitigating climate change. To this end, a wide range of works has aimed to investigate the mechanisms that govern behaviour with regard to energy use. This has been the topic of investigation in the domain of social and environmental psychology, in computing technology, and in interactive design. Understanding behaviour and its change in general is widely discussed in many studies in marketing and advertising. Disseminating ideas and engaging people via social media are also relevant to consider in this context.

A compendium of these studies has been gathered as part of the Decarbonisation Methodology developed within the DecarboNet project (see D1.1.2). This methodology offers guidance for designing tools and practices for engaging users with climate change awareness raising initiatives. The methodology is based on an in-depth review of relevant literature from multiple disciplines, as well as findings from project experiments and user engagement events (workshops). One of the main components of the methodology is a set of recommended interventions to increase user engagement and to encourage behaviour change.

In this deliverable we present the efforts of WP4 towards monitoring these interventions and assessing their impact in terms of behaviour change. We show how these interventions were: (i) monitored and assessed during the EH and COP21 social media campaigns and (ii) incorporated and assessed in the DecarboNet tools, particularly in Climate Challenge. To do this assessment we make use of the behaviour analysis methodology developed within WP4 by using the NLP tools developed in WP2 and the insights of behavioural theories analysed by WP1. Our behaviour analysis methodology combines theories of behaviour (particularly Robinson's Five Door Theory of behaviour change [Robinson, 2005]) and computational models to analyse online user behaviour towards climate change.

In D4.2 from year 2 of DecarboNet, we described our model and service for categorising user behaviour from social media data. During the last year of the project, we extended the model with additional annotations, and improved its performance with a new classifier from 65.7% to 71.2% accuracy. We have also applied the model to two new datasets; COP21 and Earth Hour 2016, as well as to a new dataset from Climate Challenge.

This deliverable provides a clearer linkage to the Decarbonisation Methodology (D1.1.2), and highlights the impact of a number of interventions on user behaviour. Also included in this deliverable is a new User

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Categorisation model that was developed in the last year of DecarboNet, to distinguish between the various types of Twitter accounts.

The rest of the deliverable is structured as follows: Section 2 presents a summary of the different studies of awareness and behaviour change considered within the Decarbonisation methodology, as well as the different identified intervention strategies. Section 3 presents how user behaviour has been analysed for various social media campaigns and how different intervention strategies have been assessed within the context of social media campaign communication. Section 4 presents how user behaviour has been analysed in the context of Climate Challenge and how the different intervention strategies incorporated in this application have been assessed. Section 5 concludes the deliverable.

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2. Theoretical background on Behavioural Change

In this section, we provide a summary of related literature, and summarise the set of interventions recommended in the Decarbonisation Methodology for influencing behaviour change.

As mentioned in the introduction, people typically do not understand the correlation between their individual behaviour and its global impact, thus underestimating their power to influence climate change. Particularly, the lack of self-efficacy is one of the reasons that prevent people to take part in the climate change battle [Shaw, 2015].

The impact of individual behaviour on the global scenario is not obvious, and people usually underestimate their power to change reality. Understanding the mechanisms that govern behaviour with regard to energy use, and fostering changes towards conservation, has been a topic of investigation in the domain of social and environmental psychology [Abrahamse, 2005], in computing technology [Fogg, 2013], and in interactive design [Froehlich, 2010]. Understanding behaviour and its change in general is also widely discussed in marketing and advertising, particularly by using social media [Berger, 2013][Vaynerchuk, 2013][Robinson, 2005][Ariely, 2014a][Eyal, 2014].

In this section, we first take a look at theoretical studies to get insights into which communication strategies and technologies have been proposed to influence people's behaviour in favour of a product or idea. We dissect the more general studies, and then focus on studies about behavioural change. By analysing these studies we aim to look at the following aspects: how do we get people informed? How do we get people to talk and discuss? How do we make people feel connected to the cause? How do we get people to act in new ways (behavioural change)? And how does this relate to behaviour with regard to climate change and energy use?

2.1. Awareness and Engagement

Before a behavioural change can be triggered we need to consider how to make users aware of the topic, in our case climate change, and aware of their own behaviour towards the topic. One of the key recommendations proposed by Ariely [Ariely, 2014a] is that the user not only needs to be aware of the subject, but they also need to be aware of the various options to act. To have impact, the first thing a pro-environmental campaign needs is *to have a clear story to tell, with a very concrete action connected to it*.

This is particularly complex in the case of climate change, since it is a very broad subject that represents many different smaller stories, connected to

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multiple behavioural actions. Campaigners and technology designers should therefore be able to break down those stories and actions for the public.

In addition to the previous recommendations, Berger [Berger, 2013] highlights the need for “word of mouth", i.e. the need for social transmission, or social influence, to spread the message and increase awareness. Berger and his colleagues analysed several viral campaigns and concluded that to make a campaign “engaging" it should follow the six principles of contagiousness, or STEPPS: *Social currency* (people share things that make them look good); *Triggers* (it is part of the users' everyday life, and on top of their minds); *Emotional resonance* (when users care about something, they share it with others); *Public* (the idea or product is built to show and built to grow); *Practical value* (people like to share practical or helpful information); and *Storytelling* (people tend to share stories, not information).

Climate change campaigners and technology designers should therefore focus on creating *innovative useful messages with an emotional undertone and a memorable story line*. Vaynerchuk [Vaynerchuk, 2013] emphasises the issue of differentiating each social medium when communicating a story, since different social media platforms are generally used for different needs and use different algorithms to promote content in the users' news feeds. It is therefore important for campaigners to *get familiar with the different social media platforms where the campaign will be communicated*.

Works like Campbell [Campbell, 2010], Kazakova [Kazakova, 2009], Cheong [Cheong, 2010] and Proskurnia [Proskurnia, 2016] have focused on analysing the characteristics of the climate change social media campaigns, including previous editions of EH, and the mechanisms used to engage with the public during these campaigns. Our work [Fernandez, 2015] complements these by studying the effect of some of those mechanisms and their impact on public engagement. We conclude that, in the context of these campaigns, *more engaging posts tend to be slightly longer (in the case of Twitter they use nearly all 140 characters available), are easier to read, have positive sentiment and have media items (original/funny photos linked to the message) associated to them.* Also, *symbolism needs to be focused around climate change related topics*. Superheroes, celebrities, and other types of symbols that are sometimes associated to these social media campaigns, create buzz but do not generate awareness or engagement towards climate change. Proskurnia [Proskurnia, 2016] adds to these conclusions the fact that first-degree neighbours are essential to drive user engagement, i.e., popular users with a higher number of engaging followers are key to propagating the message during social media campaigns.

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2.2. Behaviour Change

Pro-environmental campaigns and technology not only aim to raise awareness and create engagement, but ideally also to trigger behavioural changes, for instance by encouraging individuals to reduce their consumption of energy. Different scientific domains such as psychology, anthropology, sociology, and philosophy have put effort into understanding the forces that drive people's behaviour around protecting the natural environment [Blunck, 2014], [Corner, 2014]. This “not emotionally neutral subject" [House of Commons, 2014] has been conceptualised as Behaviour Change Theory, a field of study that transcends environmental purposes, being also applied to health, education and dissemination of new products or concepts.

Behaviour Change Theory is mainly dominated by two complementary approaches: models of behaviour and theories of change. Models of behaviour can be applied to understand specific behaviour and identify factors of influence, mainly at the individual level [Darnton, 2008]. Theories of change, on the other hand, explain the behavioural change process through social science lenses, being particularly helpful for developing interventions leading to a desired behaviour change. Theories are more generic, usually not taking into account contexts, perceptions and needs of a particular group of people [Robinson, 2005].

By integrating a number of formal theories from psychology and social sciences in terms of “what it takes for new practices or products to be adopted by groups of people", Robinson developed the 5 Doors theory [Robinson, 2005]. This generic theory aggregates elements from Diffusion of Innovations [Rogers, 2003] and the Self-Determination theory of motivation,[1] among others. Instead of promoting changes to people's beliefs or attitudes, the 5 Doors theory focuses more on “enabling relationships between people and modifying technological and social contexts".

