MENTAL MODELS UNDER IDEOLOGICAL CONSTRAINTS:
THE PSYCHOLOGICAL SIGNATURES UNDERSCORING
AUDIENCE SEGMENTS OF CLIMATE CHANGE

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This thesis is presented for the degree of
Doctor of Philosophy of The University of Western Australia
School of Psychological Science
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This thesis has been substantially accomplished during enrolment in this degree.

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Signature: _______________________________

Date: 11/10/2021
Abstract

There is a pressing need to bolster public support for effective climate change mitigation policies. Much of climate and policy science communication can be classified as ‘one-size-fits-all,’ where the same strategies are used for all individuals. Yet, mounting evidence suggests the general public is not homogeneous in their receptivity to climate and policy science information. Instead, the public can be divided into homogeneous segments, each possessing a unique interpretation of climate change underpinned by their psychological characteristics. Messages can be tailored to the informational needs of each segment, in a manner that addresses misconceptions, leverages motivations, and accounts for cognitive characteristics and ideologies.

Contemporary approaches to audience segmentation typically use a top-down approach, whereby concepts salient in scientific literature determine the number and nature of segments. Instead, the current thesis develops and implements a bottom-up approach to segmentation, whereby views are gauged using concepts of climate change prominent in public discourse. In Chapter 1, I outline the two aims of this thesis. The first aim is a descriptive aim to identify audience segments of Australians using a bottom-up approach. The second aim is an explanatory aim to identify the psychological characteristics that underpin each segment. One characteristic—the mental model—receives unique emphasis, as mental models provide insight into how lay people’s understandings and misconceptions combine to inform risk perceptions and decision making. Yet, mental models are understudied within the audience segmentation domain. In Chapter 2, I review the mental model literature. I find that researchers have applied a problematically narrow definition of mental models when investigating mental models of climate change.

This thesis includes two empirical chapters investigating Australian samples. In Chapter 3, I use social media to identify prominent climate change topics within public discourse ($N = 201,506$ tweets). This is achieved using a novel mixed-methods framework that blends data science with qualitative techniques. I find five prominent
topics of climate change discussion, some of which have been omitted in top-down approaches. In Chapter 4, I report two audience segmentation studies. Both studies identify audience segments using a bottom-up approach (the Q methodology), whereby participants indicate their views on the climate change concepts derived from the text analysis reported in Chapter 3. In the first study, I integrate my bottom-up approach to segmentation with a top-down consideration of theory by identifying the psychological characteristics that are diagnostic of each segment ($N = 435$). The bottom-up approach indicates three segments exist along a spectrum of climate change scepticism: Acceptors, Fencesitters, and Sceptics. The top-down inspection of the psychological characteristics of segments suggests Acceptors, Fencesitters, and Sceptics also sit upon a dimension of political ideology (from left-wing ideology to right-wing ideology), worry about climate change (decreasing in amount of worry), and environmental worldviews (increasing in worldview that the environment is able to easily recover from the effects of human activity). Sceptics display uniquely high self-perceived (but not actual) levels of climate change knowledge whereas Fencesitters display the greatest levels of dispositional conspiratorial ideation and Acceptors display the lowest levels of dispositional conspiratorial ideation. Moreover, each segment has unique mental models of climate change. In the second study, I replicate the audience segmentation solution of the first study ($N = 413$). Additionally, I demonstrate each segment varies in their tendencies to update their beliefs when contradicted by scientific information. These tendencies can be understood by recourse to the psychological characteristics of each segment.

Overall, my results suggest that scientific communication tailored for different segments may be more effective than a ‘one-size-fits-all’ approach. In Chapter 5, I synthesise the findings of this thesis. To communicators, this thesis provides strategies to tailor communication to each segment. To scientists, this thesis provides methodological innovations and theoretical developments. In particular, I challenge the assumptions of the mental models of climate change literature by identifying converging evidence that climate change views are underpinned by two different categories of mental models: (1) mental models of effective mitigation and (2) mental models of cause and consequence.
I conclude the final chapter by motivating future directions for research from the limitations of this thesis.
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Authorship Declaration

This thesis contains works that have been published and prepared for publication. Supplementary materials for manuscripts are presented as appendices.

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I, Simon Farrell (coordinating supervisor), certify that the student's statements regarding their contribution to each of the works listed above are correct. As all co-authors' signatures could not be obtained, I hereby authorise inclusion of the co-authored work in the thesis.

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Climate change is one of the greatest threats to the physical, biological, and human worlds (Schneider, 2011). Effective mitigation of climate change threats requires international cooperation. In 2016, the Paris Agreement under the United Nations Framework Convention on Climate Change was ratified. Parties to the agreement have agreed to cooperate to keep global temperature increases well below 2 degrees Celsius above pre-industrial levels (United Nations, 2015). The continued cooperation of democratic countries in the Paris Agreement is partly determined by public support. However, support for any one climate policy is unlikely to arise from a strong consensus, as the public holds a myriad of concerns, motivations, ideologies, and misunderstandings. The heterogeneity of public opinion can undermine international cooperation, ultimately exacerbating the preventable risks of climate change.

Many interventions have been proposed to unify support for climate change policy. For example, telling people the proportion of climate scientists who accept anthropogenic climate change (97%) can increase concern about and belief in climate change (van der Linden et al., 2015; van der Linden et al., 2019). The increased concern and belief enhances endorsement of policies to mitigate climate change (van der Linden et al., 2015; van der Linden et al., 2019). However, such interventions treat the public as homogeneous in the process by which beliefs are updated. This is not always the case, as interpretation of climate change information may be influenced by motivations, ideologies and worldviews (Feygina et al., 2010; Kahan, 2012). For example, Hart and Nisbet (2012) exposed Americans to news stories describing climate change risks, and then measured support for mitigation policies. Compared to controls who were not exposed to an article, liberals who read a news story demonstrated greater support for policy. In contrast, conservatives demonstrated equal or lower levels of support to their
counterparts in the control condition. As demonstrated here, a failure to acknowledge the heterogeneity of characteristics in an audience may lead to an unintentional ‘backfire’ of communication.

Although one-size-fits-all approaches may be effective on aggregate, the benefit of tailoring messages to different segments of the populations has long been appreciated in marketing. In the 1950s, Wendell Smith identified the heterogeneity of consumers’ motivation to purchase products. Through profiling consumers on their motivations, companies could tailor their advertisements and generate more purchases (W. R. Smith, 1956). This marketing philosophy is found in contemporary practices, such as the tailored and targeted advertisement of Internet websites (e.g., services offered by Google and Facebook). For science communication, tailoring messages to audience segments has a successful history within the health domain (Lustria et al., 2013; Noar et al., 2007). For climate change specifically, a substantial effort has been made to formulate and understand segments (Hine et al., 2014). Typically, researchers use top-down approaches to derive segments. This involves examining responses to questionnaires selected on the basis of theoretical relevance. One limitation of this approach is that lay views are ultimately constrained by the researcher’s choice of questionnaires.

There are two overarching aims for this thesis, one descriptive and the other explanatory. The descriptive aim is to identify audience segments using a bottom-up approach, rather than a top-down approach. To achieve this, I will analyse the discourse on climate change, allowing me to identify the most salient aspects of the public’s climate change perceptions. I will then use exemplars from the discourse as stimuli for the Q methodology—a philosophy, method, and analytical framework for investigating the subjectivity of phenomena (Brown, 1980).

The second overarching aim is explanatory: to identify the determinants of segment membership. I expect divisions in conceptions of climate change will be underpinned by various motivations, ideologies, and knowledge. Thus, although segments will be derived using a bottom-up approach, we integrate a top-down approach to relate the derived segments back to theory. One theoretical construct of particular interest to this thesis is the mental model. Mental models are internalised representations
of the world, which individuals use to generate descriptions, explanations, and predictions (Chi, 2008; Granger et al., 2002; Jones et al., 2011; Rouse & Morris, 1986). Different mental models of climate change generate different predictions (Gentner & Gentner, 1983)—an individual who believes climate change is driven by human activity predicts different climate change consequences than individuals who believe climate change is driven by natural fluctuations (Capstick & Pidgeon, 2014). This thesis will critically explore the role of the mental model concept, and its interaction with other facets of cognition and society, in determining segment membership.

The current chapter will outline a research programme to address the two aforementioned aims. I begin by introducing the Q methodology as an alternative to contemporary audience segmentation approaches. Following this, I will unpack the complexities of mental model theory. Throughout, I introduce five research questions that will be addressed in the empirical chapters of the thesis.

1.1 The Descriptive Aim: Identifying Audience Segments

1.1.1 Audience Segmentation in Social Marketing

Social marketing uses marketing concepts and techniques, such as audience segmentation, to influence behaviour on a large scale for the benefit of society (Corner & Randall, 2011; Kotler & Zaltman, 1971; Lazer & Kelley, 1973; Maibach et al., 2008). Stated another way, social marketers sell a social good in the same manner as marketers would sell a commercial good. As in marketing, social marketers use audience segmentation as a tool for handling and catering to the heterogeneity of consumers. Through segmentation, interventions can be modelled on the current perceptions, motivations, and behaviours of relatively homogeneous groupings of consumers. Each segment may then be targeted with communication specifically tailored to their characteristics. Thus, the psychological and social make-up of the public provides an actionable steer for the development of interventions (Corner & Randall, 2011).
An example of social marketing is the ‘Travelsmart’ initiative established by the Australian government for suburban areas. The initiative successfully reduced car use by 14% over an 18 month period (Australian Department for Transport, Energy, and Infrastructure, 2009). Travelsmart used several social marketing techniques, such as: placing the focus on the consumer, engagement using motivational techniques, such as individual interviews; affirming messages to reinforce behaviour; and constructing individually tailored travel plans to minimise vehicle use; removing behavioural barriers, such as providing maps and providing individuals with local alternatives to travel; and collecting feedback and evaluation, through surveys recording Global Positioning Systems and odometers (Corner & Randall, 2011). Segmentation was used to identify strategies to collaborate with three segments of community groups: high membership and high influence (e.g., Rotary); high membership and strong networks (e.g., church groups); and people with particular needs (e.g., Job Networks; Australian Department for Transport, Energy, and Infrastructure, 2009).

### 1.1.2 Audience Segmentation in Climate Change Communication

Many studies have researched audience segmentation applications to climate change communication (Hine et al., 2014). Perhaps the most established and longest running project is *Six Americas*, part of the Yale Program on Climate Change Communication (Maibach et al., 2011; Yale Program on Climate Change Communication, 2021). The Six Americas refers to the six audience segments initially identified by Maibach et al. (2011) in a nationally representative survey of Americans. The researchers tested participants on a myriad of constructs of presumed importance to communicating climate change. A six segment solution was identified, and termed the ‘Six Americas’.

Although multidimensional, the Six Americas may be ordered on continuous dimensions of belief and concern in climate change, as shown in Figure 1.1, ranging from the ‘alarmed’, a community most accepting of climate change science; via the ‘concerned’; the ‘cautious’; the ‘disengaged’; the ‘doubtful’; to the ‘dismissive’, a community which
rejects climate science. However, segments that differ in concern about climate change are similar in other aspects. For example, the ‘alarmed’ and the ‘dismissive’ are unified in their self-reported unwillingness to change their own opinions (Maibach et al., 2011). Conceptual replications and similar studies reveal comparable segments with other nations, such as Australia (Hine et al., 2013; Morrison et al., 2013; Morrison et al., 2018; Neumann et al., 2021) and Germany (Metag et al., 2017). Through understanding the unique and shared characteristics of segments, the Yale Program for Climate Change Communication has provided guidelines for tailoring communication to each group (Roser-Renouf et al., 2015).

Many audience segmentation applications to climate change follow the general approach of Maibach et al. (2011). Namely, variables which potentially determine segments are selected from constructs known to correlate with climate change perceptions, policy support, and pro-environmental behaviour. Following this, participants are typically clustered or grouped using statistical techniques (e.g., median split, Latent Class Analysis). Although this formula for audience segmentation was identified in a review by (Hine et al., 2014), more recent studies continue to derive segments in this fashion, such as with modelling and clustering of survey data (Chrst et al., 2018; Doherty & Webler, 2016; Hine et al., 2016; Metag & Schäfer, 2018; Morrison et al., 2018; Neumann et al., 2021; Wonneberger et al., 2020). Generally,
this research is exploratory and descriptive in nature. To understand segments, studies often validate the profile solution by testing for differences in segment scores of psychological characteristics, such as policy preference or pro-environmental behaviour (e.g., Maibach et al., 2011). The interpretation of profiles then requires developing qualitative descriptions on the basis of differences in variable scores across profiles. However, the variables used in segmentation can be conceptually disjointed and therefore difficult to synthesise into a coherent, conceptual description. Thus, researchers must incorporate their own deliberated or tacit understandings when interpreting segments and recommending communication techniques on the basis of segment solutions.

Although top-down approaches are used in the majority of climate change audience segmentation studies, there are bottom-up approaches to segmentation, such as the Q methodology (Brown, 1980; Hine et al., 2014; Stephenson, 1953). The Q methodology is a method, analysis, and philosophy that prioritises meaningfully representing the subjectivity of participants. The method involves participants assigning rank-orders to statements concerning a phenomenon, usually along a dimension of agreement (e.g., ‘like my point of view’). The distribution of possible rankings is constrained by the researcher, such that only a few statements may be assigned extreme rankings—forcing participants to carefully select statements that best represent their point of view (for an example, see Figure 4.1). The rank-ordering of statements, hereby referred to as a Q sort, is the operationalised subjectivity of a participant.

The Q methodology differs from contemporary segmentation approaches in the selection of stimuli. Typically, segmentation will be based on systematically varied responses to inventories selected by the researcher, and is thus generated top-down from deliberate or tacit understandings. Although these inventories may reveal useful information on the psychological determinants of climate change beliefs, the expressed views of the participant are necessarily constrained by the researcher’s preconceived notions of theory. In contrast, the statements in a Q sort are usually generated using bottom-up approaches. A set of statements is generated to capture the breadth of conversational possibilities concerning the phenomenon at hand (Brown, 1980; 1

1Although text statements are common, other stimuli may be used (e.g., images).
Figure 1.2. An example of a Q sort distribution for 40 statements. Each statement must be placed into a single box. The numbers along the top vertical line are ranks (-6 to +6). Numbers below boxes are the total number of statements that may be assigned to each rank. Participants can assign statements to more central ranks than at extreme ranks. Reprinted from Doing Q Methodological Research: Theory, Method and Interpretation (p. 80), by S. Watts and P. Stenner, 2012, SAGE Publications Ltd. Copyright 2012 by S. Watts and P. Stenner. Reprinted with permission.

Stephenson, 1986). The wide range of opinions to rank and the myriad of possible ranking permutations ensures the Q methodology is sensitive to the subjectivity of each individual.

To calculate a segmentation solution, one can compute the correlation between Q sorts. The greater the correlation, the more similar the viewpoint of the two participants who completed the sort. A matrix of correlated Q sorts can be subjected to a factor analysis, which will output a number of factors. Each factor represents a unique viewpoint of the phenomenon at hand, and thus, each factor corresponds to a segment of unique views. Participants can be assigned to segments on the basis of their factor loadings.

Despite the advantages of the Q methodology, applications to climate change audiences are rare. Wolf et al. (2009) used the Q methodology to identify four profiles of viewpoints in coastal communities in British Columbia. The first is ‘the communitarian’ who thinks the causes and mitigation of climate change rest with individuals. The second is ‘the systemist’, who views climate change as a symptom of human societies and demonstrates a low faith in technological innovations to mitigate climate change. The third profile is ‘the sceptic’, who insists more evidence is required before acting to
mitigate climate change. Lastly, ‘the economist’ posits that mitigation is the responsibility of the global community and can be achieved with economic instruments. In another application, Hobson and Niemeyer (2012) segmented climate change sceptics into five ‘discourses’. These discourses were distinguished on various dimensions, such as causal scepticism. For some, nobody is in a position to claim climate change is real (emphatic negation); for others, climate change is real but is predominately driven by natural causes (earnest acclimatisation) or is probably an inherently uncertain, anthropogenic phenomenon (noncommittal consent). These two studies demonstrate that the Q methodology may be used to obtain a deep understanding of the viewpoints of audiences and segments.

The Q methodology is a promising yet underemployed tool to segment audiences. The scarcity of Q methodology research is likely due to the resources required to collect data—the procedure is typically time intensive and administered face-to-face. As such, studies typically involve small sample sizes, as obtaining larger samples may be too costly or infeasible. Although applications to larger samples are possible through the use of mail surveys and Internet interfaces, these remain rare (Brown, 2002). In part, this is due to many Internet platforms being prohibitively expensive or outdated. I address this pragmatic barrier by developing and distributing a free, open-source application to perform the Q methodology.

Research Question 1
What set of statements best represents the national discourse on climate change?

Research Question 2
Using the Q methodology, what profiles best describe the Australian general population’s views of climate change?

To date, no research has used the Q methodology to segment the climate change views of a national audience (specifically Australians). In this work, I address this gap in the literature by answering two research questions. For the first research question (Research Question 1), I develop and use a novel mixed-methods framework to analyse social media data. I explore the topics of Australians’ discussions on climate change. Although not all Australians use Twitter, the research is bottom-up as it derives concepts
from the views of users, rather than the views of scientific experts. From this, I derive statements that capture the breadth of each topic. For the second research question (Research Question 2), I use the statements developed from the former question in a Q sort task.

1.2 The Explanatory Aim: Mental Models as a Foundation for Interpretation

*Research Question 3*

_How do mental models of climate change relate to segment membership?_

This thesis critically examines the role of mental models in climate change cognition. An investigation into mental models will yield useful advice for effective tailoring of risk communication and education (Chi, 2013; Granger et al., 2002). Mental models are a lens through which individuals understand and react to the world (Johnson-Laird, 1983). For example, consider two mental models identified by previous research: the first model posits greenhouse gas emissions are the predominant cause of climate change, whereas the second model posits toxic air pollution is the predominant cause (Kempton et al., 1995; Reynolds et al., 2010). When making decisions on climate risks, information about water vapour emissions is relevant to the first mental model but not the second. Thus, understanding the mental models of an audience provides insights into the logic by which trusted information will be transformed into action or knowledge (Granger et al., 2002), and which policies will be endorsed or dismissed (Bostrom et al., 2012).

Empirical research frequently seeks to identify a single mental model domain—one of change in _physical_ climate (e.g., Reynolds et al., 2010; Sterman & Booth Sweeney, 2007). However, the discourse on climate change is far broader than physical climate (Jang & Hart, 2015; O’Neill et al., 2015; Pathak et al., 2017; Pearce, 2014; Velti & Atanasova, 2017). Climate change discourse includes many other systems, such as government, economics, and human behaviour. For some segments, mental models of systems other than climate may take precedence in reasoning. To address the gap in
Chapter 1. Overview

the literature, this thesis will answer Research Question 3 through an empirical study. Alongside the Q sort task to segment audiences, participants will complete a mental model survey. Thus, the bottom-up derivation of segments will be supplemented by an top-down analysis of mental model characteristics.

**Research Question 4**

*Do mental models of climate change uniquely predict segment membership, when other relevant constructs are considered?*

Despite arguments that mental models are constrained by ingrained knowledge and personal dispositions (e.g., Johnson-Laird, 1983; Norman, 1983), the interactions between mental models of climate change and other aspects of cognition are not well understood (Mayer et al., 2017). In particular, normative judgements (e.g., “should the world behave this way?”), such as those generated by ideology, worldview, values, and emotions, can legitimise the structure of mental models (e.g., “could the world behave this way?”; Boschetti & Andreotta, 2017; Inayatullah, 2004; Kunda, 1990). Thus, mental models may mediate the relationship between normative judgement and segment membership.

One example of this phenomenon is motivated reasoning. Individuals may construct and use their mental models to generate inferences that reinforce their own normative judgements (Hart & Nisbet, 2012; Kunda, 1990). For example, reasoning may be identity-protective (Kahan, 2012), where mental models are processed in a way that supports inferences closely tied to one’s identity or the identity of their affinity group (e.g., the United State’s Democratic Party and their voters), and rejects inferences closely tied to the perceived outgroup (e.g., the Republican Party and their voters). As the public discourse contains normative judgements on climate change topics, and these topics form the basis for the statements used in the Q methodology, the audience segments identified in this thesis will likely differ in worldviews, ideologies, emotions, conspiracist ideation, and personality. It may be these differences that account for the relationships between mental models and segments, identified by answering Research Question 3. To explore this possibility, I will answer Research Question 4 by including measures of psychological characteristics (outlined in Chapter 4), such as worldviews,
political ideologies, emotions, conspiracist ideation, and personality. These measures will accompany the aforementioned mental model survey.

**Research Question 5**

How does the magnitude and direction of belief updating in response to scientific information differ across segments?

Differences in mental models—and the normative influences that support them—will influence how incoming information is perceived. Information from scientific organisations, such as the Intergovernmental Panel on Climate Change, will likely be at odds with the beliefs and mental models of laypeople, as these are often laden with misconceptions (outlined in Chapter 2). Some segments may be motivated (via ideology, personality, conspiracist ideation, etc.) to discount incoming scientific information, whereas other segments may be motivated to revise their beliefs. Research Question 5 will be addressed by exposing participants from different segments to scientific information that contradicts their beliefs and measuring the degree to which they update their belief. The answers to Research Question 5 will provide evidence-based recommendations for conveying scientific information to audiences.

### 1.3 Summary

In summary, audience segmentation forms the basis of social marketing programs to understand a population and influence behaviour. The Q methodology is an underused, yet promising, segmentation tool to identify the subjective viewpoints of an audience. However, pragmatic barriers inhibit its use. In this thesis, I will overcome these barriers by developing an Internet application for the Q methodology. The statements used in the Q methodology studies will be derived bottom-up from a mixed-methods exploration of social media data. Thus, we ensure participants will indicate their point of view using meaningful statements relevant to the social commentary they may encounter, rather than statements deemed relevant by researchers and their theories.

However, I do not omit a consideration of psychological theory. A supplementary top-down analysis will be used to identify the psychological characteristics unique to
Chapter 1. Overview

Each segment. Throughout the thesis, I will critically examine the role of mental models in determining climate change viewpoints and corresponding segment membership. I will explore the possibility that mental models may be constrained by other aspects of cognition responsible for normative judgement, such as political ideology, worldview, and values. The specific outcomes of this thesis are answers to each of the research questions proposed in this chapter. More generally, this thesis will identify the myriad of climate change views that exist within society and their psychological underpinnings.

1.4 Thesis Outline

This thesis contains five chapters. Following this chapter, Chapter 2 provides a review of mental model theory and research, both generally and in relation to climate change. I firstly formulate a definition of mental models used throughout the remaining chapters. Using this definition, I argue that the treatment of mental models in empirical research on climate change cognition is problematically narrow. Without acknowledging these shortcomings, the specific role of mental models in generating climate change inferences cannot be adequately understood from both a theoretical and applied perspective. This chapter will offer a more extensive motivation for the research questions subsumed within the explanatory aim of this thesis.

Two empirical chapters—Chapters 3 and 4—are presented in manuscript formats. Chapter 3 presents a novel mixed-methods framework for analysing large data sets. Using this framework, I identify the common topics of Australian climate change discourse on social media. I construct statements that capture the breadth of each topic. This set of statements represents the common discussion points in social discourse, thereby answering Research Question 1. It is these statements that are used in the subsequent Q sort studies of this thesis.

Chapter 4 contains two empirical studies involving the Q methodology. The first is an investigation into segments and their psychological underpinnings. I collect Q sort and survey inventory responses across a wide range of psychological constructs, including mental models. Participants are segmented into discrete groupings on the
basis of their Q sort results (Research Question 2). A regression model is constructed to predict segment on the basis of construct scores (Research Questions 3 & 4). This study identifies the qualitative differences between climate change views and their psychological determinants. In particular, it provides insight into which aspects of mental models uniquely contribute to segment membership, and which are overshadowed or overridden by other psychological dispositions.

The second study of Chapter 4 investigates segment differences in belief updating tendencies. Following a Q sort, participants provide numerical estimates for a set of climate change drivers or outcomes. Then, participants are shown a scientific estimate, and asked to re-estimate the same driver or outcome. This study tests the degree to which individuals from each segment differ in their revision of mental model beliefs when confronted with scientific evidence. Additionally, the study provides an opportunity to demonstrate the replicability of the segmentation solution developed in the first study of Chapter 4.

The general discussion of Chapter 5 integrates the literature reviews of Chapters 1 and 2 with the empirical results of Chapters 3 and 4. Within this chapter, I identify the implications of the thesis for both theory and practice. A bibliography for all cited material is presented after Chapter 5.
Chapter 2

Conceptualising Mental Models of Climate Change

2.1 Mental Models

In his seminal book, *The Nature of Explanation*, Craik (1943) proposed a hypothesis on human thinking. He argued that the fundamental feature of thinking is its capacity to predict events.\(^1\) Through prediction, humans achieve goals and avoid harm. To predict, humans engage in three essential processes: (1) an external process or event is translated into symbols (such as words or numbers); (2) the symbols are manipulated through reasoning (such as inference or deduction) into another set of symbols; and (3) the symbols are retranslated into an actionable process or event. Through these three processes, thought is a ‘small-scale world’ through which humans simulate reality. For example, before crossing a road, a human can translate their world into symbols, and through reasoning and retranslation, predict under what conditions it is safe to cross. Humans need not translate their entire world. A successful prediction of crossing the road requires reasoning translation of the relative speed and position of oncoming traffic, rather than the translation of colour of the car. This concept of a ‘small-scale world’ capable of predicting events became known as a ‘mental model’ (Johnson-Laird et al., 2004).

Mental models are used to explain human reasoning and behaviour in a range of disciplines, such as: cognitive psychology, human-machine factors, system dynamics, risk communication, education, creativity, and philosophy. The diverse perspectives, methodologies, and goals of each of these disciplines have spawned a sprawling,

\(^1\)The hypothesis that the brain or mind functions to reduce prediction error extends beyond the field of psychology to neuroscience and philosophy (Hohwy, 2013).
contradictory literature of mental model theories. For example, some researchers suggest mental models are resistant to change (Moray, 1999; Seel et al., 2009) whereas other researchers suggest mental models are unstable and change over the course of a single conversation (Forrester, 1971; Norman, 1983). Some researchers describe mental models as made of mental images (Forrester, 1961; D. L. Schwartz & Black, 1996), other researchers describe mental models as mental ‘movies’ (Thagard & Findlay, 2010)—yet other researchers argue mental models are distinct from mental images entirely (Johnson-Laird, 2006). In the case where mental models are not made of images, models are suggested to be built from intuitive theories (Fischhoff et al., 1993) or beliefs (Chi, 2013; Chi & VanLehn, 2012; Sterman, 1994). Some argue that mental models are abstracted from perception (Meadows et al., 1974; Seel et al., 2009) whereas others argue they are necessarily entangled in embodied experience (Jones, 2012; Thagard & Findlay, 2010). Owing to the plethora of contradictory definitions, the mental model construct is poorly specified (Doyle & Ford, 1999; Doyle et al., 1998).

A complete account and reconciliation of all theoretical perspectives is beyond the scope of this thesis. However, the application of mental model theory requires some synthesis of the seemingly contradictory theories. To this end, I follow Nersessian (2002) in conceptualising the literature as two separable lineages. The first lineage defines mental models as transient representations created in working memory (a temporary memory store that occupies consciousness capable of manipulating information; Baddeley & Hitch, 1974; Ranganath & Blumenfeld, 2005). The second lineage defines mental models as enduring structures in long term memory (an enduring memory store that supports memory for events across long timespans of minutes or more; Ranganath & Blumenfeld, 2005). I then integrate these two lineages to develop a working definition of mental models (Section 2.1).²

Following this synthesis of theory, I will present empirical research on mental models of climate change (Section 2.2). I will argue that the mental model theory used in empirical research is a narrow application of the mental model construct outlined by my

²Some theorists argue mental models in working memory and mental models in long term memory are two ends of a dimension of conceptualisation, rather than a qualitative division (e.g., Moray, 1999). My working definition of mental models can be easily reconciled under such a dimensional conceptualisation.
working definition (Section 2.3). I conclude by outlining how the current thesis will avoid the same shortcomings of contemporary research on mental models of climate change.

2.1.1 Mental Models Created in Working Memory

To understand the world and its inter-related parts, humans construct mental models (Bower & Morrow, 1990; Johnson-Laird et al., 2004). For example, a mental model of text (such as a novel) requires readers to identify and track entities (such as characters) and the causal relations among entities (such as affection between characters; Bower & Morrow, 1990). That is, mental models are structural analogues—they correspond as far as possible to the structure of the world at hand (Doyle & Ford, 1999; Doyle et al., 1998; Johnson-Laird, 1983; Nersessian, 2002). The mental model is used to comprehend and evaluate the sequential messages in the text. Readers tend to recall their mental model of a text, rather than the text itself (Bower & Morrow, 1990; Johnson-Laird, 1983).

A considerable degree of effort in cognitive science has been devoted to understanding the code of mental representations generally, and mental models specifically (Johnson-Laird, 1983; Nersessian, 2002). Understanding how entities are represented in the mind can indicate what operations on these entities are considered valid, and therefore, what reasoning and inferences are most likely in human cognition. To this end, Nersessian (2002) outlines two possible forms of representation relevant to mental models: propositional and iconic.

Propositional representations, such as linguistic and formulaic representations, represent the world descriptively (Nersessian, 2002). The relationship between a propositional representation and the world it represents can be evaluated as true or false. Operations on a propositional representation are rules-based (“IF . . . , THEN . . . ”). Manipulation of represented entities requires an explicit specification of relevant parameters and transformational states. Representations of this kind are necessarily

---

3Mental models of text are also known as a situation model.
4An extreme interpretation of Craik's (1943) thesis is that mental models do not need to represent entities, only the relationship between entities (D. Williams, 2018).
5I have adopted the language of Nersessian (2002). Drawing from philosophy, I will use the term 'propositional' to refer to the language-like encoding and manipulation of entities (Fodor, 1975; Fodor, 1978). In comparison, cognitive scientists may use the 'propositional' to refer to more 'symbolic' representations.
amodal, whereby parameters, relations, and entities are encoded as tokens (see Figure 2.1). That is, irrelevant perceptual features are not encoded in the representation. Formulations of mental models as solely propositional representations are rare, though see Holland et al. (1986) for an example.

In contrast to propositional representations, accounts of iconic representations are more common. Iconic representations are imagistic or perceptual representations of entities (see Figure 2.1; Nersessian, 2002). The relationship between an iconic representation and the world it represents may be evaluated along a dimension of ‘goodness of fit’. Valid operations transform coded entities and relations in manners consistent with the perceived constraints of the modelled world. Unlike propositional representations, implicit rules can be used to transform representations. For example, humans can reason about the relative rotational velocities of gears by relying on the qualitative relationships between gears, rather than relying on explicit rules of dynamics (D. L. Schwartz & Black, 1996). Like propositional representations, iconic mental models may be amodal (e.g., Johnson-Laird, 1983). However, iconic mental models may be...
Table 2.1. The mental models constructed by individuals typically omit scenarios.

<table>
<thead>
<tr>
<th>Phrase</th>
<th>Mental models</th>
<th>Fully explicit models</th>
</tr>
</thead>
<tbody>
<tr>
<td>If A, then B</td>
<td>A \ B</td>
<td>A \ B, \neg A \ B</td>
</tr>
</tbody>
</table>


modal, whereby superficial perceptual features are encoded into the representation (e.g., D. L. Schwartz & Black, 1996).

One of the most prominent theories of mental models was developed by Philip N. Johnson-Laird (Johnson-Laird, 1983, 2006; Johnson-Laird et al., 2004). Johnson-Laird argues that mental models are amodal representations which are generally iconic. However, propositional representation may be required to represent some worlds (such as the encoding of negation; see Johnson-Laird, 2006). Through laboratory-based experiments with Ruthe Byrne and colleagues (Johnson-Laird, 2004, 2013; Johnson-Laird et al., 1999), Johnson-Laird concluded that reasoning required models, each of which represents a possible world. When creating mental models, the reasoner attempts to create an isomorphic (one-to-one) mapping of worldly entities to tokens. For example, a human interpreting the statement “if A, then B” represents the entities relevant to the interpretation, \{A, B\}, as a model which maintains the entities and their relationship (‘exist together’).

When building mental models, humans follow tendencies that may produce misleading inferences. One such tendency is the principle of truth—a bias for representing what is true, at the expense of what is false (Johnson-Laird, 2013). In the conditional “if A, then B”, the world in which the antecedent (“if A”) is true is represented explicitly (Johnson-Laird et al., 1999). Although reasoners may construct a model where the antecedent is false, this model tends to be implicit (see Table 2.1). That is, the model is left empty until the modeller chooses to complete it. However, reasoners tend to lose access to these implicit models, failing to return to complete and use these models when
required. This influences inferences when the assumptions of explicit models are violated (e.g., A is false), leading some reasoners to incorrectly conclude that the probability of both A and B coexisting is 1 given no other information (Johnson-Laird et al., 1999).

Mental models in working memory can be conceptualised as a translation and coordination between knowledge structures stored in long term memory and perceptual experience (see Figure 2.2). Johnson-Laird accounts for some of the influence of knowledge structures on mental modelling through a cognitive process of modulation (Johnson-Laird & Khemlani, 2017; Johnson-Laird et al., 2015). Modulation blocks the construction or use of a mental model which contradicts long term understandings. For example, a world where “If it rains, then it will pour” has no model where it does not rain and it pours, as pouring requires rain (Johnson-Laird & Byrne, 2002; Johnson-Laird et al., 2015; Quelhas et al., 2010). Modulation leads reasoners to include contextual information (e.g., tense, implications of causality) not necessary for correct inferences (Juhos et al., 2012). The notion that mental models coordinates knowledge structures is a commonality shared between the two mental model lineages described here. As such, this notion is revisited below.

### 2.1.2 Mental Models stored in Long Term Memory

Mental models in working memory are transient in nature. Once a task has been completed, the mental model in working memory is discarded. However, some researchers argue mental models are enduring conceptualisations of the world (Doyle et al., 1998; Gentner & Gentner, 1983). Here, a mental model is a legacy of human experience and knowledge acquisition of systems (Rouse & Morris, 1986; Wilson & Rutherford, 1989). As with mental models stored in working memory, mental models in long term memory represent salient entities and relationships between entities (Doyle et al., 1998; Nersessian, 2002). However, these mental models persist beyond any one task, allowing humans to flexibly apply their knowledge to multiple interactions with the same system (Wilson & Rutherford, 1989).
Mental models of a system are generative, such that inferences can be traced to a specific model (Nersessian, 2002). For example, Gentner and Gentner (1983) found novices relied on existing, enduring mental models of analogous dynamics to generate inferences of electrical systems. The two most commonly used mental models were mental models of flowing water and mental models of moving crowds (see Table 2.2). Using their mental model of flowing water as an analogue, a novice could successfully deduce that the addition of a battery (water reservoirs) to a circuit (hydraulic system) will increase the current (flow) of electricity (water) in the wire (pipes). In contrast, a mental model of electricity as moving crowds is less likely to deduce this circuitry behaviour, as it is difficult to create an accurate analogue of batteries (perhaps loudspeakers). However, a mental model of teeming crowds is more likely to generate correct inferences of circuits with two resistors (gate) than a mental model of flowing water (constriction in pipe). These patterns of errors and correct inferences were confirmed by assessments of novice reasoners and various circuitry questions. Thus, inferences and systematic errors by novices could be traced to a specific mental model.

Mental models stored in long term memory are used in the fields of system dynamics (Doyle & Ford, 1998; Gentner & Gentner, 1983), human-machine interaction (Moray, 1999; Norman, 1983; Rouse & Morris, 1986), educational psychology (Chi &
Table 2.2. Analogues used to inform mental models of electrical circuits.