The theory consists of 5 conditions that must be present in a cycle of behaviour change (see Figure 1). It is important to highlight that when mapping this theory to analyse user behaviour, our interpretation is that each of these conditions maps to a different behavioural stage, our assumption being that users shape their social media messages differently according to the stage in which they are at:

- *Desirability*: For someone to adopt a new behaviour into their lives, they have to want it. People in this stage are motivated (desire) to

[1] https://en.wikipedia.org/wiki/Self-determination_theory

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reduce their frustrations, which can be about day-to-day inconveniences (e.g. high expense on their electricity bill), or about deeper personal frustrations (e.g. living in a less polluted environment to recover lost health);

- *Enabling context*: People in this stage are changing their environment to enable a new behaviour. That includes infrastructure, services, social norms, governance, knowledge -- literally anything that could exert a positive or negative influence on a specific behaviour;

- *Can do*: People in this stage are already acting. This stage focuses on increasing the person's self-efficacy and lowering the perceived risks of change by building a set of tactics;

- *Positive buzz*: People in this stage communicate their experiences and success stories, which helps create buzz and increase other people's desires;

- *Invitation*: People in this stage invite and engage other people to their cause. Who issues the invitation is vital to engage others. A good inviter wins people's attention and commitment by authentically modelling the change in their own lives.

The 5 Doors theory correlates closely with empirically generated theories of behaviour, such as the one developed by Green Energy Options (GEO)[2] when conducting energy trials.[3] This model consists of five stages that refer to the level of awareness and involvement with a cause and the sort of tactics a sender should employ to nudge the user in the direction of change: (i) *Enrol*: establish means to generate / spread interest; (ii) *Educate*: help people understand/ gain confidence in their ability; (iii) *Engage*: facilitate to take action; (iv) *Encourage*: provide feedback and encouragement; and (v) *Expand*: provide opportunities to share and expand.

Since intervention strategies, or tactics to nudge the user in the direction of change, are generally different according to the stage in which the user is, it is important for campaigners and technology designers to: (i) identify the different behavioural stages of their audiences in order to generate more targeted strategies, and (ii) make sure that a campaign/technology is covering all possible stages so that all users find support to progress. A key contribution of WP4 is therefore directed towards providing computational methods able to automatically categorise users into different stages of

[2] http://store.greenenergyoptions.co.uk/
[3] http://www.decarbonet.eu/wp-content/uploads/sites/23/2014/10/D5-1_final.pdf

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behaviour based on their social media contributions (see Section 3) and their interaction with technology (see Section 4).

Figure 1: Five Doors Theory of Behaviour Change

2.3. Intervention Strategies

Intervention strategies are used when aiming to change behaviours. Multiple works in the literature have emerged in the last few years studying the effects of different intervention strategies, particularly with the goal of reducing energy use [Abrahamse, 2005], [Froehlich, 2010]. While Abrahamse [Abrahamse, 2005] analyses interventions from the social and environmental psychology perspective, Froehlich [Froehlich, 2010] focuses on how to design for eco-feedback within the human-computer interaction context.

In the course of the project we have investigated various intervention strategies that could stimulate behavioural change (see Table 1). These are still very broad strategies that can be executed in various ways and contexts (environmental campaigns, technology design, etc.). The most effective introduction of these strategies is a combination of multiple strategies, presented in a custom designed environment.

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Table 1: Selected interventions

strategy	**description**
information	The first step into getting people aware and acting upon a cause is to have information about the subject ready. The way the information on a subject/cause is presented and provided is an important factor: it needs to be easy to understand, easy to remember, attractive, and presented at the right place and time.
public commitment or pledging	Facilitating a public pledge or promise to do something helps people commit to a cause. This is usually associated with a specific target (of reduction). Both the type of commitment and the person or group to whom the commitment is made, are factors that impact behaviour. Pledging, next to declaring 'public commitment', could bring a set of individuals together to act toward a common goal. Making actions public and visible gives people reason to imitate - and with that comes social currency (people want to be part of something).
Goal-setting	Goals can be established by users or by third parties (like utility companies) to keep a cause on top of mind. It is person-based instead of focused on the social environment. These are practical and attainable solutions. A more challenging goal is usually more effective, however, a goal should remain feasible otherwise people will easily abandon their commitment.
Triggering discussions	Exchanging ideas and freely expressing opinion are important ways to raise awareness collectively. Debating (online) is a promising strategy for engagement. Intriguing dilemmas may trigger discussions.
Informative feedback & tangible insights	Factual feedback could include different levels of information (e.g., immediate feedback, consumption over time periods, the possibility to navigate through aggregated periods, etc.) and could come in multiple shapes and flavours including personalised energy bills, smart meters, in-home displays, web, mobile for interactive TV applications, etc. Tangible insights, concrete results or physical representation make feedback more relatable.

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Social feedback	Social feedback covers all types of social context for comparison and discussion among peers. It is about giving people reason to showcase or elevate their social status, and interact in a playful way. Both offline and online social contexts can be considered.
Collaboration & collective motivation	Collaboration between users aims at aggregating efforts to reach a bigger achievement. Interaction also improves social currency, since it creates a sense of belonging. When a group commits to something the social pressure supports the motivation of each individual in the collective.
Competition	Competition could inspire people to want to do better than others and work harder on their change. People like to compare themselves with others, to determine their place in a social context. The competition needs to be between parties that respect one another in some way. Without that, a user is not interested in comparison. Playful (gaming) elements prove to be great motivators for continuation of change.
(Variable) rewards	Rewards provide extrinsic motivations, usually with the intent to promote short-term behaviour change. Making rewards variable improves the willingness of a user to continue behaviour. People have different reasons to want to change their behaviour. Rewards should be in line with these reasons.
Incentives	Incentives are less concrete rewards, mostly aimed at starting and continuing behaviour. These could be long-term rewards, particularly associated with the cause itself, or for the 'greater good'. Acknowledgements of positive behaviour may already promote the behaviour.
Personalisation	Personalisation is based on studying (the consumption of) individual users and households and providing them with tailored recommendations that fit their own patterns. Also, the more an approach is based on the values and interests of a user, the more effective it is. Their reason to act might be different from what a change agent might think (or want).
Emotional involvement	Promoting behaviour change cannot solely consider rational choices driven by for example financial situations

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	or benefits for the environment. People need to feel comfortable to evaluate and discuss the trade-off between cause choices (in this case environmentally friendly) and individual values, such as comfort, security, and so on. This can inspire commitment through emotional engagement.
(Technological) learning *tools*	The learning tools (technical) that help users get further insight on their own behaviour. For energy use, monitoring tools can help people understand their own situation and can give them handles to act in favour of the cause.

As mentioned before, these different intervention strategies can be used alone or combined to promote or influence a behaviour change. According to [Robinson, 2005], people in different stages of behaviour change can be influenced by different incentives (or interventions). A summary of the intervention strategies that can be considered to encourage a behavioural change at each stage is presented in Table 2. This mapping builds on Robinson's theory [Robinson, 2005] and on our previous analysis on the role of social media in the perceptions and behaviours towards climate change [Piccolo, 2015].

Table 2: Behavioural Stages and Intervention Strategies

Behavioural Stage	Intervention Strategy
Desirability	Providing *Information* in an attractive way (see Section 2.1), and proposing *dilemmas* to trigger discussion about the extent of the problem and its impact are some of the interventions that can help users in this stage
Enabling Context	*Information*, *rewards* and *incentives* are important intervention strategies at this stage. Providing appropriate links to dedicated portals so that the user can learn about their options, as well as providing rewards and incentives can help motivating the user for change. Also having access to the personal experiences reported by other users via social platforms
Can Do	Helping the user to set realistic *goals* and promoting *public commitments* (e.g., link to petitions to be signed) are some of the strategies to help users to drive their change further. In addition, providing frequent and focused *feedback* and challenges negative

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	thoughts are also strategies to build self-efficacy
Buzz	Providing *feedback*, as well as *social feedback* (i.e., encourage the user to share their success stories, comment over them and help them to discuss their achievements with their peers) are some of the intervention strategies recommended at this stage
Invitation	Promoting *collaboration*, i.e., encourage the users to invite and collaborate with others to reach a bigger achievement

In the next two sections we describe how in DecarboNet we have studied, deployed and assessed a selection of these intervention strategies in the context of (i) pro-environmental campaigns, particularly the EH and COP21 social media campaigns and (ii) technology design and development, particularly Climate Challenge.

3. Deployment and Assessment of Intervention Strategies for Social Media Environmental Campaigns

Several campaigns and initiatives have emerged in the last few years from governments and organisations with the aim of involving individuals closely in the climate change problem.[4] An example of these campaigns is the EH movement, promoted by WWF and studied in the context of DecarboNet. Although the design and deployment of EH campaigns were out of the control of DecarboNet, the project was still able to analyse the impact of these campaigns and to understand the influence of various parameters and interventions on user engagement and behaviour.

As mentioned earlier, it is often difficult to understand how these campaigns are received by the public, which interventions have been put in place during the course of these campaigns (e.g., information, feedback, collaboration), and whether interventions are being successful, especially when the amount of traffic generated on social media around them is so vast (more than 2.5 billion Twitter impressions and over 18.7 million Facebook impressions were reported for the Earth Hour 2016 campaign).[5] Manual analysis is impractical, and thus automated techniques need to be used; however, it is not clear exactly how this data should be analysed and how we can gain useful insights

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[4] http://www.theguardian.com/global-development-professionals-network/2013/nov/15/top-10-climate-change-campaigns
[5] https://www.earthhour.org/sites/default/files/Earth\%20Hour\%202016\%20Report.pdf

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that can ultimately be used to improve not only communication but actually effect behavioural change. Simple statistical analysis of outreach is insufficient to gain proper insight; we need to understand also the semantics of messages so that we can better correlate social communication and interventions with environmental behaviour.

To bridge this gap, our work in WP4 proposes an approach based on Natural Language Processing (NLP) and Machine Learning (ML) that automatically identifies the different behavioural stages which users are at, by filtering and analysing large amounts of user-generated content from social media. We follow in our approach the behavioural stages identified by Robinson [Robinson, 2005] in his 5 Doors Theory of behaviour change. This approach is based on insights from the Decarbonization methodology (WP1) as well as from the NLP tools developed by WP2.

In addition, we combine the learnings from different theories towards awareness, engagement and behaviour with the learnings acquired after analysing online behaviour from three large-scale social media movements (EH2015, EH2016 and COP21), and translate these into a set of social media campaign recommendations with respect to interventions. The social media campaigns selected, our behaviour analysis approach, as well as results obtained after analysing these pro-environmental campaigns and our recommendations are described in the following sections.

3.1. Pro-enviromental Campaigns

We analyse behaviour in the context of three of the largest, more recent, movements for climate change reflected in social media: Earth Hour 2016 (EH2016) and 2015 (EH2015) and the 2015 United Nations Climate Change Conference (COP21).

Earth Hour (EH)[6] is a large-scale campaign launched by the World Wide Fund For Nature (WWF) every year to raise awareness about environmental issues. The event aims to encourage individuals, communities, households and businesses to turn off their lights for one hour, from 8:30 to 9:30 p.m. on a specified evening towards the end of March, as a symbol for their commitment to the planet. It started as a lights-off event in Sydney, Australia in 2007. Since then it has grown to engage more than 178 countries worldwide.[7]

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[6] https://www.earthhour.org/

[7] https://www.earthhour.org/sites/default/files/Earth\%20Hour\%202016\%20Report.pdf

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Today, Earth Hour engages a massive mainstream community on a broad range of environmental issues. The one-hour event continues to remain the key driver of the now larger movement. WWF's Earth Hour is a unique opportunity to understand user engagement and behaviour towards climate change, and the possibilities to facilitate more sustainable behaviours.

COP21 is the 2015 United Nations Climate Change Conference. This conference was held in Paris, France, from 30 November to 12 December 2015. The conference negotiated the Paris Agreement, a global agreement on the reduction of climate change, the text of which represented a consensus of the representatives of the 196 parties attending it. COP21 is part of a series of periodic meetings that began at the Rio Earth Summit in 1992, where the highest world authorities debate thresholds between socio-economic development and carbon emission reduction, and try to produce consensual plans to control the impact of climate change. Multiple organisations, including WWF, launched social media campaigns around COP21, generating a large world-wide social media reaction. This movement is a reflection of society's pressure on governments to commit to the agreements and to make better environmental choices.

3.2. Behaviour Analysis Approach

Our assumption when analysing behaviour change via social media communication is that different users in different behavioural stages communicate differently. Our first task has therefore been to validate this assumption by conducting an online survey (Section 4.1.1) Having acquired an understanding of how different behavioural stages are communicated, we developed an approach for automatically identifying the behavioural stage of users, based on three main steps: (i) a manual inspection of the user-generated content (in our case Twitter data) to identify how different behavioural stages are reflected in terms of linguistic patterns (Section 4.1.2); (ii) a feature engineering process, in which the previously identified linguistic patterns are transformed into numerical, categorical and semantic features, which can be automatically extracted and processed (Section 4.1.3); and (iii) the construction of supervised classification models which aim to categorise users into different behavioural stages based on the features extracted from their generated content (Section 4.1.4). In addition to these three steps used to categorised users in different behavioural stages we have developed an approach to categorise social media users, since it is often difficult to know what type of audience these campaigns are reaching and engaging; the citizens, or other organisations (Section 4.1.5).

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3.2.1. Social Media Reflection of Behaviour

To test our assumption that users at different behavioural stages communicate differently, we conducted an online survey between September and October 2014 targeting internet users in communities and workplaces. The survey received answers from 212 participants. A description of the elaborated questionnaire, the demographic characteristics of the users who completed it, and an analysis of the obtained answers can be found in [Piccolo, 2015]. For the purpose of this research, we focus on two main questions from it in which we ask users: (i) how they identify themselves within the five stages of behaviour; and (ii) to provide examples of messages they will post on Twitter. By performing this exercise, we gathered 161 examples of posts associated to a particular behavioural stage. Examples of the messages reported by the users are displayed in Table 3

Table 3: Examples of posts reflectint the 5 different behavioural stages

Behavioural Stage	Examples of Posts
Desirability	Our buildings needs 40% of all energy consumed in Switzerland!
Enabling context	I am considering walking or using public transport at least once a week
Can do	If you are not using it, turn it off!
Buzz	I'm so proud when I remember to save energy and I know however small it's helping
Invitation	Take 15 minutes out to think about what you do now and what you could do in the future. Read up on the subject and decide what our legacy will be

In addition to this set of examples, we annotated 100 tweets (a sample of 20 tweets per stage) randomly selected from our collected datasets (see Section 3.3.1). These tweets were annotated by two different researchers. Discussions were raised about those tweets where disagreements were found. If the disagreement could not be resolved, the tweet was marked as ambiguous and discarded. Examples of tweets annotated under each category are displayed in Table 4.

Table 4: Examples of posts reflectint the 5 different behavioural stages

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Behavioural Stage	Examples of Posts
Desirability	- It was such a horrible storm today! Doesn't feel like the normal rain that we are used too isn't it?! Climate change? - Wondering what the grand bargain between the US and China on climate change is going to look like. Without one, we're all in deep trouble.
Enabling context	- Changing a light bulb. Fluorescent Lights last longer, use less energy, and save you money. - Cold air hand dryers utilise high air speed to dry hands quickly, helping to provide ongoing energy savings: http://t.co/8Ssq1aa6xs once a week
Can do	- UN Campaign on Climate Change - sign the petition to Seal the Deal at Copenhagen http://www.sealthedeal2009.org #cop15 - Track your energy savings with this student-developed website \#macewanu \#yeggreen http://t.co/jckR9XAFKu http://t.co/2V2wEFkqg1
Buzz	- Filling my tires and saving one tank of gas per year! Climate Crisis Solution \#06 - We thought we'd achieve10\% energy savings thru efficiency.We were SO WRONG.It's 40\% so far!
Invitation	- We hope you're all participating in Earth Hour tonight! It starts at 8:30!!! http://t.co/2VI8xxo2IA - I'm switching off for Earth Hour at 8.30pm on 28 March, will you join me? #EarthHourUK http://t.co/eitii1ojqW

3.2.2. Manual Inspection of Linguistic Patterns

To identify the key distinctive features of tweets belonging to each behavioural stage, a manual inspection of the previously annotated tweets was performed by two Natural Language Processing (NLP) experts. During this process, a number of linguistic patterns were identified as potentially useful to help characterise the different behavioural stages. The list of identified patterns is given below:

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- *Desirability*: Tweets categorised in this behavioural stage tend to express negative sentiment and emotions such as personal frustration, anger and sadness. They usually include URLs to express facts, and questions asking for help on how to solve their problem/frustration.