<table>
<thead>
<tr>
<th>Mapping</th>
<th>Electrical circuit</th>
<th>Water flow model</th>
<th>Moving crowd model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Object</td>
<td>circuit</td>
<td>hydraulic system</td>
<td>race course</td>
</tr>
<tr>
<td></td>
<td>electricity, electrons</td>
<td>water</td>
<td>mice</td>
</tr>
<tr>
<td></td>
<td>wire</td>
<td>pipe</td>
<td>wide corridor</td>
</tr>
<tr>
<td></td>
<td>battery</td>
<td>pump or reservoir</td>
<td>loudspeaker</td>
</tr>
<tr>
<td></td>
<td>resistor</td>
<td>constriction in pipe</td>
<td>gate in barrier</td>
</tr>
<tr>
<td>Attribute</td>
<td>VOLTAGE</td>
<td>PRESSURE OF water</td>
<td>PRESSURE OF mice</td>
</tr>
<tr>
<td></td>
<td>RESISTANCE</td>
<td>NARROWNESS OF pipe</td>
<td>NARROWNESS OF gate</td>
</tr>
<tr>
<td></td>
<td>CURRENT</td>
<td>FLOW OF pipe</td>
<td>PASSAGE RATE OF mice</td>
</tr>
</tbody>
</table>

Note. Partially reprinted from “Flowing Waters or Teeming Crowds: Mental Models of Electricity” by D. Gentner and D. R. Gentner. 1983, in D. Gentner and A. L. Stevens (Eds.), Mental models (p. 120), Erlbaum. Copyright 1983 by Taylor and Francis Group, LLC. Reprinted with permission.

VanLehn, 2012), natural resource management (Jones, 2012; Jones et al., 2011), and risk communication (Granger et al., 2002). Research in these disciplines does not focus on the nature and algorithmic manipulation of mental model representations, but rather the contents of mental models (Nersessian, 2002). Consequently, there are few theoretical claims for how the contents of mental models in long term memory are represented and transformed; though, some theoretical perspectives exist (e.g., Moray, 1999).

Without a strong theoretical consensus for the representation and operations to generate inferences, many researchers adopt a functional definition of mental models. Functional definitions link mental model content directly to behaviour. The most cited functional definition comes from Rouse and Morris (1986, p. 6), where “mental models are the mechanisms whereby humans are able to generate descriptions of system purpose and form, explanations of system functioning and observed system states, and predictions of future system states.” In this treatment, mental models are black boxes, where it is impossible to differentiate between content and process (Rouse & Morris, 1986; Wood et al., 2012). For example, when an individual offers a climate prediction, the functional treatment cannot differentiate between dependencies on complex knowledge structure (recalling a previous declaration of the climate prediction) or dependencies on complex cognitive processes (e.g., deliberated mental simulation of physical climate processes),
or a hybrid of the two (Wood et al., 2012). In fact, from a functional perspective, it is impossible to know whether the reasoner has used any mental models to generate inferences.

Functional definitions allow researchers to consider the implications of mental models on behaviour whilst circumventing the consideration of the specific representation and computational processes of mental models. However, without a consideration of representation and process, mental models cannot be disentangled from more generalised forms of knowledge, such as schemata (Wilson & Rutherford, 1989). Schemata are abstracted categorical ‘blocks’ of knowledge of the world. When a human perceives their world, schemata compete for representation of perception. A schema which best accommodates perception is instantiated, though another may be instantiated if incoming perception contradicts the currently selected schema (Wilson & Rutherford, 1989). Within a functional framework, both mental models and schemata contain abstracted knowledge. Thus, if mental models are to be a useful account for human reasoning, mental models must be differentiated from schemata and similar constructs.

As the everyday world is complex, it is unlikely that humans have schemata perfectly parameterised for phenomena. As such, the activation of a single schema cannot fully explain interpretation (Holland et al., 1986). Interpretation requires the combination of multiple schemata into a composite representation of the world, termed ‘descriptions’ (Norman & Bobrow, 1979). Similarly, mental models have been conceptualised as the total set of schemata instantiated at any one time (Rumelhart, 1984). Both mental models and schemata possess computational abilities (Johnson-Laird, 1983; Wilson & Rutherford, 1989). Ultimately, it is dynamic properties which differentiates mental models from schemata. Mental models can simulate the time evolution of novel processes, providing a representational flexibility which exceeds those of generalised knowledge structures (Holland et al., 1986; Johnson-Laird, 1983; Wilson & Rutherford, 1989). In sum, mental models are flexible computational representations which coordinate long term abstract knowledge (such as schemata) with features of the current task and environment.
Mental models can be coordinated with each other, and other generalised knowledge structures, to construct a mental model of a novel or unfamiliar system. This is exemplified with the aforementioned work on generative analogies, such as drawing on a mental model of crowds to ‘flesh out’ a mental model of electricity (Gentner & Gentner, 1983; Holland et al., 1986). As salient features of the environment and the goal of processing are identified, other related pieces of abstracted knowledge and mental models may also be called upon to alter the mental model in question. Thus, the same mental model in long term memory may produce different inferences due to changes in the task demands and the properties of the environment.

### 2.1.3 Commonalities in Mental Model Lineages

Despite the distinctions raised, mental models in working memory share properties with mental models in long term memory. First, for both lineages, many theorists argue that reasoning requires multiple mental models, rather than a single model (A. Collins & Gentner, 1987; Granger et al., 2002; Johnson-Laird, 1983; Vosniadou & Brewer, 1992). For example, people create multiple mental models in working memory to interpret text (e.g., those seen in Table 2.1). When multiple mental models are used, the inference generated from the mental model perceived to be most valid or correct is selected (A. Collins & Gentner, 1987; Johnson-Laird, 1983; Nersessian, 2002).

For more complex tasks with multiple levels of possible abstraction (such as writing computer code or operating manufacturing plants), multiple mental models are used, each at a distinct level of abstraction (Moray, 1999; Wilson & Rutherford, 1989). Here, abstraction refers to a process whereby mental models are transformed into another model which is structured or processed in a qualitatively different fashion. Mental models may be abstracted along two dimensions: (1) across a part-whole hierarchy, or (2) across a functional hierarchy (e.g., a means-ends dimension, an abstract-concrete dimension; Rasmussen, 1986).

Regarding the part-whole hierarchy, people may use mental models which aggregate entities in a mental representation into a superordinate grouping. For example,
a bicycle rider fixing a bicycle may require a mental model which represents the relationship between wheels, chains, gears, and pedals. However, when riding a bicycle, mental models may aggregate the relationship between multiple bicycle entities—a rider could successfully infer the conditions for acceleration with a mental model of two entities (faster pedal rotation causes acceleration). This latter mental model is homomorphic (many-to-one mapping), such that it is impossible to reconstruct an accurate world (a bicycle) from the mental model of the reasoner (e.g., a link between pedalling and acceleration; Moray, 1999).

Homomorphic representations challenge Johnson-Laird’s theory, which argues reasoners attempt to construct isomorphic models to represent all entities relevant to the reasoning at hand. Johnson-Laird’s conclusions are supported by laboratory studies on human inferences of simple and novel syllogisms, probabilities, kinematic systems, and text. These studies constitute a special case, where both the researcher and reasoner could create an exhaustive, usually small, set of relevant entities. However, well-defined sets are rare in the complex world beyond the laboratory: the boundary of systems may be unclear, and humans lack the cognitive resources to discern and maintain a cognitive representation of all relevant worldly entities (Simon, 1997). Thus, a synthesised definition of mental models requires mental models to be homomorphisms (many-to-one mappings between the world and model), with isomorphism (one-to-one mapping) as a special case.

Mental models may also be abstracted along a functional hierarchy. For example, a mental model can be conceptualised as belonging on some means-end hierarchy (see Figure 2.3; Rasmussen, 1986). The lowest level represents the physical form, the middle levels represents the causality between components, and the highest level represents the purpose of a system. Mental models from different levels of abstraction produce different inferences. For example, a pendulum swings because: gravity interacts with tensile forces in the pendulum string to cause repetitive cycles of motion (abstract function reasoning); or because pendulums were built by humans with the intent to swing (functional purpose reasoning). This contradicts Johnson-Laird’s theory, which posits mental models as representing the structure of the world. Instead, mental models

are more generally capable of representing the structural, functional, or purposive nature of the world (Nersessian, 2008; Rasmussen, 1986).

The human-machine interaction literature has described reasoners using multiple mental models to diagnose and address faults (for an example, see Figure 2.4). In general, experts maintaining the standard function of machines use relatively holistic mental models at a high level of functional abstraction (Moray, 1999; Rasmussen, 1986). However, in the presence of malfunction, experts will utilise mental models from different levels of abstraction.

Another commonality across mental model lineages is that few theorists specify the conditions in which humans use mental models instead of other cognitive processes. This theoretical shortcoming may be the result of the limitations of the empirical techniques used to study mental models of each lineage. As discussed, those who study mental models in long term memory may omit considerations of process; consequently, it is difficult to infer when reasoning has relied upon mental models. Those who study mental models in working memory often consider process, but typically do so
in laboratory experiments with narrowly defined stimuli; consequently, it is difficult to generalise findings to other tasks. Endsley (1995) proposed that surprising system behaviour will cause reasoners to use mental models to reason, though this claim requires empirical testing. Given mental models are unique in their dynamic capabilities, mental models may be most useful for novel problems or to generate predictions. Ultimately, the conditions in which mental models are used is an unanswered empirical question.

### 2.1.4 The Nature of Representation

This chapter has presented the mental modelling process as an internalised cognitive representation of the world, abstracted from many of the perceptual features of the environment. However, some psychologists argue cognition is not internalised in this way, instead, it is *embodied*. That is, there is a shared representational code between perception and action (Chandrasekharan, 2009; Nersessian, 2008). An extreme
embodiment thesis expresses all cognition in purely sensory-motor terms. Mental models cannot be entirely embodied, as the utility of the mental model concept is rooted in its capacity to abstract the world beyond purely perceptual features (Thagard & Findlay, 2010). However, it is likely mental models are inextricably shaped by sensory-motor experience.

In both children and adults, abstract concepts may be grounded in perceptual systems (Michotte, 1963; Thagard & Findlay, 2010; Vosniadou, 2009). For example, novices categorise heat and energy as physical substances (Chi, 2008). Embodied representations are present in common language, such as the pushing or pulling of a force (Thagard & Findlay, 2010). Initially, abstract concepts may be assigned to physical ontologies, as these are innate or developed from a young age (Thagard & Findlay, 2010; Vosniadou, 2009). More abstract ontologies, such as the notion of a process, may be represented in the same embodied code as notions of matter (Vosniadou, 2009).

The moderate embodiment hypothesis is evidenced by the use of multimodal signals in reasoning. Humans can integrate multimodal cues to infer common causes (e.g., visual and audio cue, see Körding et al., 2007). Additionally, humans can generate multimodal predictions from a mental model of a common cause. For example, a baby could infer shaking a rattle will lead to the movement of the rattle and the production of sound (Thagard & Findlay, 2010). The moderate embodiment hypothesis indicates mental models represent the sensorimotor experience of a world; though, mental models can represent abstracted features, such as the structure, function, or purpose of a world.

In addition to embodiment, mental models may be distributed (Jones, 2012; Nersessian, 2008). That is, representation is not constrained to an individual mind, but instead distributed across the individual, the environment, and social agents. Cognition can be distributed across the environment through the use of external tools, such as referring to a book or the Internet to produce inferences and guide decision-making (Kirsh, 1995; E. R. Smith & Semin, 2004). Cognition can be delegated to other social agents, such as group decision making or referring to a doctor for a health-related inference. The notion of distributed cognition harmonises well with embodied cognition—a mental model may contain embodied processes that ‘point’ to physical or
social entities (e.g., a mental model of car navigation may ‘point’ to a road map for less familiar routes; Jones, 2012; E. R. Smith & Semin, 2004). In this sense, the notion that a mental model is an *internal* representation of an *external* world is dismantled. By extending a moderate embodiment thesis to include distributed cognition, mental models must be understood as being coupled, or interdependent, with the world it represents (Nersessian, 2008).

The distributed nature of cognition implies a diverse and dynamic environment can both enhance the flexibility of reasoning (e.g., mental model of human health can draw from doctors or WebMD) as well as destabilise it. These mental model properties have been corroborated through both theoretical arguments (e.g., Doyle & Ford, 1999; Doyle et al., 1998; Forrester, 1971) and empirical studies (Jones, 2012). Changes in the immediate environment of the reasoner can prompt reasoners to elaborate upon certain aspects of their model, a process reframed as ‘leaning on’ the world in the distributed cognition literature (E. R. Smith & Semin, 2004). Although the concept of distributing cognition across social agents may seem more radical, the concept has long been appreciated by researchers who study ‘shared’ or ‘team’ mental models, which can only arise through group-level processes (Klimoski & Mohammed, 1994).^6^

### 2.1.5 The Synthesis of Mental Model Lineages

I will now synthesise the two divergent lineages described above. In doing so, I attempt to provide a definition for mental models that reconciles contradictory aspects. Where possible, I incorporate divergent viewpoints through adopting a minimal definition. However, to guard against vague definitions, I cannot incorporate all conceptualisations of the ‘mental model’.

To summarise, mental models are _cognitive representations of a world_ (real or imagined), _inextricably shaped by sensorimotor experience_. _Mental models are not solely internalised in cognition or abstracted from an external world_. _Instead, mental models are distributed across an individual’s cognition and their physical and social environment._

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^6^As with mental models, the notion of ‘team’ or ‘shared’ mental models is a notoriously poorly defined. I do not define the term here, instead referring readers to a review by Klimoski and Mohammed (1994).
mental model corresponds to the perceived structure, function, purpose, or sensorimotor experience of the world it represents. However, not all mental models can capture the complete complexity of a world, and are thus homomorphic representations of entities and relationships between entities, relevant for the reasoning at hand. Not all human reasoning requires mental models; however, some reasoning requires multiple mental models. Mental models can be used to infer or deduce descriptions, explanations, and predictions of a world. Thus, mental models are a valuable tool for decision-making.

I have argued mental models draw from general knowledge structures. For both lineages of mental models, the concept of knowledge and the concept of meaning is often used interchangeably (e.g., Johnson-Laird’s concept of modulation). However, meaning-making is a separable concept from knowledge; the former is a dynamic process. An understanding of meaning is critical to my working definition of mental models, as meaning-making processes allow the modeller to construe function and purpose in unfamiliar environments. However, general discussions of meaning-making can be difficult to follow without example. As such, I explore meaning in the next subsection when examining mental models of climate change.

2.2 Mental Models of Climate Change

Mental models of anthropogenic climate change precede the reality of anthropogenic climate change that follows from the industrial revolution. For example, the cold winters in Central Europe during the mid- to late-1500s were attributed by some to witchcraft or the punitive action of a wrathful god. Both causal attributions generate accurate predictions (or postdictions) of events that coincide with cold winters. Witches sowed disease and discord, rendering women, animals, and crops infertile. Thus, witches accounted for the persistent cold weather, livestock epidemics, low crop yield, and the sudden death of children. In the case of wrathful divinity, the Old Testament documented God’s capacity to punish society’s moral transgressions with extreme weather and pestilence. Where these mental models of climate change differed from reality was the implication for effective mitigative action. Neither witch persecutions nor Christian
compliance are effective in restoring change in the climate. During the 20th century, before scientists reached a consensus on anthropogenic global warming, some laypeople attributed perceived changes in weather and climate to human activity. The artillery used during World War I, the use of atomic bombs, and the launching of space shuttles were claimed to create a persistent change in climate (Kempton et al., 1995; Kimble, 1962). However, these lay attributions are inferred from anecdotal evidence (such as newspaper articles), rather than systematic research.

A scientific investigation into lay mental models of climate change began in the 1990s, allowing researchers to describe nuance obscured in archival history. During this scientific inspection, mental models were treated to be enduring, consciously-accessible, inferential tools used to interpret and transform scientific information (Bostrom et al., 1994; Kainiemi et al., 2015). The literature began with studies from two groups of researchers. The first group used a risk communication approach to identify discrepancies between inferences and scientific fact (Bostrom et al., 1994; Read et al., 1994). The second group employed a cognitive anthropological approach of interviews and surveys to identify common prior concepts used by individuals to conceptualise climate change (Kempton et al., 1995). Although similar in approach and outcome, these two groups of researchers differed in their analytical objectives—the first examined differences between inferences whereas the second examined differences between models.

The outcomes of preliminary research into mental models revealed fundamental lay misconceptions of climate change. Specifically, the public both overemphasised causal mechanisms that were peripheral or unrelated to climate change and de-emphasised causal mechanisms that were core to climate change. Often, the public failed to differentiate climate change from distal phenomena (e.g., stratospheric ozone depletion, Bostrom et al., 1994; Kempton et al., 1995). I will refer to this as a mental model configuration, whereby a mental model of climate change has been configured to operate in a similar manner to another phenomenon or mechanism. For example, a mental model of climate change may be configured to operate as a mental model of stratospheric

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7Other writers have referred to each configuration as a ‘model’ or ‘concept’. With this, there is an implicit assumption that an individual’s mental model of climate change may only match one ‘model’. However, the ‘models’ presented within this thesis are not mutually exclusive. To relieve myself from this unnecessary assumption, I use term “configuration”.
ozone depletion, where climate change is caused by ozone depletion and the release of Chlorofluorocarbons (CFCs) into the atmosphere. Configurations capture core salient entities and relationships responsible for generating a wide range of inferences. Often, configurations are incongruent with climate science.

Through understanding the common lay configurations, one can understand what inferences are most likely to be generated by the public. In the following review (Section 2.2), I present the three dominant theoretical perspectives on measurement of mental models of climate change. Following this, I present the evidence for specific lay configurations. I will argue these configurations account for systematic misconceptions of climate change and exaggeration of distal features, leading the public to overestimate the effectiveness of ineffective interventions.

### 2.2.1 Measuring Configurations

Broadly, three methodological techniques have been used to measure and conceptualise mental models of climate change (Table 2.3). Firstly, mental models may be examined through interrogation of specific, narrow aspects of climate change; for example, examining lay conceptualisations of CO\textsubscript{2} accumulation in the atmosphere (Cronin et al., 2009; Guy et al., 2013; Moxnes & Saysel, 2008; Sterman & Booth Sweeney, 2007) or the mechanism by which the greenhouse effect raises the global mean surface temperature (Harris & Gold, 2018; Niebert & GropengieSSer, 2013, 2014). As the system in question is well understood and fully specified, there exists a 'scientifically valid' solution and many 'scientifically invalid' solutions. This methodology follows a similar vein to that used to study mental models in working memory, where the system at hand could be represented as an isomorphism. Researchers seek to map common errors to a presumed typology of underlying models. However, the degree to which mental models are actually used in these tasks is unclear. It may be more appropriate to refer to a generalised category of mental representations, rather than mental models specifically (Sterner et al., 2019). In the discussion of configurations, this literature is used to indicate how cognitive biases and heuristics constrain mental model processes, leading to predictable errors in lay reasoning.
Table 2.3. Empirical investigations of mental models on climate change can be divided into three categories.