- *Enabling Context*: Tweets categorised under this behavioural stage tend to be expressed in a neutral sentiment and emotion. They generally provide facts about how to solve a certain problem, in particular numerical facts about amounts of waste, energy reduction, URLs pointing to information, and conditional sentences to indicate that, by performing certain actions, benefits can potentially be obtained.

- *Can do*: Tweets categorised under this behavioural stage tend to be expressed in a neutral sentiment and generally contain suggestions and orders directed to self and others (I/we/you should) (I/we/you must).

- *Buzz*: Tweets categorised under this behavioural stage tend to have positive sentiment and emotions of happiness and joy, since they generally talk about the user's success stories and about the actions they are already performing in their engagement towards climate change and sustainability.

- *Invitation*: Tweets categorised under this behavioural stage tend to have positive sentiment and emotions of happiness or cuteness, since they are focused about engaging others in a positive and funny way. The text generally contains vocative forms (friends, guys) calling others to join the cause.

3.2.3. Feature Engineering

In order to automatically extract the linguistic features represented in the patterns described above, NLP tools (provided by GATE[8] via WP2) were used. These included basic linguistic pre-processing (such as part-of-speech tagging and verb chunking) [Cunningham, 2002] and more complex tasks such as opinion mining and emotion detection [Maynard, 2015]. The features extracted were:

Polarity: positive, negative, neutral

Emotions

[8] https://gate.ac.uk

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- Positive (joy/surprise/good/happy/cheeky/cute)
- Negative (anger/disgust/fear/sadness/bad/swearing)

Directives

- Obligative (you must do) - e.g., you must turn off the light
- Imperative (do) - e.g., turn off the light!
- Prohibitive or negative imperative (don't do) - e.g., do not turn off the light
- Jussive or imperative in the 1st of 3rd person - e.g., go me!
- Deliberative (shall/should we) - e.g., shall we turn off the light?
- Indirect deliberative (I wonder if) - e.g., I wonder if we should turn off the light
- Conditionals (if/then) - e.g., if you don't turn off the light your bill will increase
- Questions (direct/indirect)

URLs (yes/no) indicates if the message points to external information or not

We can clearly see how some of these linguistic modalities correlate with the behaviour model. For example, deliberatives are strongly associated with stage 1 (Desirability), while conditionals are often linked with stage 2 (Enable context) and jussives with stage 4 (Buzz or self-reporting). However, the boundaries between these stages are often quite fuzzy, and people's online behaviour will not always correlate exactly with a single stage. We should also note that not every occurrence of one of the linguistic patterns will reflect the correct stage: not every conditional sentence will necessarily reflect the “enabling context" stage, for example. We use these linguistic patterns only as a broad guideline to help with the categorisation. Furthermore, NLP tools are never 100% accurate, and this holds particularly for some of the harder tasks such as opinion mining and emotion detection. Performance varies greatly depending on the task: direct questions can be recognised at near 100% accuracy, but correct assignment of opinion polarity may only be around 70% accurate. Nevertheless, the NLP tools developed in DecarboNet to extract these annotations have been updated and improved as shown in the following sections.

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3.2.4. Behaviour Classification Model

Using the feature extractors, we process the 261 annotated posts, i.e. posts with associated behavioural stages (see Section 3.2.1) and use them to generate different classifiers. In particular, Naive Bayes, Support Vector Machines (SVM), and decision trees have been tested using 10-fold cross validation. The best performing classifier was the J48 decision tree, obtaining 71.2% accuracy. Decision trees discriminate the most distinctive attributes first and separate the population (in this case the set of posts) based on the identified distinctive features.

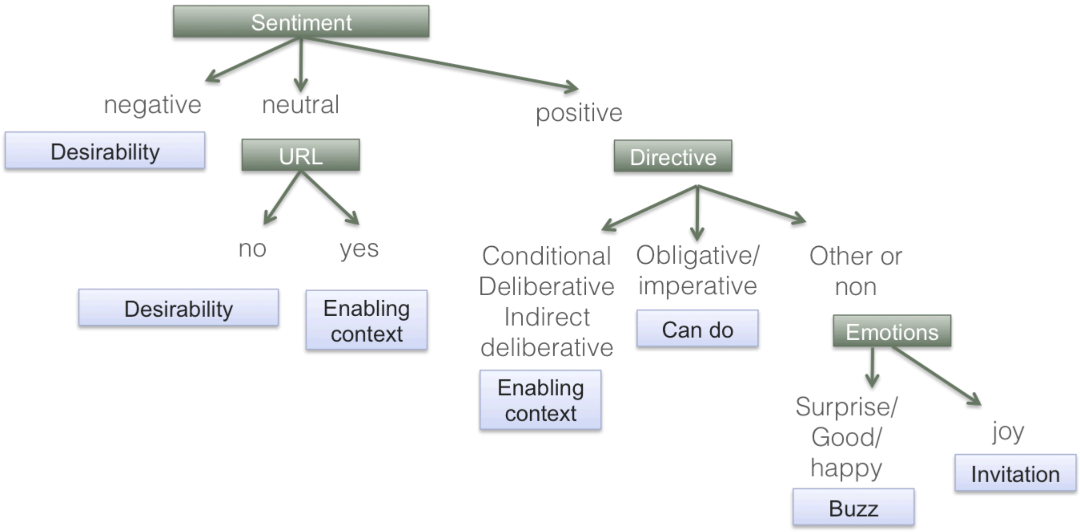

Figure 2: Behaviour Classification Model

As we can see in Figure 2, the most discriminative feature is sentiment. If the sentiment of the post is negative, the classifier automatically categorises it as stage 1 (desirability). If the sentiment is neutral the classifier checks if the post contains a URL. Posts with neutral sentiment are classified as: stage 1 (desirability) if they do not contain a URL or stage 2 (enabling context) if a URL is present. Note that URLs are an indication of additional information, generally facts associated with the message.

If the sentiment is positive, the classifier looks at the type of directive used. If the directive is conditional, deliberative or indirect deliberative, the post is classified as stage 2 (enabling context). If it is obligative or imperative the post is classified as stage 3 (can do). If there are no directives, or other kinds of directives, in the text, the classifier looks at emotions in order to discriminate. If the emotion is joy, the post is categorised as stage 5 (invitation); if the emotion is happy, good or surprise, the post is categorised as stage 4 (Buzz).

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Our model provides an easily understandable set of rules to categorise posts into behavioural stages. To identify the behavioural stage of each user over time, we consider their contributions in a month period, and assign to the user the most popular behaviour stage among their posts. If there is no majority class, or if the user did not post anything related to climate in that period, we consider them as “unclassified".

3.2.5. User Categorisation Model

When analysing user behaviour via social media it is important to consider that multiple social media accounts do not represent individuals but organisations, such as Companies, News Agencies, Non-Governmental Organisations (NGOs), etc. Particularly, during the EH movements, NGOs such as EH, WWF, GreenPeace, etc. displayed a significant online presence. A key aspect of our work is therefore to be able to differentiate and select those accounts that belong to individuals, so that we can further analyse their behaviour.

While this problem is shared across social media user studies, to the best of our knowledge categorising social media accounts has not been extensively investigated. One of the most well-known initiatives up to date is RepLab 2014,[9] which has attempted to address this problem in the context of online reputation. This initiative [Amigo, 2014] proposed an author categorisation task to classify Twitter profiles with more than 1,000 followers into ten categories: Company, Professional, Celebrity, Employee, Stockholder, Investor, Journalist, Sportsman, Public Institution, and Non-Governmental Organisation (NGO). These categories were selected considering the literature of online reputation. Our goal in DecarboNet is slightly different, since we do not only aim to categorise users with a high number of followers (i.e., users with an established reputation) but to distinguish individuals vs. organisations, independently of their popularity and reputation. We therefore propose an approach to automatically categorise Twitter user accounts into individuals vs. organisations based on three main steps:

- In order to distinguish between different account types, we have collected examples of accounts that belong to individuals and organisations, particularly Companies, News Agencies and NGOs. We have selected these types of organisations due to their strong presence in social media environmental campaigns. To perform this step we have made use of Twitter Lists. User profile information from

[9] http://nlp.uned.es/replab2014/

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these accounts has been extracted, downloaded and pre-processed for training purposes.

- Feature engineering has been performed to describe user profile data by processing textual, numeric and media attributes of the collected Twitter profiles.