<table>
<thead>
<tr>
<th>Category</th>
<th>Operationalisation of scientific knowledge</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mental models used to reason in narrow, well-defined tasks</td>
<td>Scientifically accepted physical principals of ideal systems</td>
<td>Accumulation task (e.g., Sterman &amp; Booth Sweeney, 2007)</td>
</tr>
<tr>
<td>Mental models used for broad climate change phenomena</td>
<td>Expert consensus</td>
<td>Mental Models Approach (e.g., Read et al., 1994)</td>
</tr>
<tr>
<td>Culturally shared mental models</td>
<td>Irrelevant</td>
<td>Cultural Consensus Analysis (e.g., Crona et al., 2013)</td>
</tr>
</tbody>
</table>

The second broad category of techniques explore mental models of the broad, general issue of climate change. These techniques focus on identifying understandings of interactions of physical climate with natural (e.g., ocean), biological (e.g., biodiversity), and human (e.g., industry, health) systems. The most prominent of these methodologies is the *Mental Models Approach* (Bostrom et al., 1994; Granger et al., 2002; Read et al., 1994). The approach adopts a theoretical orientation common in studies of system understanding, risk perception, and naïve reasoning. Within this perspective, mental models are enduring conceptualisations of the causality of a system, used to generate descriptions, explanations, and predictions of that system (Gentner & Gentner, 1983; Rouse & Morris, 1986). This involves eliciting elements of mental models of climate change (e.g., causal understanding, system predictions) from both scientific experts and laypeople with semi-structured interviews on small samples. The conclusions of these interviews are then generalised through confirmatory surveys (Palmgren et al., 2004; Reynolds et al., 2010; Tobler et al., 2012). Expert consensus is represented as an influence diagram (Figure 2.5), which captures salient entities and relationships. The Mental Models Approach is then used to identify misconceptions of laypeople; that is, instances where mental models deviate from a shared mental model of experts. It is assumed that through targeting these misconceptions with communication, the public can be better informed and make more accurate risk assessments.

The techniques and assumptions of the Mental Models Approach are present in many approaches exploring mental models of the broad phenomenon of climate change.
Researchers have adapted the Mental Models Approach to better fit the research question at hand (Cao & McGill, 2013; Chowdhury et al., 2012; Mayer et al., 2017; Thomas et al., 2015). Some mental model studies may use only interviews (Hill & Thompson, 2006; Shaffer & Naiene, 2011) or only surveys (Lombardi & Sinatra, 2012; Lombardi et al., 2013; Raimi et al., 2017; Rosentrater et al., 2013). Other techniques, such as Fuzzy Cognitive Mapping, attempt to represent mental models as a diagram of interrelated entities, which influence one another (Henly-Shepard et al., 2015; Htun et al., 2016). In the foregoing discussion, this literature provides evidence for the nature of configurations.

A third category of techniques contextualises mental models of climate change within social and cultural contexts. For example, Cultural Census Analysis has been applied to assess which consequences of climate change are shared across societies (Crona et al., 2013; Klein et al., 2014). Within these techniques, there is no need for a consideration of scientific understanding or an objective reality—the shared
conceptualisation of climate change (or lack thereof) is the phenomenon of interest. In contrast to the other methodologies presented here, applications of assessing cultural understandings are relatively rare. However, some techniques used to identify mental models of the broad phenomenon of climate change incorporate considerations of cultural constructions (e.g., Kempton et al., 1995). In the foregoing discussion of configurations, I draw from this literature to provide insight into how and why specific configurations have been adopted by laypeople.

Critically, all three categories of methodologies are based on two assumptions. Firstly, mental models are assumed to be easily accessible through the paradigms used in each study (Kainiemi et al., 2015). Secondly, mental models are collapsed across contexts and levels of abstraction into a singular mental model. For example, influence diagrams map a single, large model which could be used to generate a range of inferences. This contrasts with the dominant theoretical perspective—multiple mental models are used in reasoning. Following a discussion on configurations, I will return to the issues of abstraction and multiple mental models of climate change.

2.2.2 Stratospheric Ozone Depletion Configuration

Laypeople may categorise climate change as a subset, or result of, stratospheric ozone depletion (Bostrom et al., 1994; Chowdhury et al., 2012; Huxster et al., 2015; Kempton et al., 1995; Lombardi et al., 2013; Niebert & Gropengießer, 2013; Read et al., 1994). Although ozone depletion and climate change are scientifically linked, the phenomena and its complexities do not clearly underlie lay perceptions (Kempton et al., 1995; Read et al., 1994). Instead, ozone depletion and chlorofluorocarbons (CFCs) are endorsed as substantial contributors to climate change (Kempton et al., 1995). Congruent with an ozone depletion configuration, laypeople may predict sunburn (Bostrom et al., 1994) and skin cancer (Lombardi & Sinatra, 2012; Read et al., 1994) to result from climate change. Moreover, the American public of the 1990s erroneously considered reducing the use of aerosol spray cans to be effective in mitigating climate change (Kempton et al., 1995; Read et al., 1994), despite the fact CFCs were banned by the United States since 1978. Thus, misconceptions of ozone depletion can also influence mental models of
climate change. This is also seen when laypeople conflate stratospheric ozone depletion with tropospheric ozone pollution, leading to analogous errors in their mental models of climate change (Kempton et al., 1995).

The early research of Kempton et al. (1995) argued the public’s established mental models of ozone depletion could inform their emerging mental models of climate change, as both phenomena share broad system features and causes. Specifically, the public construed new models of climate change as a subset of their existing models of ozone depletion. Reinforcing this conceptualisation, the early 1990s media would occasionally conflate ozone depletion and climate change (Bostrom et al., 1994; Kempton et al., 1995). More recently, ozone depletion has received less media attention and society is generally more educated about climate change (Reynolds et al., 2010). Given this, one may expect stratospheric ozone depletion configurations of mental models to be less prevalent. This expectation is corroborated by open-ended questions, which demonstrate fewer American laypeople produce explanations or predictions for climate change congruent with an ozone depletion configuration (Reynolds et al., 2010), indicating inferences from ozone configurations are not salient compared to alternative inferences. However, closed-ended questions reveal a substantial proportion of people endorse ozone depletion as a causal mechanism for climate change (Chowdhury et al., 2012; Huxster et al., 2015; Niebert & GropengieSSer, 2013; Reynolds et al., 2010). Although ozone phenomena has receded in the public consciousness since the early 1990s, lay mental models of climate change continue to be inextricably linked to perceptions of stratospheric ozone depletion and pollution.

### 2.2.3 Air Pollution Configuration

Mental models of climate change may conflate air pollution and greenhouse gases (Bostrom et al., 1994; Bostrom et al., 2012; Lombardi & Sinatra, 2012; Read et al., 1994). An air pollution configuration emphasises the role of artificial—typically toxic—pollution, predominantly produced by industrial or automobile activities (Kempton et al., 1995). The air pollution configuration correctly highlights that CO<sub>2</sub> released from the burning of fossil fuels and industrial processes contributes to climate change (Kempton
et al., 1995). These activities accounted for 65% of all greenhouse gas emissions in 2010 (IPCC, 2014). However, the role of less industrial and indirect anthropogenic processes may be obscured, such as land clearing and farming (Kempton et al., 1995).

The air pollution configuration incorrectly characterises greenhouse gases as toxic and centralised, though in reality, such gases tend to be non-toxic and dilute (Kempton et al., 1995). This is congruent with the sensorimotor influence on mental models. Centralised, toxic, and coloured air pollutants are more visceral, and therefore, may be perceived to be more harmful than dilute, non-toxic gases.

Mental models with an air pollution configuration diverge from scientific understandings of effective mitigation. As general air pollution is a perceived cause of climate change, strategies regulating pollution may be seen as effective strategies to mitigate climate change (Bostrom et al., 1994; Kempton et al., 1995; Reynolds et al., 2010). In both open-ended and closed-ended responses, Americans claim stopping or limiting pollution, industry emissions, and automobile use will successfully mitigate climate change (Bostrom et al., 1994; Read et al., 1994; Reynolds et al., 2010). Although some of these strategies could be successful (e.g., limiting automobile use), others may be indirect, ineffective (e.g., compliance with the Clean Air Act; Read et al., 1994; Reynolds et al., 2010), or even counterproductive (e.g., the filtering of smokestacks; Kempton et al., 1995).

### 2.2.4 Poor Environmental Practice Configuration

Laypeople may use a mental model that assumes poor environmental practices (e.g., pollution, deforestation) cause climate change (Read et al., 1994; Reynolds et al., 2010). In contrast, the causal role of neutral or good environmental practices (e.g., the contribution of swamps to global warming) to climate change processes are underestimated (Reynolds et al., 2010). Survey results indicate beliefs that environmental harms causes climate change are related, but distinct, from beliefs that carbon emissions cause climate change (Bostrom et al., 2012). Whether a cause is harmful is a larger predictor of lay endorsement than whether a cause is plausible (Read
et al., 1994; Reynolds et al., 2010). This configuration is corroborated by historical accounts, such as the aforementioned media articles of the 20th century, which suggest that the poor environmental practices of the time (e.g., artillery use, space programs) were perceived by some to cause changes in weather and climate.

A poor environmental practice configuration of a mental model emphasises good environmental practice as mitigation techniques, as these may offset the generalised harm produced from poor environmental practice. For example, planting trees and changing from Styrofoam to paper may be perceived as effective mitigation strategies, whereas putting dust in the stratosphere is judged to worsen or accelerate changes in climate (Read et al., 1994; Reynolds et al., 2010). As above, survey results indicate the perceived effectiveness of green policies in mitigating climate change is related, but distinct, from policies which reduce carbon emissions (Bostrom et al., 2012). Moreover, whether a mitigation strategy is good environmental practice is predictive of lay perceptions of effectiveness, whereas the plausibility of a mitigation strategy is not (Read et al., 1994; Reynolds et al., 2010).

### 2.2.5 Photosynthesis Configuration

The photosynthesis configuration emphasises the role of deforestation in causing climate change (Kempton, 1991; Kempton et al., 1995). This contrasts with the scientific understanding that the burning of fossil fuels contributes far more greenhouse gas emissions than the felling of forests. Thus, the photosynthesis configuration overemphasises the process of removing atmospheric carbon dioxide. Additionally, the photosynthesis configuration is an overextension of the photosynthesis model of oxygen production, often simplified by scientific textbooks and websites (see Figure 2.6 for an example; Kempton et al., 1995). The emission of oxygen from plants may be conflated with the amount of oxygen in the atmosphere. As a result, laypeople may believe deforestation causes both climate change and a shortage of oxygen (Kempton et al., 1995; Read et al., 1994; Reynolds et al., 2010). This prediction may be accompanied by frightened affect and other dystopian forecasts for the results of climate change (Kempton et al., 1995). Such predictions deviate from scientific understanding. Oxygen is required for
human survival, and there exists a large stock of oxygen within the atmosphere. Although it is true that photosynthesis produces oxygen, changes in atmospheric oxygen is only observable across long timescales. If all vegetation were removed from the earth, humans would likely starve before suffocating (Kempton et al., 1995).

### 2.2.6 Weather Configuration

Laypeople may create mental models where the concepts of weather and climate are treated as interchangeable concepts (Bostrom et al., 1994; Reynolds et al., 2010). For example, Reynolds et al. (2010) found 35% of their lay sample agreed that “Climate means pretty much the same thing as weather”. This differs from scientific conceptualisations; weather is the observable state of the atmosphere at a given place and time, whereas climate is the generalised and prevailing weather conditions of a particular region. Compared to others who distinguish between weather and climate, laypeople who conflate weather and climate are more likely to endorse scientifically
implausible causes of climate change, and less likely to endorse scientifically plausible causes of climate change (Reynolds et al., 2010).

Generally, warm weather increases belief in climate change (Capstick et al., 2015). This could be explained by weather-configured mental models of climate change, where warmer weather is interchangeable with warmer climate. Zaval and colleagues 2014 challenged this conclusion when they found the effect of warm weather on climate change belief does not differ between groups of participants who receive information that distinguishes climate change from local weather, compared to participants who received a control passage on sleep (Zaval et al., 2014). However, Zaval and colleagues did not measure weather-climate conflation following exposure to information; therefore, their manipulation may not have been successful in overhauling weather configurations. Alternatively, conflating weather and climate may be an inference from a mental model of climate change, rather than a generative premise of a mental model.

### 2.2.7 Greenhouse Gas Configuration

Scientific knowledge and international agreements are built on the understanding that successful climate mitigation requires a reduction in greenhouse gas emissions (IPCC, 2014; United Nations, 2015). Yet, the lay configurations presented thus far fail to produce such an inference. However, some laypeople demonstrate knowledge of the causal and mitigative mechanisms of greenhouse gases generally, and carbon dioxide (a greenhouse gas) specifically (Bostrom et al., 2012; Huxster et al., 2015; Reynolds et al., 2010). Factor analyses of causal and mitigative beliefs distinguish between carbon emissions and generalised environmental harm, and between carbon policies and general environmental policies (Bostrom et al., 2012). These findings emphasise a distinction between greenhouse gas configurations and poor environmental practice configurations (Bostrom et al., 2012).

Understanding the causal and mitigative mechanisms of greenhouse gases does not guarantee a mental model will generate scientifically valid inferences. Reasoners may combine a greenhouse gas configuration with an ozone configuration,
Chapter 2. Conceptualising Mental Models of Climate Change

Figure 2.7. Many Australians support a wait-and-see approach to climate change mitigation (light blue and pink). Partially reprinted from Lowy Institute Poll 2020. Retrieved from https://poll.lowyinstitute.org/report/. Copyright 2020 by the Lowy Institute for International Policy.

erroneously believing that climate change is caused by greenhouse gases deteriorating the stratospheric ozone layer. Alternatively, laypeople may adopt a greenhouse gas configuration, but endorse a wait-and-see approach, whereby mitigative policies can be delayed until more damage from climate change is observed (see Figure 2.7; Lowy Institute, 2020).8 Although wait-and-see approaches may be functional in everyday life (e.g., cooking food until it changes colour), such strategies fail in systems with delayed responses from causes and complex feedback loops. For example, both experts and novices fail to make the necessary changes early enough when managing livestock simulations that model the complex feedback between animals and food (Moxnes, 1998). As with livestock management, climate and its change is a complex, unintuitive system resulting in misperceptions of feedback and leading individuals to adopt inefficient wait-and-see approaches (Sterman, 2011).

Both laypeople and systems experts may misconstrue system dynamics, such as stocks and flows (Guy et al., 2013; Moxnes & Saysel, 2008; Niebert & Gropengiesser, 2014; Sterman & Booth Sweeney, 2007; Xie et al., 2018). A stock is an accumulated

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8 One shortcoming of the Lowly Institute poll is the conflation of cost and delay of action in responses.
Figure 2.8. Stocks and flows can be distinguished using a bathtub analogy. There are two flows in this scenario. The inflow is water flowing into the bathtub from the tap (litres/min, shown in red on the graph). The outflow is the water draining out the bathtub through the drain (litres/min, shown in blue on the graph). The water remaining in the bath (litre) is a stock. At any given time (e.g., ‘Now’ on the graph), the current level of the stock equals the area under the inflow curve minus the area under the outflow curve. That is, the current level of the stock is a function of historic inflow and outflow.


resource, whereas flows are a rate of change in stock, as seen in Figure 2.8. In the case of a greenhouse gas configuration, the atmospheric accumulation of CO₂ (stock) is dependent on the history of natural and anthropogenic CO₂ emissions (inflows) and sequestration (outflows). Different units of measurement are used to quantify stocks (e.g., tonnes) and flows (e.g., tonnes per year), and as such, stocks cannot be directly compared to the quantity of a flow (i.e., stocks and flows are incommensurable). However, reasoners will often violate the incommensurable property of stocks and flows, both generally and specifically when considering CO₂ accumulation (Cronin et al., 2009; Moxnes & Saysel, 2008; Sterman, 2010, 2011; Sterner et al., 2019).

When asked to stabilise atmospheric CO₂ stock by controlling inflow, some reasoners incorrectly pattern match by indicating and arguing that stocks can be stabilised by stabilising inflow (as seen in Figure 2.9; Sterman & Booth Sweeney, 2007). Through stabilising inflow at a rate greater than outflow, the amount of atmospheric CO₂ must
Figure 2.9. An example of a carbon stabilisation task. Participants are shown (A): a figure presenting the historical amounts of CO₂ in the atmosphere until 2015, followed by a future scenario, where the amount of atmospheric CO₂ stabilises. Participants are asked to select which of the figures (B, C, D, or E) would result in the future scenario of A. Emissions is the flow of CO₂ into the atmosphere, uptake is the flow of CO₂ out of the atmosphere. Partially reprinted from “Knowing How and Knowing When: Unpacking Public Understanding of Atmospheric CO₂ Accumulation”, by E. O. Sterner, T. Adawi, U. M. Persson, and U. Lundqvist, 2019, Climatic Change, 154(1), p. 54. Released in 2019 under the Creative Commons Attribution 4.0 International License.

necessarily increase. Reasoners who are exposed to stock-flow analogies (e.g., water flowing into a bathtub; Guy et al., 2013; Moxnes & Saysel, 2008) and training in system dynamics (Sterman, 2010) may exhibit fewer errors, though neither technique prevents pattern matching.
The erroneous use of pattern matching and violation of the incommensurable properties of flows may be explained by embodied experience. As aforementioned, novice reasoners can exhibit a tendency to erroneously ground novel processes as objects (e.g., energy, heat). Chen (2011) argues reasoners may conceptualise flows as objects, rather than processes. From this perspective, flows and stocks are comparable objects, where the stock is the difference between the inflow and outflow. When stocks are necessarily coupled with flows, pattern matching is not only viable but sensible. However, in reality, this is a gross violation of physical principles.

Laypeople may further differ in their application of greenhouse gas configurations in their treatment of natural and anthropogenic emissions. Some of the public believes anthropogenic influences are minimal compared to natural contributions to climate change (Huxster, 2013; Leviston et al., 2015), despite a consensus among scientists that climate change is driven by anthropogenic processes (Cook et al., 2013). This configuration can be further extended to account for denial, whereby laypeople argue that observed changes are part of a natural variation outside of human influence (Hobson & Niemeyer, 2012). Novice reasoners also erroneously distinguish between the properties of natural and anthropogenic CO$_2$ atmospheric stock, even though none exist (Niebert & Gropengiesser, 2013).