- Multiple classifiers have been trained and tested based on the selected features and training data, obtaining up to 0.82 F-measure with the best performing model.

These three steps are detailed in the following subsections.

Collecting Twitter Accounts

To obtain examples of social media accounts for the different categories we have made use of Twitter Lists. A Twitter list is a curated group of Twitter accounts. Any Twitter user can create lists and can also subscribe to the lists of other users. At the moment, Twitter does not provide any specific functionality to search for Twitter Lists, but these lists are indexed by Google, which enables a thematic search of the available Twitter lists. For example, to search for Twitter Lists about companies, we performed the following query via the Google search engine: *site:twitter.com inurl:lists company*. Lists were then sorted via their popularity (i.e., the number of subscribers), and the user accounts of the top 15 lists for each category were crawled using the Twitter API. We collected a total of 3,283 accounts using this method, along with their corresponding attributes (name, description, number of followers, etc.), leading to *1726* Twitter accounts representing organisations and *1557* representing individuals.

Feature Engineering

We perform feature engineering to describe user profile data based on the textual, numeric and media attributes of the collected Twitter profiles. We consider five different types of features:

- *Syntactic Features:* Syntactic features are based on the assumption that users that belong to the same category may describe themselves using the same type of terminology. For example, organisations generally describe themselves using terms such as business, newspaper, organisation, company, etc. Using the description field of all the users in our training dataset we have generated a word-vector representation for each category: $C\_organisation = \{w_1, w_2, ..., w_n\}$, $C\_person = \{w_1, w_2, ..., w_m\}$. To assess how syntactically similar the description of a user profile u is to the vocabulary of each of the categories, we extract the word-vector representation of u based on the account's name and description $u = \{w_1, w_2, ..., w_j\}$ and compute the cosine similarity between the vector representation of *u* and the vector representation of each of the categories.}

- *Semantic Features:* Semantic features take into account the entities and types that emerge from the name and description of each Twitter profile *u*. To extract these entities and types we make use of the TextRazor Natural Language Processing API.[10] For example, for the Twitter account @BarackObama, the semantic annotator recognises entities and concepts such as *Person*, *President*, and *Government Title*. As with syntactic features, semantic features are based on the assumption that users that belong to the same category may describe themselves using the same semantic concepts. Using the description field of all the users in our training dataset, we generated a concept-vector representation for each category: $SC\_organisation = \{c_1, c_2, ..., c_n\}$, $SC\_person = \{c_1, c_2, ..., c_m\}$. To assess how semantically similar the description of a user profile *u* is to the semantic description of each of the categories, we extract the semantic-vector representation of u based on the account's name and description $su = \{c_1, c_2, ..., c_j\}$. and compute the cosine similarity between the semantic vector representation of *u* and the semantic vector representation of each of the categories.

- *Network Features*: Network features take into account the position of the user within the network. Network features include: number of followers, number of friends, and number of lists the user is a member of.

- *Activity Features*: Activity features take into account the actions of the user and how frequently those actions are performed. In particular, we take into account two types of actions: posting and favouring. The first feature, PostRate, represents how many times a user posts per day whether the second, FavouringRate, represents how many times per day the user favours someone else's content.

- *Avatar Features*: Avatar features take into account the image that the user projects of themself. The assumption is that organisations are more likely to include an image in their profile, particularly an icon, while a user account representing an individual is more likely to include a profile picture with an image (face) of the individual. The avatar features considered are: (i) DefaultProfile, if true indicates that the user has not set up a Twitter avatar, and (ii) NumFaces. This feature

[10] https://www.textrazor.com

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indicates if the profile picture of the user contains a human face. It is computed using the OpenCV image processing library.[11]

Author Categorisation

Using the feature extractors, we process the 3,283 collected and annotated (company vs. individual) Twitter accounts, and use them to generate different classifiers. In particular, Naive Bayes, Support Vector Machines (SVM), Decision Trees and Logistic Regression have been tested using 10-fold cross validation. The best performing classifier is the Logistic Regression model, obtaining 0.82 F-measure. This generated model is later used in our analysis (see Section 3.3.3) to filter Twitter accounts belonging to individuals.

3.3. Analysing Pro-enviromental Campaigns

We describe in this section the experiments conducted to assess the behaviour of the participants of the EH2016, EH2015 and COP21 social media movements, following the proposed approach and the effectiveness of different intervention strategies.

3.3.1. Data Collection

The first step to perform these experiments was to collect data for the three social media movements: EH2016, EH2015 and COP21. We monitored these events on Twitter by collecting tweets containing particular hashtags, such as #EH16 #EH15, #earthhour, #changeclimatechange, etc. in the case of EH2016 and EH2015, and #COP21, #COP21Paris, #parisclimatetalks, etc. in the case of COP21. We used the Twitter IDs of the participants of these events to generate a second collection and gather historical tweets from their timeliness. Up to 3,200 posts were collected from each individual, which is the maximum allowed by the Twitter API. This provides information for up to several years for some users. The rationale behind the selection of these users is that they are already engaged with the environment, as demonstrated by their participating and tweeting about these campaigns, and that the Twitter accounts refer to persons and not to organisations. Our dataset for EH2016 contains 62,153,498 posts from 32,727 users; EH2015 contains 56,531,349 posts from 20,847 users; the one for COP21 contains 48,751,220 posts from 17,127 users.

3.3.2. User Filtering

As discussed in Section 3.2.5, it is important to distinguish between different types of social media profiles, particularly organisations vs. individuals. We

[11] http://opencv.org/

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have therefore used our proposed author categorisation model to filter those accounts that represent organisations from our previously collected datasets. Our results show that 17% of user accounts participating in EH2016 belong to organisations, 15% for EH2015 and 2% in the case of COP21. After filtering the identified accounts and their corresponding posts we remain with 27,163 users and 44,367,133 posts for EH2016, 17,719 users and 39,267,884 posts for EH2015, and 13,016 users and 28,200,780 posts for COP21. Note that the post reduction for each dataset is higher than the user reduction, since the organisations filtered from the datasets (EH, WWF, Greenpeace, etc.) tend to broadcast a high number of posts.

3.3.3. Data Filtering

We collected 3,200 posts from the timelines of each of the users who participated in the social media movements. Naturally, these users post about environmental issues, but they also post about their jobs, hobbies, personal experiences, and so on. To identify which of the content produced by the users relates to their environmental behaviour, we used the Term Extraction tool ClimaTerm[12] developed by WP2 and documented in [Maynard, 2015]. ClimaTerm automatically identifies instances of environmental terms in text. Some of these are found directly in ontologies such as GEMET, Reegle and DBpedia, while others are found (using linguistic techniques) as variants of such terms (e.g. alternative labels, or hyponyms of known terms). Using these annotations helps us to identify, from the timeline of each individual user, which of their posts are related to climate change and sustainability. 658,140 posts were identified as climate-related by the ClimaTerm tool in the EH2016 dataset, 447,892 posts in the EH2015 dataset, and 250,215 in the case of COP21.

3.3.4. Behaviour Analysis

We have made use of the filtered tweets to categorise users in different behavioural stages over time. In particular, we take into account monthly behaviour before, during and after the days in which EH2016, EH2015 and COP21 were celebrated. We focused on the analysis of these particular months, since being aware of the users' behavioural categorisation during these time periods may enable campaigners to use more targeted messages and interventions.

The results of our behaviour analysis study are presented in Figure 3 for EH2015, Figure 4 for EH2016, and Figure 5 for COP21. These images display the percentage of users classified under each behavioural stage in the

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[12] http://services.gate.ac.uk/decarbonet/term-recognition

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months around the campaigns, as well as the users that are not categorised. Users are not categorised either because they did not produce any posts related to environmental issues in the analysed month, or because our approach could not distinguish a clear stage for the user based on their generated content.

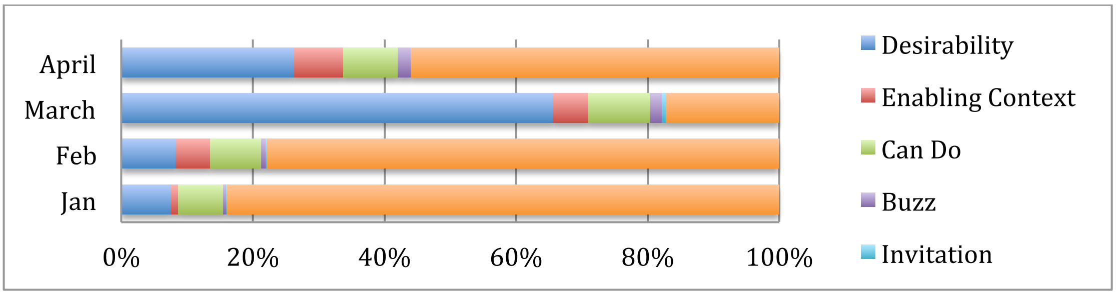

Figure 3: EH2015 - Number of users associated to each behavioural category

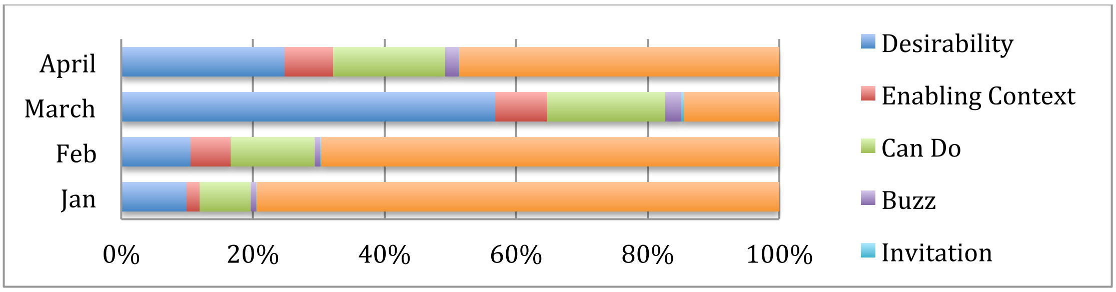

Figure 4: EH2016 - Number of users associated to each behavioural category

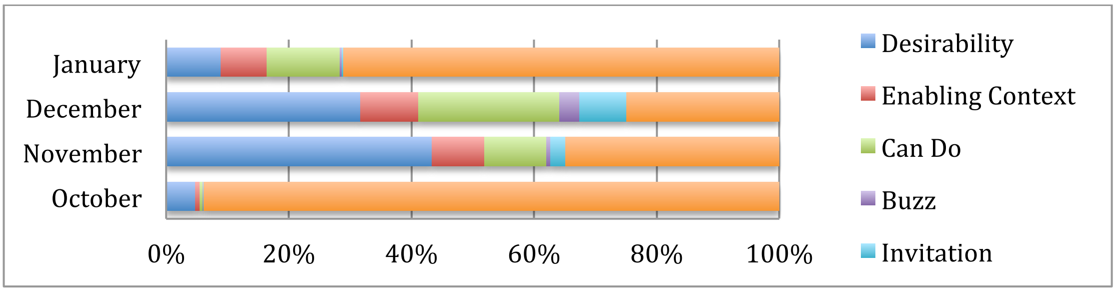

Figure 5: COP21 - Number of users associated to each behavioural category

Table 5: Behaviour Analysis results

EH2016	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
Jan	2711	543	2087	234	33	21,555
Feb	2871	1654	3476	221	42	18,899
Mach	15456	2135	4879	658	99	3,936
April	6754	2003	4632	544	21	13,209
EH2015	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
Jan	1344	199	1201	88	20	14,867
Feb	1476	924	1378	121	22	13,798
Mach	11621	956	1655	332	100	3,055
April	4657	1324	1465	350	17	9,906
COP21	Desirability	Enabling Context	Can Do	Buzz	Invitation	Non-classified
October	621	98	57	15	12	12,213
November	5640	1112	1321	88	321	4,534
December	4124	1234	2987	432	998	3,241
January	1156	987	1543	44	34	9,252

The number of users in each stage for the three datasets is reported in

Table 5. As we can see from these figures, there is a significant peak of activity around the time of the campaigns that decays later on. During the time of the campaigns, users produce more content related to environmental issues and it is therefore possible to classify them in different behavioural stages.

Out of this time window, a higher percentage of users go uncategorised, mainly because they have not produced any content around environmental issues. In general, what we observe from all campaigns is that the highest percentage of users are in the Desirability stage. The second most popular stage is Can do. This indicates that users are either at the stage where they want to change their behaviour, or at the stage where they are already acting. An interesting observation, particularly between the EH2016 and EH2015 results is that in 2016 there is a high percentage of users in the Can do stage vs. the Desirability stage, which may indicate a successful evolution in the environmental behaviour adopted by users and therefore a successful use of interventions.

Not many users, however, fall in the invitation or buzz stages, i.e., not many users are trying to engage others. As analysed in our previous work [Fernandez, 2016] and on WP6 deliverables (D6.2.2. and D6.2.3), during the EH campaigns, messages reflecting buzz and invitation stages tend to come from environmental organisations such as WWF or Earth Hour. This changes slightly for the COP21 movement, where a subset of users are actively inviting

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others to put pressure on their Governments so that they keep meeting climate change commitments. The percentage of users at the enabling context state is generally stable, but as with the Can do stage, this percentage is also slightly higher for EH2016 than for EH2015, indicating a behavioural evolution and a higher interest for learning about climate change and the environment.

3.4. Social Media Campaign Interventions: Recommendations

What do these results teach us, and how can we use these learnings for further campaign improvements? We summarise the results of studying behaviour in these three campaigns and our previous learnings from our literature review in three recommendations:

- Our results show that most of the social media participants are at the desirability stage. There is something they want to change but they do not know how. This correlates with the observations of [House of Commons, 2014] and the identified lack of self-efficacy. A big part of a campaign's effort should therefore be concentrated on providing messages with very concrete suggestions on climate change actions. These messages should also be innovative, useful, and about day to day activities to maximise the STEPPS criteria [Berger, 2013].

- There are very few individuals in the invitation stage. Most invitation messages during these campaigns are posted by organisations, although this seems to change with the type of social media movement. A social media movement, such as COP21, which is more oriented to act and change policy, involves more users in the invitation stage, who aim to attract others to their cause. However, as stated by Robinson [Robinson, 2005], for an invitation to be effective, it is vital who issues the invitation. Ideal inviters are those who have embraced change in their own lives and can serve as role models. It is our recommendation to identify these really engaged individuals and community leaders and involve them more closely in the campaigns, invite them to share their stories, and provide feedback, so that they can inspire others. In addition, as reflected by Proskurnia [Proskurnia, 2016], the more connected these individuals are in the network, the higher the level of engagement they can potentially generate.

- Communication in our collected data generally functions as broadcasting, or one-way communication, from the organisations to the public. However, frequent and focused feedback is an intervention strategy that can help build self-efficacy and nudge the users in the can do and buzz stages in the direction of change. Our recommendation for

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campaigners is therefore to dedicate efforts towards engaging in discussions and providing direct feedback to users.

In addition to the behaviour analysis approach developed in WP4 and the reported analysis, various analyses of EH were done in DecarboNet, some of which was reported in D6.2.1, D6.2.2, and D6.2.3.

While not directly correlated with behaviour, this analysis was focused on determining the patterns of EH tweets that generated heightened attention. Fifteen user and content features were calculated and used to build a model to predict the engagement level generated by EH tweets. The *user features* were focused on the characteristics of the participant (e.g., her number of followers, followed, and number and rate of posting), whereas the *content features* described the EH tweets themselves. Most of the used features can be mapped to a good degree to intervention strategy recommended by the Decarbonisation methodology:

Table 6: Earth Hour analysis features

Strategy	Analysis Feature	Relation to strategy
information	Complexity, length, informativeness, and readability of tweets. URL count.	Reflects whether or not the information provided in the tweets were easy to read and novel in relation to what was tweeted already. URLs in tweets (referral count) point users to further information.
emotional involvement	Polarity of tweets. Media.	Sentiment of tweets portray different emotional directions (negative, positive, neutral. Including images or videos in tweets is a way to emotionally charge the message.
triggering discussions	Post count, post rate	Number and rate of posting can reflect how often users initiate or contribute to discussions.

The results obtained from analysing the 2014, 2015 and 2016 EH posts showed that, posts generating higher attention levels are slightly longer, easier to read, and tend to repeat terms existing in other posts (**information**). Results also showed that positive sentiment increases the level of engagement (**emotional involvement**). It was also found that incorporating media into the tweets has a positive impact on user engagement with the campaign (**emotional involvement**). Number and rate of posting appeared to

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have a moderate impact, although it must be noted that these features are of the participants, and not of the campaigners (**triggering discussions**).