Greenhouse gas configurations may produce misconceptions through the misleading application of sensiromotor schemas. For example, reasoners may use a container schema to inform their mental model of climate change. A container schema involves conceptualising a facet of the world as a container, with a boundary, an interior, and an exterior (Johnson, 1987; Lakoff, 1990). The container schema is intimately understood by humans, as their own body may be understood as a container, through which the external world is separated and perceived. In everyday experience, the container schema can form a useful lens to understand the world. However, in the case of climate change, combining a greenhouse gas configuration with a container schema can generate misleading inferences. For example, novice reasoners may believe greenhouse gases form a boundary in the atmosphere, which generates misunderstandings of the
mechanisms for climate change, as seen in Figure 2.10 (Libarkin et al., 2015; Niebert & Gropengiesser, 2013).

### 2.3 Reconceptualising Mental Models of Climate Change within Cognitive Theory

“If the organism carries a ‘small-scale model’ of external reality and of its own possible actions within its head, it is able to try out various alternatives, conclude which is the best of them, react to future situations before they arise, utilise the knowledge of past events in dealing with the present and future, and in every way react in a much fuller, safer, and more competent manner to the emergencies it faces.” Craik (1943, p. 61)

When Kenneth Craik first proposed the mental model construct, he highlighted its capacity to adequately predict and prepare humans for future emergencies. Yet, laypeople frequently reason with mental models of climate change imbued with misconceptions. Despite this, novice reasoners may believe they know the appropriate mechanisms for combating climate change (Huxster et al., 2015). The mental models laypeople hold predict their support and perceived effectiveness of climate policies (Bostrom et al., 2012). Even though many Australians believe the government is not
doing enough to address climate change (Essential Media Communications, 2019), common mental model configurations lead laypeople to support ineffective policies. Through a consideration of mental models, communicators can understand both the inferences most sensible to laypeople, as well as how laypeople may interpret climate change messages (e.g., citizens may conflate air pollution with greenhouse gas emissions; Granger et al., 2002).

So far, I have argued mental models are a basis for the interpretation of the world, and therefore account for climate change views. Thus, it is expected mental models form a useful basis for understanding and communicating with audience segments. The contrasting mental model configurations presented in Section 2.2 may account for different views. However, these configurations are derived from research that applies a narrow definition of mental models. As a result, the relationship between mental models and inferences are obscured.

There are three narrow assumptions of research on mental models of climate change. Firstly, studies may assume individuals hold a single mental model of climate change. Secondly, studies may assume mental models of climate change are exclusively structural or causal analogues of the world. Thirdly, studies may assume mental models are uniformly shaped by motivation, meaning-making, and normative judgements (that is, judgements about what ‘should’ be; Mayer et al., 2017). I challenge each of these assumptions, in turn. By doing so, I outline a nuanced relationship between mental models of climate change and the features of cognition responsible for establishing meaning, judgement, and motivation. Many of these relationships are relatively unknown. If addressed, the specific function and importance of the mental model construct in establishing climate change inferences can be better understood and used in communication practices.
2.3.1 **Unsound Assumption: Physical Climate is Core to Mental Models of Climate Change**

A mental model generates descriptions, explanations, and predictions for the system it represents. The primary focus of studies of mental models of climate change relates to aspects of the physical climate. Humans systems, such as industry, economy, and health, are only examined to the degree they are perceived by laypeople to influence, or be influenced by, the physical system of climate. However, public discourse on climate change does not solely pertain to physical climate. For example, studies of social media data reveal users discuss climate change action and policy (Jang & Hart, 2015; T. P. Newman, 2016; O’Neill et al., 2015; Pathak et al., 2017; Pearce, 2014; Veltri & Atanasova, 2017), both of which exist in systems of human behaviour, economics, and government. Although mental models of climate change as a physical system predict policy support (Bostrom et al., 2012), mental models of economics, government, and human behaviour may also contribute to judgements. For some, inferences of physical climate may be deduced from mental models of social systems.

Earlier in the chapter, I demonstrated that multiple mental models could be abstracted along a functional hierarchy (e.g., means-ends), and decomposed along a part-whole hierarchy. This framework can be applied to configurations, such as the photosynthesis configuration in Figure 2.11. Although the exemplars used in Figure 2.11 contain mental models of physical systems (e.g., air composition, respiration), other mental models concern groups within human society (e.g., the dynamic between “they” and “them”). Thus, in some instances, both mental models of physical climate and mental models of societal processes (e.g., normative judgements, perceptions of social hierarchy, in-group and out-group perceptions) are required for climate change reasoning.
Figure 2.11. Reconceptualising configurations as multiple mental models. Kempton et al. used a comment by a participant as evidence of a photosynthesis configuration: ‘That's what scares me...When they cut all the forests down, they say, pretty soon we're not going to have any oxygen left to breathe. Why do they let them do that?’ (p. 69, Kempton et al., 1995). The same comment may be reconceptualised as multiple mental models, which span a functional hierarchy (vertical) and part-whole hierarchy (horizontal). Each circle is a mental model. Gray circles are models explicitly declared in participant's comments, yellow are latent. Numbers represent the order in which these models are referenced.

<table>
<thead>
<tr>
<th>Decomposition of Whole system</th>
<th>Collection of biological entities</th>
<th>Biological entity</th>
<th>Physical environment</th>
<th>Molecular</th>
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<tr>
<td><strong>Abstraction</strong></td>
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<tr>
<td>Functional meaning; purpose</td>
<td>8 “why do they let them do that?”</td>
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<td>Abstract function</td>
<td>1 “they”</td>
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<td>Generalised function</td>
<td>6 respiration</td>
<td>7 suffocation of humans</td>
<td>4 photosynthesis</td>
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<td>Physical function</td>
<td>2 deforestation</td>
<td>3 no forests</td>
<td>5 no oxygen</td>
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<td>Physical form</td>
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**2.3.2 Unsound Assumption: Mental Models of Climate Change are Exclusively Structural or Causal Analogues**

In Section 2.1, I concluded mental models could form functional analogues that represent purpose and meaning. This formulation has been largely ignored in empirical studies of mental models of climate change (for an exception, see Kempton et al., 1995). It is
likely mental models of function are used to interpret anthropogenic climate change, as mental models of purpose and meaning are often used to interpret human behaviour more generally (Rasmussen, 1986).

As a demonstration of a functional analogue, consider values. Values are beliefs infused with affect, which transcend any one situation or action (S. H. Schwartz, 2012; S. H. Schwartz, 1992). Individuals may attribute different levels of importance to different values, generating a value ‘hierarchy’ which motivates behaviour. Pro-environmental behaviour may be partly driven by the hierarchy and trade-off of self-transcending values (e.g., altruism) against self-enhancing values (e.g., materialism; Corner et al., 2014). Values serve as a standard upon which aspects of the world are evaluated (S. H. Schwartz, 2012; S. H. Schwartz, 1992). Behaviours congruent with the goals of an individual’s most cherished values are judged as good.

When function deviates from purpose, mental models are used to support reasoning (Endsley, 1995). As is the case with an operator diagnosing a fault in suboptimal production of a manufacturing plant, so does the layperson diagnosing a fault in a non-ideal world. However, individuals cherish different values, and thus, emphasise different goals and corresponding aspects of the world. Only entities and relationships perceived to be salient to the reasoning at hand are represented in mental models. The layperson who cherishes materialism may be less likely to represent ‘future generations’ in their mental models than the layperson who cherishes universalism, a value which emphasises understanding and protecting the welfare of all people and nature (S. H. Schwartz, 2012). Value judgements are imbued in many mental model configurations, including historical accounts (e.g., climate change is caused by transgressions against God) and in the Poor Environmental Practice configuration, where ecological damage caused by human activity is judged in a negative light (Kempton et al., 1995).
2.3.3 Unsound Assumption: Motivations and Meaning-Making Uniformly Shape Mental Models

I have established that the construction and use of mental models are supported by background knowledge and cognitive aspects responsible for construing meaning. However, when the empirical literature considers mechanisms for determining purpose and function, the mechanisms are treated to be exogenous variables that uniformly shape mental models (Mayer et al., 2017). However, the influence of mechanisms on mental models, such as values, can vary depending on the decision made by individuals (Bessette et al., 2017; Kahneman et al., 1998; S. H. Schwartz, 1992).

In light of this shortcoming of the literature, a Values-Informed Mental Models Approach has been implemented to identify links between values and parts of mental models (Bessette et al., 2017; Mayer et al., 2017). This approach has revealed empirical values are relevant when reasoners define the objectives of mental models (Mayer et al., 2017). Additionally, values are relevant to the interpretation and evaluation of judgements for both scientists, and more generally with stakeholders (Bessette et al., 2017; Mayer et al., 2017).

However, the Values-Informed Mental Models Approach and the Mental Models Approach suffer from the same shortcoming. Both collapse multiple mental models into a single model. As a result, these approaches are unable to distinguish between: (1) a functional mental model that represents value, and (2) a causal or structural analogue constrained by value. Thus, values may influence mental models, but it is not clear which models are constrained by, or represent, values.

Additionally, the Values-Informed Mental Models Approach fails to consider other cognitive mechanisms for establishing meaning and building functional mental models. For example, political ideologies provide normative information on the ideal system states (Jost et al., 2009). In some instances, political ideology has been conceptualised as a shared framework of mental models (Denzau & North, 1994). Other features of cognition, such as worldviews and system justification, also serve to legitimise specific
mental models (Dryzek, 2013; Kay & Jost, 2003; Price et al., 2014; van der Linden, Maibach et al., 2017). As an example, consider system justification—a tendency to defend the status quo (Kay & Jost, 2003). Some mitigative climate change policies threaten the status quo. To the individual high in system justification, mitigation serves the unfavourable function of disrupting a fair system (van der Linden, Maibach et al., 2017). To the individual low in system justification, mitigation serves the favourable function of disrupting an unfair system. Congruent with these explanations, system justification is negatively associated with environmentally-friendly behaviours. Thus, differences in legitimatised system function may generate differences in mental models at a functional level and ultimately promote different actions.

Mental models at the lower levels of the functional-hierarchy (e.g., causal and structural) may also be shaped by the cognitive architecture used in meaning-making. As a simple demonstration, the degree to which individuals perceive human activity changes the climate is associated with political ideology—lefter-leaning individuals are more likely to endorse anthropogenic influences than their righter-leaning counterparts (Feygina et al., 2010; Kahan & Corbin, 2016). In this instance, there are two explanations for the influence of ideology on mental model aspects.

Firstly, ideology may dictate some mental model components, as is the case in strongly motivated reasoning. Here, individuals may be biased to reason in a manner that supports inferences which reinforce their own ideologies, worldviews, and values (Hart & Nisbet, 2012; Kunda, 1990). For example, reasoning may be identity-protective (Kahan, 2012), ultimately supporting inferences closely tied to ones identity or the identity of their affinity group (e.g., the United State’s Democratic Party), and rejecting inferences closely tied to the perceived outgroup (e.g., the Republican Party). As reasoning itself may be motivated, individuals may adopt a specific mental model of climate change, when that mental model is a symbol of ingroup membership. Alternatively, individuals may ad hoc engineer a mental model which supports identity-protective inferences. Identity-protection is not the only motivation which may shape reasoning. Worldviews (Price et al., 2014), values (Corner et al., 2014; O’Brien & Wolf, 2010; S. H. Schwartz, 1992), political ideology (Fielding et al., 2012; Zia & Todd, 2010), emotions (Leiserowitz, 2006), climate
scepticism (Capstick & Pidgeon, 2014), conspiracist ideation (Lewandowsky, Oberauer et al., 2013), and personality (Yu & Yu, 2017) may all motivate individuals to construe the world in a particular manner. Within this explanation, mental models of climate change are proxies for a myriad of motivations and cognitive constraints.

Alternatively, ideology may shape but not predetermine mental model reasoning. For example, a Democrat voter may be motivated to argue climate change is primarily the result of human activity, that the impacts of climate change will generally be negative, and that certain policies (endorsed by the Democratic Party) will be effective (Hart & Nisbet, 2012). In this sense, some, but not all, mental model dynamics are determined by ideology. However, unlike the second explanation offered above, these mental models are more than proxies for motivation and are run independently.

2.4 Conclusion

Within this chapter, I developed a working definition of mental models. Using this definition, I identified unsound assumptions of the current literature on climate change. By tailoring study design and interpretation with these unsound assumptions in mind, I ensure this thesis will not follow the same shortcomings as the literature that preceded it.

A thorough investigation of the strength of each unsound assumption outlined in this chapter is beyond the scope of the current work. However, in Chapter 4, I challenge the assumption that cognitive devices for inferring meaning and purpose are exogenous variables that uniformly shape mental models. This assumption is tested by empirically mapping the links between mental model components and a wide range of constructs related to motivation and meaning making, such as personality, political ideology, worldview, conspiracist ideation, system justification, and values. In Chapter 5 (general discussion), I argue that the contemporary formulation of mental models of climate change must be revisited to account for my findings. Specifically, I motivate new explanations for mental model content and function using the unsound assumptions that I have highlighted in the current chapter.
Chapter 3

Identifying Prominent Climate Change Concepts in Social Media

3.1 Foreword

In Chapter 1, I highlighted that contemporary approaches to audience segmentation are top-down. Such approaches divide participants based on concepts presumed to be relevant by researchers. In Chapter 2, I emphasised that research on mental models of climate change is problematically narrow. Thus, the concepts assumed to be relevant by researchers is likely to omit climate change concepts salient to the public. This chapter aims to identify the salient concepts of the public, through a novel mixed-methods analysis of Australian’s social media data. Specifically, I analysed Twitter data from 2016. An entire year was selected, as climate change discussions change over time. The year 2016 was chosen specifically due to its recency, as the research began in early 2017.

This chapter is presented as a journal article manuscript. A version of the manuscript was published in Behavior Research Methods for a special issue entitled Beyond the lab: Using big data to discover principles of cognition. The goal of the article was to highlight a novel framework for blending data science with qualitative techniques to gain insight into social media data. As such, the chapter places a strong emphasis on the analytical approach of the empirical work. This chapter is accompanied by supplementary material presented in Appendix A. Note that I use the term ‘we’ throughout the chapter to refer to the collective contributions of the manuscript co-authors.

Where possible, data and scripts from this research have been made available for download at https://github.com/AndreottaM/TopicAlignment. Importantly, this repository includes code for a web application to visualise and compute the reliability
of topic models (see chapter for explanation). The repository provides free open-source code for researchers who seek to identify the replicability of their own topic models.

The full reference for the journal article manuscript used in this chapter is:

3.2 Abstract

To qualitative researchers, social media offers a novel opportunity to harvest a massive and diverse range of content, without the need for intrusive or intensive data collection procedures. However, performing a qualitative analysis across a massive social media data set is cumbersome and impractical. Instead, researchers often extract a subset of content to analyze, but a framework to facilitate this process is currently lacking. We present a four-phased framework for improving this extraction process, which blends the capacities of data science techniques to compress large data sets into smaller spaces, with the capabilities of qualitative analysis to address research questions. We demonstrate this framework by investigating the topics of Australian Twitter commentary on climate change, using quantitative (Non-Negative Matrix inter-joint Factorization; Topic Alignment) and qualitative (Thematic Analysis) techniques. Our approach is useful for researchers seeking to perform qualitative analyses of social media, or researchers wanting to supplement their quantitative work with a qualitative analysis of broader social context and meaning.
Chapter 3. Identifying Prominent Climate Change Concepts in Social Media

3.3 Introduction

Social scientists use qualitative modes of inquiry to explore the detailed descriptions of the world that people see and experience (Pistrang & Barker, 2012). To collect the voices of people, researchers can elicit textual descriptions of the world through interview or survey methodologies. However, with the popularity of the Internet and social media technologies, new avenues for data collection are possible. Social media platforms allow users to create content (e.g., Weinberg & Pehlivan, 2011), and interact with other users (e.g., Correa et al., 2010; Kietzmann et al., 2011), in settings where “Anyone can say Anything about Any topic” Allemang and Hendler (AAA slogan, 2011, pg. 6). Combined with the high rate of content production, social media platforms can offer researchers massive and diverse dynamic data sets (Gudivada et al., 2015; Yin & Kaynak, 2015). With technologies increasingly capable of harvesting, storing, processing, and analyzing this data, researchers can now explore data sets that would be infeasible to collect through more traditional qualitative methods.

Many social media platforms can be considered as textual corpora, willingly and spontaneously authored by millions of users. Researchers can compile a corpus using automated tools and conduct qualitative inquiries of content or focused analyses on specific users (Marwick, 2014). In this chapter, we outline some of the opportunities and challenges of applying qualitative textual analyses to the big data of social media. Specifically, we present a conceptual and pragmatic justification for combining qualitative textual analyses with data science text-mining tools. This process allows us to both embrace and cope with the volume and diversity of commentary over social media. We then demonstrate this approach in a case study investigating Australian commentary on climate change, using content from the social media platform: Twitter.
3.3.1 Opportunities and Challenges for Qualitative Researchers using Social Media Data

Through social media, qualitative researchers gain access to a massive and diverse range of individuals, and the content they generate. Researchers can identify voices which may not be otherwise heard through more traditional approaches, such as semi-structured interviews and Internet surveys with open-ended questions. This can be done through diagnostic queries to capture the activity of specific peoples, places, events, times, or topics. Diagnostic queries may specify geotagged content, the time of content creation, textual content of user activity, and the online profile of users. For example, Freelon et al. (2018) identified the Twitter activity of three separate communities (‘Black Twitter’, ‘Asian-American Twitter’, ‘Feminist Twitter’) through the use of hashtags\(^1\) in tweets from 2015 to 2016. A similar process can be used to capture specific events or moments (Denef et al., 2013; Procter et al., 2013), places (Lewis et al., 2013), and specific topics (Hoppe, 2009; Sharma et al., 2017).

Collecting social media data may be more scalable than traditional approaches. Once equipped with the resources to access and process data, researchers can potentially scale data harvesting without expending a great deal of resources. This differs from interviews and surveys, where collecting data can require an effortful and time-consuming contribution from participants and researchers.