4. Deployment and Assessment of Intervention Strategies for Technology Design and Development

In addition to studying interventions and their impact on behaviour in social media campaigns, we have also analysed users' behaviour and the impact of introducing several intervention strategies in technology design, particularly within Climate Challenge.

4.1. Climate Challenge

Climate Challenge is a game with a purpose, which provides an engaging way to help people learn more about Earth's climate, assess climate knowledge, and promote the adoption of sustainable lifestyle choices. The Climate Challenge was launched in March 2015 and offers 12 monthly game rounds per year where users accumulate points by solving game tasks, which can be related to:

- *Awareness*: Multiple-choice questions with a predefined answer on climate change knowledge. The difficulty gradually increases over time.
- *Pledges*: Inspired by the Environmental Recommendations Database13 of the Worldwide Fund for Nature (WWF), this pledging task asks for feedback on practical recommendations to reduce personal energy consumption and for making more sustainable lifestyle choices. The task also allows sharing recommendations on social media. When answering a pledge, users can state whether: (i) they are already doing it, (ii) they are not doing it, but are keen to try, or (iii) they refuse to do it for some reason.
- *Sentiment*: This task inquires whether users perceive specific keywords from climate-related media coverage as positive, neutral or negative. This task was set to enable users to support the production of a sentiment lexicon of environmental topics.
- *Prediction*: Users guess the future state of our planet, in terms of both global and regional indicators. For example, the question: "What percentage of land area in the Northern Hemisphere will have a 'white

[13] www.wwf.ch/tipps

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Christmas' (with snow)?". Results are compared to the average estimated by users' friends, the entire pool of game participants, and to a selected group of experts by the Climate.gov team of NOAA, the National Oceanic and Atmospheric Administration.

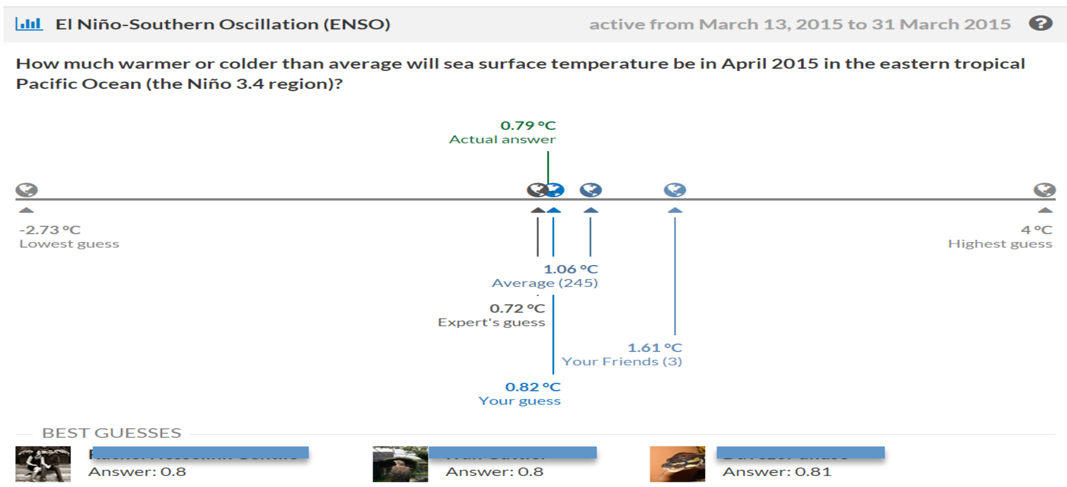

Figure 6: Comparative results of a prediction task, including a list of top-ranked players

4.2. Intervention Strategies

To analyse interventions and behaviour in the context of the Climate Challenge we have studied the different features that can be extracted from the log analysis of this game and how these features (i) reflect interventions and (ii) can be used to recognise engagement and behaviour change.

Table 7 below describes the analysis features used in this study, and how these features correspond (strongly or loosely) to the list of interventions identified by the Decarbonisation methodology (see Section 2.3).

Note that not all the interventions used by CC can be assessed with regards to their impact on engagement or behaviour. This is mainly due to the lack of specific quantitatively measurable features that can reflect certain intervention strategies. Other type of assessments can be used to enrich our analysis, such as user questionnaires and interviews.

Table 7: Climate Challenge analysis features

Strategy	Analysis Feature	Relation to strategy

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rewards	Total points acquired	Points are awarded by CC to users
pledges	Number of pledges answered	Reflects the overall position of a user from pledged.
	Number of pledged accepted	Shows how many pledges the user is doing already.
	Number of pledged refused	Shows how many pledges the user has rejected.
collaboration	Number of predictions (guessing answers)	Shows the number of times the user collaborated with the other participants, by submitting a prediction.
information	Number of multiple choice questions answered	Proxy of the amount of information the user read and learnt.
incentives	Number of sentiment questions answered	“Support our research” is the incentive offered here, and reflected by this feature.
feedback	Ratio of right/wrong answered	Users are told which of their answers were correct or incorrect. This could be regarded as a type of feedback.
collective motivation	Whether or not the user signed up via a social networking account (social logging)	Could be regarded as a sign that the user is motivated by the social element of the application.

4.3. Analysis of User Return

Initially, we consider as indicator of the impact of an intervention how often the user has returned to the game since the sign up. Our analysis tries to identify the favourable interventions that might have influenced users to return. Note that this, however, does not measure behavioural change towards climate, but serves as an indicator of how the different strategies and features of the game help to engage users. We define users' return as:

$$return_u = \frac{NL_u}{ND_u}$$

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where u, represents the user, NL is the number of times the user has logged into the game and ND is the number of days the user has been registered in the system.

Our conducted analysis of engagement is based on logged data of 873 users registered between 25/03/2015 and 16/08/2016. The analysis presented in this work focuses on users that provided answers to all task types, a total of 314. Table 1 shows the distribution of answered tasks in the user-generated content database.

Table 8: Overview of user-generated content. The numbers indicate how often the task was answered by users (e.g., how many pledges accepted by users)

Task Type	Total
Sentiment	23,380
Awareness	5,973
Pledges	2,802
Prediction	722

We induce a linear regression model based on a series of users' attributes or features to approximate the level of return (engagement) of each user. Table 2 describes the features considered per user for this analysis, the coefficients of the regression model and their significance.

Table 9: Regression coefficients and their significance of engagement as "return" (Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1)**

Features	Regression Coefficient	Significance
Number of answers to pledges	0.0043227	**
Number of pledges the user is already doing	-0.0015389	
Number of pledges refused	-0.0030281	.
Number of answers to awareness questions	0.0069848	***
Number of answers to prediction questions	-0.0030931	
Number of answers to sentiment questions	-0.0004374	**

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Ratio of right vs. wrong answers (suitable for awareness and sentiment questions)	-0.0208348	
Social logging (if the user signed up with a social networking account, such as Twitter or Facebook)	-0.0041342	
Total of points obtained	0.0014581	***

By inspecting the coefficients of the regression model in Table 9, we can observe how each feature would impact the likelihood of the user to return to the game. Significant variables according to the model (see sig. values) are in bold: number of answers to pledges, number of answers to awareness questions, answers to sentiment questions and the total of points obtained.

In summary, the more multiple questions (***information***) and *pledges* that are presented to the users, the more they tend to return to the game. A good performance (high number of points - ***rewards***) also influences users' return. On the contrary, the more sentiment questions (***incentives***) are presented, the more likely the user will not play the game again.

4.4. Behaviour Analysis

To study the impact of different intervention strategies in terms of behaviour we make use of the analysis methodology presented in D4.2. Using this methodology we perform a cluster analysis using K-means to determine how users of Climate Challenge group in different clusters according to the extracted behavioural features. We selected K=5 to observe how the clustering process maps with the analysis of behaviour. We normalise the attributes before performing the clustering process.

The first snapshot of data includes all activity within the game until 18/05/2015. The second snapshot of the data includes all activity within the game until 18/08/2016, i.e., more than a year ahead. Analysing these two snapshots of time will allow us to determine whether users are moving from one behavioural stage to another one. Note that the same set of users is considered for this analysis (i.e., users registered in the game after 18/05/2015 are not incorporated in the analysis). This provides us with a uniform set of 288 users for whom we can assess their progression in terms of behaviour.