Social media analyses may also be more ecologically valid than traditional approaches. Unlike approaches where responses from participants are elicited in artificial social contexts (e.g., Internet surveys, laboratory-based interviews), social media data emerges from real-world social environments encompassing a large and diverse range of people, without any prompting from researchers. Thus, in comparison with traditional methodologies (Given, 2008; Lietz & Zayas, 2010; Onwuegbuzie & Leech, 2007), participant behavior is relatively unconstrained if not entirely unconstrained, by the behaviors of researchers.

\(^1\)On Twitter, users may precede a phrase with a hashtag (#). This allows users to signify and search for tweets related to a specific theme.
These opportunities also come up with challenges, because of the following attributes (Parker et al., 2011). Firstly, social media can be interactive: its content involves the interactions of users with other users (e.g., conversations), or even external websites (e.g., links to news websites). The ill-defined boundaries of user interaction have implications for determining the units of analysis of qualitative study. For example, conversations can be lengthy, with multiple users, without a clear structure or end-point. Interactivity thus blurs the boundaries between users, their content, and external content (Herring, 2009; Parker et al., 2011). Secondly, content can be ephemeral and dynamic. The users and content of their postings are transient (Boyd & Crawford, 2012; Parker et al., 2011; Weinberg & Pehlivan, 2011). This feature arises from the diversity of users, the dynamic socio-cultural context surrounding platform use, and the freedom users have to create, distribute, display, and dispose of their content (Marwick & Boyd, 2011). Lastly, social media content is massive in volume. The accumulated postings of users can lead to a large amount of data, and due to the diverse and dynamic content, postings may be largely unrelated and accumulate over a short period of time. Researchers hoping to harness the opportunities of social media data sets must therefore develop strategies for coping with these challenges.

### 3.3.2 A Framework Integrating Computational and Qualitative Text Analyses

Our framework—a mixed-method approach blending the capabilities of data science techniques with the capacities of qualitative analysis—is shown in Figure 3.1. We overcome the challenges of social media data by automating some aspects of the data collection and consolidation, so that the qualitative researcher is left with a manageable volume of data to synthesize and interpret. Broadly, our framework consists of the following four phases: (1) harvest social media data and compile a corpus, (2) use data science techniques to compress the corpus along a dimension of relevance, (3) extract a subset of data from the most relevant spaces of the corpus, and (4) perform a qualitative analysis on this subset of data.
3.3.2.1 **Phase 1: Harvest Social Media Data and Compile a Corpus**

Researchers can use automated tools to query records of social media data, extract this data, and compile it into a corpus. Researchers may query for content posted in a particular time frame (Procter et al., 2013), content containing specified terms (Sharma et al., 2017), content posted by users meeting particular characteristics (Denef et al., 2013; Lewis et al., 2013), and content pertaining to a specified location (Hoppe, 2009).

3.3.2.2 **Phase 2: Use Data Science Techniques to Compress the Corpus Along a Dimension of Relevance**

Although researchers may be interested in examining the entire data set, it is often more practical to focus on a subsample of data (McKenna et al., 2017). Specifically, we advocate dividing the corpus along a dimension of relevance, and sampling from spaces that are more likely to be useful for addressing the research questions under consideration. By relevance, we refer to an attribute of content that is both useful for addressing the research questions and usable for the planned qualitative analysis.

To organize the corpus along a *dimension of relevance*, researchers can use automated, computational algorithms. This process provides both *formal* and *informal*
advantages for the subsequent qualitative analysis. Formally, algorithms can assist researchers in privileging an aspect of the corpus most relevant for the current inquiry. For example, topic modeling clusters massive content into semantic topics—a process that would be infeasible using human coders alone. A plethora of techniques exist for separating social media corpora on the basis of useful aspects, such as sentiment (e.g., Agarwal et al., 2011; Pak & Paroubek, 2010; Paris et al., 2015) and influence (Weng et al., 2010).

Algorithms also produce an informal advantage for qualitative analysis. As mentioned, it is often infeasible for analysts to explore large data sets using qualitative techniques. Computational models of content can allow researchers to consider meaning at a corpus-level when interpreting individual datum or relationships between a subset of data. For example, in an inspection of 2.6 million tweets, Procter et al. (2013) used the output of an information flow analysis to derive rudimentary codes for inspecting individual tweets. Thus, algorithmic output can form a meaningful scaffold for qualitative analysis by providing analysts with summaries of potentially disjunct and multifaceted data (due to interactive, ephemeral, dynamic attributes of social media).

3.3.2.3 Phase 3: Extract a Subset of Data from the Most Relevant Spaces of the Corpus

Once the corpus is organized on the basis of relevance, researchers can extract data most relevant for answering their research questions. Researchers can extract a manageable amount of content to qualitatively analyze. For example, if the most relevant space of the corpus is too large for qualitative analysis, the researcher may choose to randomly sample from that space. If the most relevant space is small, the researcher may revisit Phase 2 and adopt a more lenient criteria of relevance.
3.3.2.4 Phase 4: Perform a Qualitative Analysis on this Subset of Data

The final phase involves performing the qualitative analysis to address the research question. As discussed above, researchers may draw on the computational models as a preliminary guide to the data.

3.3.2.5 Contextualizing the Framework within Previous Qualitative Social Media Studies

The proposed framework generalizes a number of previous approaches (L. Collins & Nerlich, 2015; McKenna et al., 2017) and individual studies (e.g., Lewis et al., 2013; T. P. Newman, 2016), in particular that of Marwick (2014). In Marwick’s general description of qualitative analysis of social media textual corpora, researchers: (1) harvest and compile a corpus, (2) extract a subset of the corpus, and (3) perform a qualitative analysis on the subset. As shown in Figure 3.1, our framework differs in that we introduce formal considerations of relevance, and the use of quantitative techniques to inform the extraction of a subset of data. Although researchers sometimes identify a subset of data most relevant to answering their research question, they seldom deploy data science techniques to identify it. Instead, researchers typically depend on more crude measures to isolate relevant data. For example, researchers have used the number of repostings of user content to quantify influence and recognition (e.g., T. P. Newman, 2016).

The steps in the framework may not be obvious without a concrete example. Next, we demonstrate our framework by applying it to Australian commentary regarding climate change on Twitter.
3.3.3 Application Example: Australian Commentary regarding Climate Change on Twitter

3.3.3.1 Social Media Platform of Interest

We chose to explore user commentary of climate change over Twitter. Twitter activity contains information about: the textual content generated by users (i.e., content of tweets), interactions between users, and the time of content creation (Veltri & Atanasova, 2017). This allows us to examine the content of user communication, taking into account the temporal and social contexts of their behavior. Twitter data is relatively easy for researchers to access. Many tweets reside within a public domain, and are accessible through free and accessible APIs.

The characteristics of Twitter’s platform are also favorable for data analysis. An established literature describes computational techniques and considerations for interpreting Twitter data. We used the approaches and findings from other empirical investigations to inform our approach. For example, we drew on past literature to inform the process of identifying which tweets were related to climate change.

3.3.3.2 Public Discussion on Climate Change

Climate change is one of the greatest challenges facing humanity (Schneider, 2011). Steps to prevent and mitigate the damaging consequences of climate change require changes on different political, societal, and individual levels (Lorenzoni & Pidgeon, 2006). Insights into public commentary can inform decision making and communication of climate policy and science.

Traditionally, public perceptions are investigated through survey designs and qualitative work (Lorenzoni & Pidgeon, 2006). Inquiries into social media allow researchers to explore a large and diverse range of climate change-related dialogue (Auer et al., 2014). Yet, existing inquiries of Twitter activity are few in number and typically constrained to specific events related to climate change, such as the release of the Fifth
When longer time scales are explored, most researchers rely heavily upon computational methods to derive topics of commentary. For example, Kirilenko and Stepchenkova (2014) examined the topics of climate change tweets posted in 2012, as indicated by the most prevalent hashtags. Although hashtags can mark the topics of tweets, it is a crude measure as tweets with no hashtags are omitted from analysis, and not all topics are indicated via hashtags (e.g., Nugroho, Yang et al., 2017). In a more sophisticated approach, Veltri and Atanasova (2017) examined the co-occurrence of terms using hierarchical clustering techniques to map the semantic space of climate change tweet content from the year 2013. They identified four themes: (1) “calls for action and increasing awareness”, (2) “discussions about the consequences of climate change”, (3) “policy debate about climate change and energy”, and (4) “local events associated with climate change” (p. 729).

Our research builds on the existing literature in two ways. Firstly, we explore a new data set—Australian tweets over the year 2016. Secondly, in comparison to existing research of Twitter data spanning long time periods, we use qualitative techniques to provide a more nuanced understanding of the topics of climate change. By applying our mixed-methods framework, we address our research question: what are the common topics of Australian’s tweets about climate change?

### 3.4 Method

#### 3.4.1 Outline of Approach

We employed our four-phased framework as shown in Figure 3.2. Firstly, we harvested climate change tweets posted in Australia in 2016 and compiled a corpus (phase 1). We then utilized a topic modeling technique (Nugroho, Zhao et al., 2017) to organize the diverse content of the corpus into a number of topics. We were interested in topics which
commonly appeared throughout the time period of data collection, and less interested in more transitory topics. To identify enduring topics, we used a topic alignment algorithm (Chuang et al., 2015) to group similar topics occurring repeatedly throughout 2016 (phase 2). This process allowed us to identify the topics most relevant to our research question. From each of these, we extracted a manageable subset of data (phase 3). We then performed a qualitative thematic analysis (see Braun & Clarke, 2006) on this subset of data to inductively derive themes and answer our research question (phase 4).\(^2\)

### 3.4.2 Phase 1: Compiling a Corpus

To search Australian’s Twitter data, we used CSIRO’s Emergency Situation Awareness (ESA) platform (CSIRO, 2018). The platform was originally built to detect, track, and report on unexpected incidences related to crisis situations (e.g., fires, floods; see Cameron et al., 2012). To do so, the ESA platform harvests tweets based on a location search that covers most of Australia and New Zealand. The ESA platform archives the harvested tweets, which may be used for other CSIRO research projects. From this archive, we retrieved tweets satisfying three criteria: (1) tweets must be associated with an Australian location, (2) tweets must be harvested from the year 2016, and (3) the content of tweets must be related to climate change. We tested the viability of different markers of climate change tweets used in previous empirical work (Holmberg & Hellsten, 2016; Jang & Hart, 2015; T. P. Newman, 2016; O’Neill et al., 2015; Pearce et al., 2014; Sisco et al., 2017; Swain, 2017; H. T. Williams et al., 2015) by informally inspecting the content of tweets matching each criteria. Ultimately, we employed five terms (or combinations of terms) reliably associated with climate change: (1) “climate” AND “change”; (2) “#climatechange”; (3) “#climate”; (4) “global” AND “warming”; and (5) “#globalwarming”. This yielded a corpus of 201,506 tweets.

\(^2\)The analysis of this study was preregistered on the Open Science Framework: https://osf.io/mb8kh/. See the Supplementary Material for a discussion of discrepancies (Appendix A). Analysis scripts and interim results from computational techniques can be found at: https://github.com/AndreottaM/TopicAlignment.
Figure 3.2. Flowchart of application of a four-phased framework for conducting qualitative analyses using data science techniques. We were most interested in topics that frequently occurred throughout the period of data collection. To identify these, we organized the corpus chronologically, and divided the corpus into batches of content. Using computational techniques (shown in blue), we uncovered topics in each batch and identified similar topics which repeatedly occurred across batches. When identifying topics in each batch, we generated three alternative representations of topics (5, 10, and 20 topics in each batch, shown in yellow). In stages highlighted in green, we determined the quality of these representations, ultimately selecting the five topics per batch solution.
3.4.3 Phase 2: Using Data Science Techniques to Compress the Corpus along a Dimension of Relevance

The next step was to organize the collection of tweets into distinct topics. A topic is an abstract representation of semantically related words and concepts. Each tweet belongs to a topic, and each topic may be represented as a list of keywords (i.e., prominent words of tweets belonging to the topic). A vast literature surrounds the computational derivation of topics within textual corpora, and specifically within Twitter corpora (Chuang et al., 2014; Fang et al., 2016a; Nugroho, Zhao et al., 2017; Ramage et al., 2010). Popular methods for deriving topics include: probabilistic latent semantic analysis (Hofmann, 1999), non-negative Matrix Factorization (Lee & Seung, 2000), and Latent Dirichlet Allocation (Blei et al., 2003). These approaches use patterns of co-occurrence of terms within documents to derive topics. They work best on long documents. Tweets, however, are short, and thus only a few unique terms may co-occur between tweets. Consequently, approaches which rely upon patterns of term co-occurrence suffer within the Twitter environment. Moreover, these approaches ignore valuable social and temporal information (Nugroho, Zhao et al., 2017). For example, consider a tweet $t_1$ and its reply $t_2$. The reply feature of Twitter allows users to react to tweets and enter conversations. Therefore, it is likely $t_1$ and $t_2$ are related in topic, by virtue of the reply interaction.

To address sparsity concerns, we adopt the Non-Negative Matrix inter-joint Factorization (NMijF) of Nugroho, Zhao et al. (2017). This process uses both tweet content (i.e., the patterns of co-occurrence of terms amongst tweets) and socio-temporal relationship between tweets (i.e., similarities in the users mentioned in tweets, whether the tweet is a reply to another tweet, whether tweets are posted at a similar time) to derive topics (see Supplementary Material in Appendix A). The NMijF method has been demonstrated to outperform other topic modeling techniques on Twitter data (Nugroho, Zhao et al., 2017).
3.4.3.1 Dividing the Corpus into Batches

Deriving many topics across a data set of thousands of tweets is prohibitively expensive in computational terms. Therefore, we divided the corpus into smaller batches and derived the topics of each batch. To keep the temporal relationships amongst tweets (e.g., timestamps of the tweets) the batches were organized chronologically. The data was partitioned into 41 disjoint batches (40 batches of 5,000 tweets; 1 batch of 1,506 tweets).

3.4.3.2 Generating Topical Representations for Each Batch

Following standard topic modeling practice, we removed features from each tweet which may compromise the quality of the topic derivation process. These features include: emoticons, punctuation, terms with fewer than three characters, stop-words (for list of stop-words, see MySQL, 2018), and phrases used to harvest the data (e.g., “#climatechange”). Following this, the terms remaining in tweets were stemmed using the Natural Language Toolkit for Python (Bird et al., 2009). All stemmed terms were then tokenized for processing.

The NMijF topic derivation process requires three parameters (see Supplementary Material for more details, in Appendix A). We set two of these parameters to the recommendations of Nugroho, Zhao et al. (2017), based on empirical analysis. The final parameter—the number of topics derived from each batch—is difficult to estimate a priori, and must be made with some care. If \( k \) is too small, keywords and tweets belonging to a topic may be difficult to conceptualize as a singular, coherent, and meaningful topic. If \( k \) is too large, keywords and tweets belonging to a topic may be too specific and obscure. To determine a reasonable value of \( k \), we ran the NMijF process on each batch with three different levels of the parameter—5, 10, and 20 topics per batch. This process generated three different representations of the corpus: 205, 410, and 820 topics. For each of these representations, each tweet was classified into one (and only one) topic. We represented each topic as a list of ten keywords most prevalent within the tweets of that topic.

383 tweets were rendered empty and discarded from the corpus.
3.4.3.3 Assessing the Quality of Topical Representations

To select a topical representation for further analysis, we inspected the quality of each. Initially, we considered the use of a completely automatic process to assess or produce high quality topic derivations. However, our attempts to use completely automated techniques on tweets with a known topic structure failed to produce correct or reasonable solutions. Thus, we assessed quality using human assessment (see Table 3.1). The first stage involved inspecting each topical representation of the corpus (205, 410, and 820 topics), and manually flagging any topics that were clearly problematic. Specifically, we examined each topical representation to determine whether topics represented as separate were in fact distinguishable from one another. We discovered that the 820 topic representation (20 topics per batch) contained many closely related topics.

To quantify the distinctiveness between topics, we compared each topic to each other topic in the same batch in an automated process. If two topics shared 3 or more (of 10) keywords, these topics were deemed similar. We adopted this threshold from existing topic modeling work (Fang et al., 2016a, 2016b), and verified it through an informal inspection. We found that pairs of topics below this threshold were less similar than those equal to or above it. Using this threshold, the 820 topic representation was identified as less distinctive than other representations. Of the 41 batches, 9 contained at least two similar topics for the 820 topic representation (cf., 0 batches for the 205 topic representation, 2 batches for the 410 topic representation). As a result, we chose to exclude the representation from further analysis.

The second stage of quality assessment involved inspecting the quality of individual topics. To achieve this, we adopted the pairwise topic preference task outlined by Fang et al. (2016a, 2016b). In this task, raters were shown pairs of two similar topics (represented as ten keywords), one from the 205 topic representation and the other from the 410 topic representation. To assist in their interpretation of topics, raters could also view three tweets belonging to each topic. For each pair of topics, raters indicated which topic they believed was superior, on the basis of coherency, meaning, interpretability, and
Chapter 3. Identifying Prominent Climate Change Concepts in Social Media

Table 3.1. Two-staged assessment of the quality of topic derivations.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Level of inspection</th>
<th>Quality metric</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Topical representation of each batch</td>
<td>Distinctiveness</td>
<td>Degree to which topics within a batch can be distinguished from other topics of the same batch</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Coherency</td>
<td>Degree to which the topic contains keywords that are semantically similar</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Meaning</td>
<td>Degree to which the topic contains keywords that reference fewer discussions and events</td>
</tr>
<tr>
<td>2</td>
<td>Individual topics</td>
<td>Interpretability</td>
<td>Degree to which the keywords convey specific information about a topic</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Related tweets</td>
<td>Degree to which tweets in the topic reflect the keywords and meaning of the topic</td>
</tr>
</tbody>
</table>

Through aggregating responses, a relative measure of quality could be derived.

Initially, members of the research team assessed 24 pairs of topics. Results from the task did not indicate a marked preference for either topical representation. To confirm this impression more objectively, we recruited participants from the Australian community as raters. We used Qualtrics—an online survey platform and recruitment service—to recruit 154 Australian participants, matched with the general Australian population on age and gender. Each participant completed judgments on 12 pairs of similar topics (see Supplementary Material for further information, in Appendix A).

Participants generally preferred the 410 topic representation over the 205 topic representation ($M = 6.45$ of 12 judgments, $SD = 1.87$). Of 154 participants, 35 were classified as indifferent (selected both topic representations an equal number of times), 74 preferred the 410 topic representation (i.e., selected the 410 topic representation more often than the 205 topic representation), and 45 preferred the 205 topic representation (i.e., selected the 205 topic representation more often that the 410 topic representation). We conducted binomial tests to determine whether the proportion of participants of the three just described types differed reliably from chance levels (0.33). The proportion of indifferent participants (0.23) was reliably lower than chance ($p = .005$), whereas the
proportion of participants preferring the 205 topic solution (0.29) did not differ reliably from chance levels ($p = .305$). Critically, the proportion of participants preferring the 410 topic solution (0.48) was reliably higher than expected by chance ($p < .001$). Overall, this pattern indicates a participant preference for the 410 topic representation over the 205 topic representation.

In summary, no topical representation was unequivocally superior. On a batch level, the 410 topic representation contained more batches of non-distinct topic solutions than the 205 topic representation, indicating that the 205 topic representation contained topics which were more distinct. In contrast, on the level of individual topics, the 410 topic representation was preferred by human raters. We use this information, in conjunction with the utility of corresponding aligned topics (see below), to decide which representation is most suitable for our research purposes.

3.4.3.4 Grouping Similar Topics Repeated in Different Batches

We were most interested in topics which occurred throughout the year (i.e., in multiple batches) to identify the most stable components of climate change commentary (Phase 3). We grouped similar topics from different batches using a topical alignment algorithm (see Chuang et al., 2015). This process requires a similarity metric and a similarity threshold. The similarity metric represents the similarity between two topics, which we specified as the proportion of shared keywords (from 0, no keywords shared, to 1, all ten keywords shared). The similarity threshold is a value below which two topics were deemed dissimilar. As above, we set the threshold to 0.3 (3 of 10 keywords shared)—if two topics shared two or fewer keywords, the topics could not be justifiably classified as similar. To delineate important topics, groups of topics, and other concepts we have provided a glossary of terms in Table 3.2.

The topic alignment algorithm is initialized by assigning each topic to its own group. The alignment algorithm iteratively merges the two most similar groups, where the similarity between groups is the maximum similarity between a topic belonging to one group and another topic belonging to the other. Only topics from different groups (by definition, topics from the same group are already grouped as similar) and different
Table 3.2. Glossary of critical terms

<table>
<thead>
<tr>
<th>Concept</th>
<th>Definition</th>
<th>Process for derivation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Topic</td>
<td>An abstract representation of semantically related words and concepts</td>
<td>Topic Modeling</td>
</tr>
<tr>
<td>Group of topics</td>
<td>A collection of similar topics from different batches</td>
<td>Topic Alignment</td>
</tr>
<tr>
<td>Prevalent topic groupings</td>
<td>Groups of topics which contain at least three topics</td>
<td>Topic Alignment</td>
</tr>
<tr>
<td>Theme</td>
<td>A patterned meaning of tweets that distinctly answers our research question: what are the common topics of Australian's tweets about climate change?</td>
<td>Thematic Analysis</td>
</tr>
</tbody>
</table>

batches (by definition, topics from the same batch cannot be similar) can be grouped. This process continues, merging similar groups until no compatible groups remain. We found our initial implementation generated groups of largely dissimilar topics. To address this, we introduced an additional constraint—groups could only be merged if the mean similarity between pairs of topics (each belonging to the two groups in question) was greater than the similarity threshold. This process produced groups of similar topics. Functionally, this allowed us to detect topics repeated throughout the year.

We ran the topical alignment algorithm across both the 205 and 410 topic representations. For the 205 and 410 topic representation respectively, 22.47% and 31.60% of tweets were not associated with topics that aligned with others. This exemplifies the ephemeral and dynamic attributes of Twitter activity: over time, the content of tweets shifts, with some topics appearing only once throughout the year (i.e., in only one batch). In contrast, we identified 42 groups (69.77% of topics) and 101 groups (62.93% of topics) of related topics for the 205 and 410 topic representations respectively, occurring across different time periods (i.e., in more than one batch). Thus, both representations contained transient topics (isolated to one batch) and recurrent topics (present in more than one batch, belonging to a group of two or more topics).
3.4.3.5 Identifying Topics Most Relevant for Answering our Research Question

For the subsequent qualitative analyses, we were primarily interested in topics prevalent throughout the corpus. We operationalized *prevalent topic groupings* as any grouping of topics that spanned three or more batches. On this basis, 22 (57.50% of tweets) and 36 (35.14% of tweets) groupings of topics were identified as prevalent for the 205 and 410 topic representations, respectively (see Table 3.3). As an example, consider the prevalent topic groupings from the 205 topic representation, shown in Table 3.3. Ten topics are united by commentary on the Great Barrier Reef (Group 2)—indicating this facet of climate change commentary was prevalent throughout the year. In contrast, some topics rarely occurred, such as a topic concerning a climate change comic (indicated by the keywords “xkcd” and “comic”) occurring once and twice in the 205 and 410 topic representation, respectively. Although such topics are meaningful and interesting, they are transient aspects of climate change commentary and less relevant to our research question. In sum, topic modeling and grouping algorithms have allowed us to collate massive amounts of information, and identify components of the corpus most relevant to our qualitative inquiry.

3.4.3.6 Selecting the Most Favorable Topical Representation

At this stage, we have two complete and coherent representations of the corpus topics, and indications of which topics are most relevant to our research question. Although some evidence indicated that the 410 topic representation contains topics of higher quality, the 205 topic representation was more parsimonious on both the level of topics and groups of topics. Thus, we selected the 205 topic representation for further analysis.
### Table 3.3. Prevalent topic groupings (205 topic representation) and associated keywords.

<table>
<thead>
<tr>
<th>Group</th>
<th>Total batches</th>
<th>Proportion of corpus (%)</th>
<th>Common keywords</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>13</td>
<td>9.83</td>
<td>action need now</td>
</tr>
<tr>
<td>2</td>
<td>10</td>
<td>4.92</td>
<td>#greatbarriereef barrier great reef</td>
</tr>
<tr>
<td>3</td>
<td>7</td>
<td>4.53</td>
<td>coal new</td>
</tr>
<tr>
<td>4</td>
<td>6</td>
<td>3.00</td>
<td>action pai plan real</td>
</tr>
<tr>
<td>5</td>
<td>6</td>
<td>2.35</td>
<td>denial malcolm nation new one robe senat</td>
</tr>
<tr>
<td>6</td>
<td>5</td>
<td>3.54</td>
<td>hottest new record year</td>
</tr>
<tr>
<td>7</td>
<td>5</td>
<td>3.47</td>
<td>#qanda energi need renew</td>
</tr>
<tr>
<td>8</td>
<td>5</td>
<td>2.93</td>
<td>fight govt one peopl</td>
</tr>
<tr>
<td>9</td>
<td>5</td>
<td>2.45</td>
<td>#parisagr agreement pari ratifi time world</td>
</tr>
<tr>
<td>10</td>
<td>4</td>
<td>2.23</td>
<td>#qanda emiss health impact need polici risk talk</td>
</tr>
<tr>
<td>11</td>
<td>4</td>
<td>1.68</td>
<td>extrem link make now power renew scientist weather</td>
</tr>
<tr>
<td>12</td>
<td>3</td>
<td>1.84</td>
<td>debat nation one senat</td>
</tr>
<tr>
<td>13</td>
<td>3</td>
<td>1.75</td>
<td>action believ malcolm peopl real world</td>
</tr>
<tr>
<td>14</td>
<td>3</td>
<td>1.62</td>
<td>impact iss malcolm peopl</td>
</tr>
<tr>
<td>15</td>
<td>3</td>
<td>1.58</td>
<td>#qanda need real reef</td>
</tr>
<tr>
<td>16</td>
<td>3</td>
<td>1.54</td>
<td>#qldpol #scienc #wapol denier need year</td>
</tr>
<tr>
<td>17</td>
<td>3</td>
<td>1.53</td>
<td>flood iss now polici scientist</td>
</tr>
<tr>
<td>18</td>
<td>3</td>
<td>1.45</td>
<td>action impact klein naomi world</td>
</tr>
<tr>
<td>19</td>
<td>3</td>
<td>1.39</td>
<td>malcolm repo risk scientist warn</td>
</tr>
<tr>
<td>20</td>
<td>3</td>
<td>1.38</td>
<td>latest stop thank world</td>
</tr>
<tr>
<td>21</td>
<td>3</td>
<td>1.26</td>
<td>latest peopl planet thank year</td>
</tr>
<tr>
<td>22</td>
<td>3</td>
<td>1.21</td>
<td>level rise sea</td>
</tr>
</tbody>
</table>

**Note.** Only keywords shared between at least half of all topics within a group are included. Keywords in bold are shared between all topics of that group. All keywords are presented in stemmed form.
3.4.4 Phase 3. Extract a Subset of Data

3.4.4.1 Extracting a Subset of Data from the Selected Topical Representation

Before qualitative analysis, researchers must extract a subset of data manageable in size. For this process, we concerned ourselves with only the content of prevalent topic groupings, seen in Table 3.3. From each of the 22 prevalent topic groupings, we randomly sampled 10 tweets. We selected 10 tweets as a trade-off between comprehensiveness and feasibility. This thus reduced our data space for qualitative analysis from 201,423 tweets to 220.

3.4.5 Phase 4: Perform Qualitative Analysis

3.4.5.1 Perform Thematic Analysis

In the final phase of our analysis, we performed a qualitative thematic analysis (TA; Braun & Clarke, 2006) on the subset of tweets sampled in Phase 3. This analysis generated distinct themes, each of which answers our research question: what are the common topics of Australian's tweets about climate change? As such, the themes generated through TA are topics. However, unlike the topics derived from the preceding computational approaches, these themes are informed by the human coder's interpretation of content and are oriented towards our specific research question. This allows the incorporation of important diagnostic information, including the broader socio-political context of discussed events or terms, and an understanding (albeit, sometimes ambiguous) of the underlying latent meaning of tweets.

We selected TA as the approach allows for flexibility in assumptions and philosophical approaches to qualitative inquiries. Moreover, the approach is used to emphasize similarities and differences between units of analysis (i.e., between tweets) and is therefore useful for generating topics. However, TA is typically applied to lengthy interview transcripts or responses to open survey questions, rather than small units of
Table 3.4. Phases of thematic analysis

<table>
<thead>
<tr>
<th>Phase</th>
<th>Description of the process</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Familiarizing yourself with your data:</td>
<td>Transcribing data (if necessary), reading and re-reading the data, noting down initial ideas.</td>
</tr>
<tr>
<td>2. Generating initial codes:</td>
<td>Coding interesting features of the data in a systematic fashion across the entire data set, collating data relevant to each code.</td>
</tr>
<tr>
<td>3. Searching for themes:</td>
<td>Collating codes into potential themes, gathering all data relevant to each potential theme.</td>
</tr>
<tr>
<td>4. Reviewing themes:</td>
<td>Checking if the themes work in relation to the coded extracts (Level 1) and the entire data set (Level 2), generating a thematic “map” of the analysis.</td>
</tr>
<tr>
<td>5. Defining and naming themes:</td>
<td>Ongoing analysis to refine the specifics of each theme, and the overall story the analysis tells, generating clear definitions and names for each theme.</td>
</tr>
<tr>
<td>6. Producing the report:</td>
<td>The final opportunity for analysis. Selection of vivid, compelling extract examples, final analysis of selected extracts, relating back of the analysis to the research question and literature, producing a scholarly report of the analysis.</td>
</tr>
</tbody>
</table>


To ease the application of TA to small units of analysis, we modified the typical TA process (shown in Table 3.4) as follows.

Firstly, when performing Phases 1 and 2 of TA, we initially read through each prevalent topic grouping’s tweets sequentially. By doing this, we took advantage of the relative homogeneity of content within topics. That is, tweets sharing the same topic will be more similar in content than tweets belonging to separate topics. When reading ambiguous tweets, we could use the tweet’s topic (and other related topics from the same group) to aid comprehension. Through the scaffold of topic representations, we facilitated the process of interpreting the data, generating initial codes, and deriving themes.

Secondly, the prevalent topic grouping’s were used to create initial codes and search for themes (TA Phase 2 and 3). For example, the groups of topics indicate content of climate change action (Group 1), the Great Barrier Reef (Group 2), climate change deniers (Group 3), and extreme weather (Group 5). The keywords characterizing these
topics were used as initial codes (e.g., “action”, “Great Barrier Reef”, “Paris agreement”, “denial”). In sum, the algorithmic output provided us with an initial set of codes and an understanding of the topic structure that can indicate important features of the corpus.

A member of the research team performed this augmented TA to generate themes. A second rater outside of the research team applied the generated themes to the data, and inter-rater agreement was assessed. Following this, the two raters reached a consensus on the theme of each tweet.

### 3.5 Results

Through TA, we inductively generated five distinct themes. We assigned each tweet to one (and only one) theme. A degree of ambiguity is involved in designating themes for tweets, and 7 tweets were too ambiguous to subsume into our thematic framework. The remaining 213 tweets were assigned to one of five themes shown in Table 3.5.

In an initial application of the coding scheme, the two raters agreed upon 161 (73.181%) of 220 tweets. Inter-rater reliability was satisfactory, Cohen’s $\kappa = 0.648$, $p < 0.05$. An assessment of agreement for each theme is presented in Table 3.5. The proportion of agreement is the total proportion of observations where the two coders both agreed: (1) a tweet belonged to the theme, or (2) a tweet did not belong to the theme. The proportion of specific agreement is the conditional probability that a randomly selected rater will assign the theme to a tweet, given that the other rater did (see Supplementary Material for more information, in Appendix A). Theme 3, Theme 5, and the N/A categorization had lower levels of agreement than the remaining themes, possibly as tweets belonging to Themes 3 and 5 often make references to content relevant to other themes.

**Theme 1. Climate Change Action.** The theme occurring most often was climate change action, whereby tweets were related to coping with, preparing for, or preventing climate change. Tweets comment on the action (and inaction) of politicians, political parties, and international cooperation between government, and to a lesser degree, industry,
Table 3.5. Summary of themes.

<table>
<thead>
<tr>
<th>Theme</th>
<th>Number of occurrences</th>
<th>Example tweets</th>
<th>Examples of events users mention</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Climate change action</td>
<td>87 (39.55%)</td>
<td>“Yes! Let’s start working together for real solutions on climate change #QandA”</td>
<td>Paris Climate Change Agreement. Australian Federal Election.</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Proportion of agreement 0.845  Proportion of specific agreement 0.795 Related prevalent topic groupings 1, 9</td>
</tr>
<tr>
<td>2. Consequences of climate change</td>
<td>43 (19.55%)</td>
<td>“RT @user: Reefs of the future could look like this if we continue to ignore #climatechange..... https://...”</td>
<td></td>
</tr>
<tr>
<td>3. Conversations on climate change</td>
<td>35 (15.91%)</td>
<td>“RT @user: @user not so gripping from No Principles Malcolm. Not one mention of climate change in his pitch.”</td>
<td>Leader debates preceding elections in Australia and the United States. UNESCO removes content on Australia from a report of the risks of climate change to world heritage sites.</td>
</tr>
<tr>
<td>Theme</td>
<td>Number of occurrences</td>
<td>Example tweets</td>
<td>Examples of events users mention</td>
</tr>
<tr>
<td>-------</td>
<td>-----------------------</td>
<td>----------------</td>
<td>-----------------------------------</td>
</tr>
<tr>
<td>4. Climate change deniers</td>
<td>28 (12.73%)</td>
<td>“Don’t worry! According to Senator elect Malcolm Roberts, NASA fiddles the figures on Climate Change. https://…”</td>
<td>Malcolm Roberts elected in the Australian Senate. Donald Trump is elected as President of the United States. Malcolm Roberts debates Brian Cox on the panel discussion television program Q &amp; A.</td>
</tr>
<tr>
<td>5. The legitimacy of climate change and climate science</td>
<td>20 (9.09%)</td>
<td>“Do we have an international convention on ‘Cloud Seeding’? Or it comes under United Nation’s climate change agreement?”</td>
<td>CSIRO decides to cut jobs of climate researchers</td>
</tr>
<tr>
<td>N/A</td>
<td>7 (3.18%)</td>
<td>“#QandA.Climate change and jobs and growth”</td>
<td>0.964</td>
</tr>
</tbody>
</table>

*Note. Content was anonymized by replacing references to usernames with the term “user”, and replacing links to websites with “https://…”. Related prevalent topic groupings and topics are selected on the basis of sharing similar summary meaning with each theme. Prevalent topic groupings are indicated as numbers corresponding to groups shown in Table 3.3. Each topic is presented as the ten stemmed keywords belonging to that topic.*
media, and the public. The theme encapsulated commentary on: prioritizing climate change action (“Let’s start working together for real solutions on climate change”); relevant strategies and policies to provide such action (“#OurOcean is absorbing the majority of #climatechange heat. We need #marinereserves to help build resilience.”); and the undertaking (“Labor will take action on climate change, cut pollution, secure investment & jobs in a growing renewables industry”) or disregarding (“act on Paris not just sign”) of action.

Often, users were critical of current or anticipated action (or inaction) towards climate change, criticizing approaches by politicians and governments as ineffective (“Malcolm Turnbull will never have a credible climate change policy”), and undesirable (“Govt: how can we solve this vexed problem of climate change? Helpful bystander: u could not allow a gigantic coal mine. Govt: but srsly how?”). Predominately, users characterized the government as unjustifiably paralyzed (“If a foreign country did half the damage to our country as #climatechange we would declare war.”), without a leadership focused on addressing climate change (“an election that leaves Australia with no leadership on #climatechange - the issue of our time!”).

**Theme 2. Consequences of Climate Change.** Users commented on the consequences and risks attributed to climate change. This theme may be further categorized into commentary of: physical systems, such as changes in climate, weather, sea ice, and ocean currents (“Australia experiencing more extreme fire weather, hotter days as climate changes”); biological systems, such as marine life (particularly, the Great Barrier Reef) and biodiversity (“Reefs of the future could look like this if we continue to ignore #climatechange”); human systems (“You and your friends will die of old age & I’m going to die from climate change”); and other miscellaneous consequences (“The reality is, no matter who you supported, or who wins, climate change is going to destroy everything you love”). Users specified a wide range of risks and impacts on human systems, such as health, cultural diversity, and insurance. Generally, the consequences of climate change were perceived as negative.