Our first analysis, using K-means clustering algorithm with k=5, resulted in clusters of size 24, 111, 38, 101, 14. Table 10 describes how users in our dataset are grouped with respect to the selected behavioural features. The numbers on the table correspond to the centroids of each cluster.

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Table 10: Clustering results May 2015 (features and cluster means)

Features	1	2	3	4	5
Nr. of pledges answered by the user(*)	5.552	5.725	**26.454**	5.000	5.220
Ratio of pledges the user is already doing	0.632	0.567	0.642	**0.700**	0.621
Ratio of pledges accepted	0.296	**0.355**	0.269	0.200	0.287
Ratio of pledges refused	0.071	**0.777**	0.088	0.100	0.919
Nr. of points per visit	8.501	5.486	3.547	**13.745**	2.968
Social logging	0.710	0.707	0.636	1.000	**0.779**

- The **Desirability** stage is represented by cluster 5 with 24 people (8.3% of the users), the ones with the lowest level of knowledge and also the second lowest level of participation in pledges. These users are becoming aware of the climate change problem, but are not ready yet to assume a position of changing their behaviour.

- **Enabling context** is cluster 2 with 111 users (38.5%). They have a decent knowledge (5.4 points per visit), and are characterised by the lowest participation in pledges (56%), but the highest will of participation (35%). The more users participate and the more knowledge they are acquiring, the more they are enabling their context for a change in behaviour.

- **Can do** (cluster 3), 13% of the users characterised by the second highest percentage of participation in pledges (64%). These users have also acquired a relatively low number of points per visit. These users are aware of the need of changing behaviour, doing some pledges and willing to accept others.

- **Buzz** (cluster 1) refers to 35% of the users. They have high participation in pledges (63%) and a relatively good knowledge about the environment (8.5 points per visit). These users are knowledgeable and are already taking actions (pledges) to change behaviour.

- The last stage, **Invitation** (cluster 4) contains only 4.8% of the users. They are doing 70% of the pledges presented to them, and are acquiring the higher number of points per visit (13). All these users also sign up using their social media profiles. These users already doing

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pledges and using their social media profile, which reflects their willingness to disseminate the initiative among their social network.

This results show that users with the highest number of rejected pledges (**pledge** interventions), are still at the very early stage of behaviour change (**desirability** stage). 24 users were found at this stage. Users with a good correct answering ratio (**feedback**), but have the lowest participation in pledges, were at the second behaviour stage; **enabling context** (111 users). At the third behaviour stage; the **can do** stage, were users with the second highest level of participation in pledges, but with a low number of points (**rewards**). Out of 288, 38 users were regarded to be at this stage of behaviour. 101 users were at the **buzz** stage of behaviour, with a relatively high participation in pledges (0.64%) and a relatively good knowledge about the environment (8.5 points per visit). The final stage; the **invitation** stage (14 users), consisted of the ones who accepted the majority of the pledges presented to them (70%), and acquired the highest number of points. All users at this final stage also signed using a social media account (**collective motivation**). In summary, this simple assessment shows that there is a good impact of **pledges**, **awards**, **feedback**, and **collective motivation**, on behaviour change stages.

To better understand the long-term impact of these interventions we have conducted a second analysis with the same users one year later. Our second analysis resulted in clusters of size 30, 11, 43, 118, 86.

Table 11: Clustering results May 2016 (features and cluster means)

Features	1	2	3	4	5
Nr. of pledges answered by the user(*)	6.067	**30.27**	1.70	5.35	5.87
Ratio of pledges the user is already doing	**0.648**	0.644	0.438	0.604	0.567
Ratio of pledges accepted	0.255	0.267	0.484	**0.40**	0.355
Ratio of pledges refused	**0.097**	0.089	0.077	0.087	0.077
Nr. of points per visit	**12.22**	3.54	2.12	3.32	6.42
Social logging	0.667	0.636	0.723	**0.763**	0.696

- The **Desirability** stage is represented by cluster 3 with 43 people (15% of the users), the ones with the lowest level of knowledge and also the

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lowest level of participation in pledges. These users are becoming aware of the climate change problem, but are not ready yet to assume a position of changing their behaviour. As we can see, the percentage of users in this stage has increased with respect to our 2015 analysis.

- **Enabling context** is cluster 4 with 118 users (41%). They have a decent knowledge (3.32 points per visit), and are characterised by a low participation in pledges but the highest will of participation.

- **Can do** (cluster 5), 30% of the users characterised by a medium level of participation in pledges and a high level of knowledge (6.42 points per visit).

- **Buzz** (cluster 2) refers to 3.83% of the users. They have high participation in pledges and a relatively good knowledge about the environment. These users are knowledgeable and are already taking actions (pledges) to change behaviour.

- The last stage, **Invitation** (cluster 1) contains only 10.41% of the users. They are doing most of the pledges presented to them, and are acquiring the higher number of points per visit (12.22).

Table 12 below shows the percentage of users in each behaviour category in the first evaluation in 2015, and the second evaluation in 2016. The same 288 users were considered in both evaluations. We can observe that the percentage of users in the *Can do* category has doubled, whereas the *Buzz* and *Invitation* categories shrunk significantly. It is difficult to make any strong conclusions from these variations, given that these results are for the whole user groups, rather than for each individual user. Nevertheless, it is clear that far fewer users in the second evaluation were in the advanced behaviour stages, in comparison to the first evaluation. This could be due to *game-fatigue*, where returning users get less engaged and active over time, perhaps because of task repetition. This highlights the need not only for renewed questions, but perhaps also for novel interventions to be activated.

Table 12 Comparison of behaviour categorisation in Climate Challenge

4.4.1. Behaviour Stage	Users in 2015 (%)	Users in 2016 (%)
Desirability	15.5%	14.9%

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4.4.2. **Enabling context**	61 2%	41%
4.4.3. **Can do**	16.3%	30%
4.4.4. **Buzz**	14%	3.8%
4.4.5. **Invitation**	31.1%	10.4%

5. Discussion and Conclusions

Engaging people with climate change by using technology as a medium not only requires the understanding of how technology can drive a behaviour change, but also the understanding of the needs and situations of the users in order to drive such a change.

In this deliverable we have presented the research of DecarboNet towards investigating the use of technology, and in particular interventions via social technology, to understand the behaviour of users towards the environment. In particular we have made use of Twitter, a microblogging platform, and the Climate Challenge, a game with a purpose developed within the context of DecarboNet.

We have proposed a general methodology to automatically identify the user's behavioural stages towards the environment based on the 5-door theory of behavioural change [Robinson, 2011]. Our methodology is based on three main steps: (i) a manual inspection of the data to identify the actions and interactions that can be gathered from the usage of the technology, (ii) a feature-engineering process, in which the actions, interactions and contributions of the users are transformed into numerical, categorical and semantic features, which can be automatically extracted and processed, and (iii) the application of supervised and unsupervised algorithms to mine patterns from the data based on those features.

The results of our analyses show important progress towards the identification of the different behavioural stages in which users are based on their generated content and interactions and on the different interventions that can help users to move in the direction of change.

It is important to highlight that the behaviour that users display when using social media or other technologies is not exactly the same as behaviour in the physical world. People do not report everything they do and how they do it via social media. While the results of our conducted questionnaire (see Section 3.2.1) indicate an association between behavioural stages and different types of communication, our learnings about users' behaviour from their generated content may be only a partial reflection of the reality. Previous studies indicate that variances may exist between self-reported behaviour and objective, or real behaviour [Kormos, 2014]; for example, people tend to report themselves as being more environmentally friendly than they really are.

Studying the impact of interventions is a complex research area and further investigations need to be conducted to understand the different factors that influence a behavioural change (i.e., a temporal progression/regression among behavioural stages). Interventions are generally not applied in isolation. Understanding how each individual intervention influences behaviour and how combining multiple interventions can enhance this influence is still an open problem. This problem is exacerbated by the fact that external factors (outside the context of the technology) may influence the users, and therefore the same intervention may not always obtain the same results.

This deliverable aims to serve, however, as an example of how these interventions have been monitored and assessed in the context of social media campaign communication, as well as social technology development, and to provide a step forward towards understanding the use and impact of these interventions.

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A. List of Figures

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B. List of Tables

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C. List of Abbreviations

Abbreviation	Explanation
DM	Data Manager
WP	Work package

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D. References

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