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4The content of tweet are reported verbatim. Sensitive information is redacted.
5Malcolm Turnbull was the Prime Minister of Australia during the year 2016.
Theme 3. Conversations on Climate Change. Some commentary centered around discussions of climate change communication, debates, art, media, and podcasts. Frequently, these pertained to debates between politicians (“not so gripping from No Principles Malcolm. Not one mention of climate change in his pitch.”) and television panel discussions (“Yes let’s all debate whether climate change is happening... #qanda”). Users condemned the climate change discussions of federal government (“Turnbull gov echoes Stalinist Russia? Australia scrubbed from UN climate change report after government intervention”), those skeptical of climate change (“Trouble is climate change deniers use weather info to muddy debate. Careful?????????????????”), and media (“Will politicians & MSM hacks ever work out that they cannot spin our way out of the #climatechange crisis?”). The term “climate change” was critiqued, both by users skeptical of the legitimacy of climate change (“Weren’t we supposed to call it ‘climate change’ now? Are we back to ‘global warming’ again? What happened? Apart from summer?”) and by users seeking action (“Maybe governments will actually listen if we stop saying “extreme weather” & “climate change” & just say the atmosphere is being radicalized”).

Theme 4. Climate Change Deniers. The fourth theme involved commentary on individuals or groups who were perceived to deny climate change. Generally, these were politicians and associated political parties, such as: Malcolm Roberts (a climate change skeptic, elected as an Australian Senator in 2016), Malcolm Turnbull, and Donald Trump. Commentary focused on the beliefs and legitimacy of those who deny the science of climate change (“One Nation’s Malcolm Roberts is in denial about the facts of climate change”) or support the denial of climate change science (“Meanwhile in Australia... Malcolm Roberts, funded by climate change skeptic global groups loses the plot when nobody believes his findings”). Some users advocated attempts to change the beliefs of those who deny climate change science (“We have a president-elect who doesn’t believe in climate change. Millions of people are going to have to say: Mr. Trump, you are dead wrong”), whereas others advocated disengaging from conversation entirely (“You know I just don’t see any point engaging with climate change deniers like Roberts. Ignore him”). In

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6#qanda is a hashtag used to refer to Q & A, an Australian panel discussion television program.
comparison to other themes, commentary revolved around individuals and their beliefs, rather than the phenomenon of climate change itself.

**Theme 5. The Legitimacy of Climate Change and Climate Science.** This theme concerns the reality of climate change (“How do we know this climate change thing is real - not a natural cycle, not an elaborate hoax?”) and the associated practice of climate science (“#CSIROcuts will damage Aus ability to understand, respond to & plan for #climatechange”).\(^7\) Compared to other themes, content collated under this theme contained a wide variety of sentiment. Whereas some tweets endorse anthropogenic causes of climate change, others question the contribution of humans to climate change (“COWS FARTS CAUSE MORE THAN WE DO”) and question its existence entirely (“The effects of Climate Change ?? OK [xxx], lets talk facts.....which effects are those ??”).

### 3.6 Discussion

Using our four-phased framework, we aimed to identify and qualitatively inspect the most enduring aspects of climate change commentary from Australian posts on Twitter in 2016. We achieved this by using computational techniques to model 205 topics of the corpus, and identify and group similar topics that repeatedly occurred throughout the year. From the most relevant topic groupings, we extracted a subsample of tweets and identified five themes with a thematic analysis: climate change action, consequences of climate change, conversations on climate change, climate change deniers, and the legitimacy of climate change and climate science. Overall, we demonstrated the process of using a mixed-methodology that blends qualitative analyses with data science methods to explore social media data.

Our workflow draws on the advantages of both quantitative and qualitative techniques. Without quantitative techniques, it would be impossible to derive topics that apply to the entire corpus. The derived topics are a preliminary map for understanding the corpus, serving as a scaffold upon which we could derive meaningful

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\(^7\)Commonwealth Scientific and Industrial Research Organisation (CSIRO) is the national scientific research agency of Australia.
themes contextualized within the wider socio-political context of Australia in 2016. By incorporating quantitatively-derived topics into the qualitative process, we attempted to construct themes that would generalize to a larger, relevant component of the corpus. The robustness of these themes is corroborated by their association with computationally-derived topics, which repeatedly occurred throughout the year (i.e., prevalent topic groupings). Moreover, four of the five themes have been observed in existing data science analyses of Twitter climate change commentary. Within the literature, the themes of climate change action and consequences of climate change are common (Jang & Hart, 2015; T. P. Newman, 2016; O’Neill et al., 2015; Pathak et al., 2017; Pearce, 2014; Veltri & Atanasova, 2017). The themes of the legitimacy of climate change and climate science (Jang & Hart, 2015; T. P. Newman, 2016; O’Neill et al., 2015; Pearce, 2014) and climate change deniers (Pathak et al., 2017) have also been observed. The replication of these themes demonstrates the validity of our findings.

One of the five themes—conversations on climate change—has not been explicitly identified in existing data science analyses of tweets on climate change. Although not explicitly identifying the theme, Kirilenko and Stepchenkova (2014) found hashtags related to public conversations (e.g., “#qanda”, “#Debates”) were used frequently throughout the year 2012. Similar to the literature, few (if any) topics in our 205 topic solution could be construed as solely relating to the theme of “conversation”. However, as we progressed through the different phases of the framework, the theme became increasingly apparent. By the grouping stage, we identified a collection of topics unified by a keyword relating to debate. The subsequent thematic analysis clearly discerned this theme. The derivation of a theme previously undetected by other data science studies lends credence to the conclusions of Guetterman et al. (2018), who deduced that supplementing a quantitative approach with a qualitative technique can lead to the generation of more themes than a quantitative approach alone.

The uniqueness of a conversational theme can be accounted for by three potentially contributing factors. Firstly, tweets related to conversations on climate change often contained material pertinent to other themes. The overlap between this theme and others may hinder the capabilities of computational techniques to uniquely cluster
these tweets, and undermine the ability of humans to reach agreement when coding content for this theme (indicated by the relatively low proportion of specific agreement in our thematic analysis). Secondly, a conversational theme may only be relevant in election years. Unlike other studies spanning long time periods (Jang & Hart, 2015; Veltri & Atanasova, 2017), Kirilenko and Stepchenkova (2014) and our study harvested data from US presidential election years (2012 and 2016, respectively). Moreover, an Australian federal election occurred in our year of observation. The occurrence of national elections and associated political debates may generate more discussion and criticisms of conversations on climate change. Alternatively, the emergence of a conversational theme may be attributable to the Australian panel discussion television program Q & A. The program regularly hosts politicians and other public figures to discuss political issues. Viewers are encouraged to participate by publishing tweets using the hashtag “#qanda”, perhaps prompting viewers to generate uniquely tagged content not otherwise observed in other countries. Importantly, in 2016, Q & A featured a debate on climate change between science communicator Professor Brian Cox and Senator Malcolm Roberts, a prominent climate science skeptic.

Although our four-phased framework capitalizes on both quantitative and qualitative techniques, it still has limitations. Namely, the sparse content relationships between data points (in our case, tweets) can jeopardize the quality and reproducibility of algorithmic results (e.g., Chuang et al., 2015). Moreover, computational techniques can require large computing resources. To a degree, our application mitigated these limitations. We adopted a topic modeling algorithm which uses additional dimensions of tweets (social and temporal) to address the influence of term-to-term sparsity (Nugroho, Zhao et al., 2017). To circumvent concerns of computing resources, we partitioned the corpus into batches, modeled the topics in each batch, and grouped similar topics together using another computational technique (Chuang et al., 2015).

As a demonstration of our four-phased framework, our application is limited to a single example. For data collection, we were able to draw from the procedures of existing studies which had successfully used keywords to identify climate change tweets. Without an existing literature, identifying diagnostic terms can be difficult. Nevertheless, this
demonstration of our four-phased framework exemplifies some of the critical decisions analysts must make when utilizing a mixed-method approach to social media data.

Both qualitative and quantitative researchers can benefit from our four-phased framework. For qualitative researchers, we provide a novel vehicle for addressing their research questions. The diversity and volume of content of social media data may be overwhelming for both the researcher and their method. Through computational techniques, the diversity and scale of data can be managed, allowing researchers to obtain a large volume of data and extract from it a relevant sample to conduct qualitative analyses. Additionally, computational techniques can help researchers explore and comprehend the nature of their data. For the quantitative researcher, our four-phased framework provides a strategy for formally documenting the qualitative interpretations. When applying algorithms, analysts must ultimately make qualitative assessments of the quality and meaning of output. In comparison to the mathematical machinery underpinning these techniques, the qualitative interpretations of algorithmic output are not well-documented. As these qualitative judgments are inseparable from data science, researchers should strive to formalize and document their decisions—our framework provides one means of achieving this goal.

Through the application of our four-phased framework, we contribute to an emerging literature on public perceptions of climate change by providing an in-depth examination of the structure of Australian social media discourse. This insight is useful for communicators and policy makers hoping to understand and engage the Australian online public. Our findings indicate that, within Australian commentary on climate change, a wide variety of messages and sentiment are present. A positive aspect of the commentary is that many users want action on climate change. The time is ripe it would seem for communicators to discuss Australia’s policy response to climate change—the public are listening and they want to be involved in the discussion. Consistent with this, we find some users discussing conversations about climate change as a topic. Yet, in some quarters there is still skepticism about the legitimacy of climate change and climate science, and so there remains a pressing need to implement strategies to persuade members of the Australian public of the reality and urgency of the climate change problem. At the same
time, our analyses suggest that climate communicators must counter the sometimes held belief, expressed in our second theme on climate change consequences, that it is already too late to solve the climate problem. Members of the public need to be aware of the gravity of the climate change problem, but they also need powerful self efficacy promoting messages that convince them that we still have time to solve the problem, and that their individual actions matter.
Chapter 4

Evidence for Three Distinct Climate Change Audience Segments

4.1 Foreword

In Chapter 1, I outlined the two aims of this thesis: a descriptive aim and an explanatory aim. The descriptive aim sought to identify audience segments using a bottom-up approach. The explanatory aim sought to identify the psychological underpinnings of segment membership. The current chapter will address both aims of this thesis.

Concerning the descriptive aim, a bottom-up approach to audience segmentation was motivated by the possibility that the social discourse on climate change may contain concepts that are omitted by top-down approaches. This motivation is supported by evidence presented in Chapter 3. Chapter 3 identified the prominent features of Australian’s social media discussions on climate change. Some features, such as perspectives about climate change deniers (e.g., “people who deny the science of climate change should not hold public office”) and climate change conversations (“it is shameful that climate change, the greatest problem of our time, is barely discussed in the media”), are not explicitly measured in top-down approaches to segment climate change audiences. Thus, a bottom-up approach that segments individuals on their views on climate change concepts from the public discourse may yield different segments than top-down approaches. To explore this possibility, this chapter uses the Q methodology to segment an Australian audience. As discussed in Chapter 1, the Q methodology is a card sorting task used to identify the viewpoints shared between individuals. Each card is a statement on climate change, developed from a tweet that reflects one of the five themes of climate change discourse identified in Chapter 3.
Turning to the *explanatory* aim, this chapter identifies the psychological characteristics that underscore segments. This is addressed using two studies. The first study investigates whether segments systematically differ along a myriad of psychological constructs, including their mental models of climate change. To gauge mental models of climate change, I use one of the most comprehensive mental model scales (Bostrom et al., 2012). Although I highlighted concerns (in Chapter 2) about the interpretation and narrowness of mental model scales, an understanding of mental models about *physical systems* can reveal misconceptions that influence the reception of climate change messages. I return to integrate the results of this study through the lens of my mental model framework in the general discussion (Chapter 5). The second study investigates whether segments differ in their tendencies to revise their beliefs when confronted with findings from climate or policy science. By synthesising these results, I argue that the climate change views of each segment can be understood by recourse to their psychological characteristics, which have consequence for belief revision.

This chapter is presented as a journal article manuscript accompanied by supplementary material presented in Appendix B. Note that I use the term ‘we’ throughout the chapter to refer to the collective contributions of the manuscript co-authors.

Where possible, data and scripts from this research have been made available for download at https://github.com/AndreottaM/audience-segmentation-thesis. Importantly, this repository includes code for a web application to administer the Q sort task. Most Q methodology software is prohibitively expensive or outdated. The web application developed for this research provides a free, open-source alternative for researchers.

The full reference for the journal article manuscript used in this chapter is:

4.2 Abstract

Mounting evidence suggests members of the general public are not homogeneous in their receptivity to climate science information. Studies segmenting climate change views typically deploy a top-down approach, whereby concepts salient in scientific literature determine the number and nature of segments. In contrast, in two studies using Australian citizens, we used a bottom-up approach, in which segments were determined from perceptions of climate change concepts derived from citizen social media discourse. In Study 1, we identified three segments of the Australian public (Acceptors, Fencesitters, and Sceptics) and their psychological characteristics. We find segments differ in climate change concern and scepticism, mental models of climate, political ideology, and worldviews. In Study 2, we examined whether reception to scientific information differed across segments using a belief-updating task. Participants reported their beliefs concerning the causes to climate change, the likelihood climate change will have specific impacts, and the effectiveness of Australia’s mitigation policy. Next, participants were provided with the actual scientific estimates for each event and asked to provide new estimates. We find significant heterogeneity in the belief-updating tendencies of the three segments that can be understood with reference to their different psychological characteristics. Our results suggest tailored scientific communications informed by the psychological profiles of different segments may be more effective than a ‘one-size-fits-all’ approach. Using our novel audience segmentation analysis, we provide some practical suggestions of how communication strategies can be improved by accounting for segments’ characteristics.
4.3 Introduction

In 2016, the Paris Agreement under the United Nations Framework Convention on Climate Change was ratified. Parties to the agreement have pledged to cooperate to keep global temperature increases well below two degrees Celsius above pre-industrial levels (United Nations, 2015). The continued cooperation of democratic countries is partly determined by public support. Yet, public concern for climate change lags behind other social issues, such as crime and health care (Hagen et al., 2016; Lorenzoni & Pidgeon, 2006; Nisbet & Myers, 2007).

Various interventions have been proposed to increase support for climate policy. For example, telling people the proportion of climate scientists who believe in anthropogenic climate change (97%)—known as consensus messaging—enhances concern about climate change and policy support (van der Linden et al., 2015; van der Linden, in press). Such interventions treat the public as a homogeneous entity. However, reception to climate change messages can differ due to differences in motivation, ideology, and worldview (Feygina et al., 2010; Kahan, 2012). For example, Hart and Nisbet (2012) exposed Americans to a news story describing climate change risks, before measuring support for mitigation policies. Compared to controls not exposed to an article, liberals who read the news story showed greater support for mitigation policy, whereas conservatives showed reduced support. Thus, when climate change messages clash with a person’s pre-existing political beliefs, they can potentially backfire.

To improve interventions, communicators may use audience segmentation to divide the public into homogeneous groups (W. R. Smith, 1956). Messages can then be tailored to the characteristics of each group, which may enhance communication effectiveness and mitigate backfire effects (Corner & Randall, 2011). A meta-analysis of health communication suggests segmentation approaches are more effective than a ‘one-size-fits-all’ approach, particularly when psychological theory is used to understand segments (Noar et al., 2007).

Perhaps the most established audience segmentation for climate change communication is the Six Americas (Maibach et al., 2011; Yale Program on Climate
Six segments were developed from the responses of a nationally representative survey of Americans. Although multidimensional, the Six Americas may be ordered on continuous dimensions of belief and concern about climate change. The segments range from the ‘alarmed’, the segment most accepting of climate change science; via the ‘concerned’; the ‘cautious’; the ‘disengaged’; the ‘doubtful’; to the ‘dismissive’, a segment which rejects climate science. Segments that differ in their concern about climate change are similar on other dimensions. For example, the ‘alarmed’ and the ‘dismissive’ are unified in their self-reported unwillingness to change their own opinions (Maibach et al., 2011). Conceptual replications and kindred studies reveal comparable segments in other nations, such as Australia (Hine et al., 2013; Morrison et al., 2013; Morrison et al., 2018; Neumann et al., 2021) and Germany (Metag et al., 2017). By integrating segment characteristics with psychological theory, Roser-Renouf et al. (2015) provided suggestions for tailoring communication.

Most climate change audience segments, including the Six Americas, have been developed using a top-down approach. Specifically, the audience is statistically grouped across psychological characteristics known to correlate with climate change perceptions, policy support, and pro-environmental behaviour (for a review, see Hine et al., 2014). Alternatively, a bottom-up approach groups segments according to their views of lay concepts of climate change, such as those found in social media discussions. This overcomes a disadvantage of top-down approaches—they may omit features of climate change salient to the public, but not researchers. However, bottom-up approaches are sorely lacking in the climate change domain. Thus, it is unknown to what degree current understandings of segmentation are limited by researchers’ preconceptions. Here we addressed this shortcoming using a bottom-up audience segmentation approach. Additionally, we used a top-down approach to map our segmentation to theory by incorporating auxiliary measures of psychological characteristics that may account for segment differences. Critically, these auxiliary measures were used to help interpret audience segments after they had been derived—they did not contribute to the segmentation process itself.
We conducted bottom-up segmentation using the Q methodology—an analytical approach to representing viewpoints (Brown, 1980). It uses a Q sort task whereby participants rank statements about a topic, usually along a dimension of agreement. Statements can be generated using a bottom-up approach, where statements capture the breadth of conversational possibilities (Brown, 1980; Stephenson, 1986). Using factor analysis, participants are then segmented based on ranks assigned to statements.

Applications of the Q methodology to climate change audiences are rare and limited to samples isolated to a particularly small region (e.g., Hobson & Niemeyer, 2012; Wolf et al., 2009). The current research is the first to apply the Q methodology to nationally representative samples. The statements used were derived from our previous work, which identified the persistent topics of Australian climate change discourse on social media (Andreotta et al., 2019). Although social media data does not contain an exhaustive set of conversational topics, it is a reasonable compromise between analyses of documents written by specific subgroups of the population (e.g., news articles) and a prohibitively expensive study that interviews hundreds of citizens. Therefore, the statements used in the Q methodology allowed participants to express their viewpoint in terms of the diversity of opinions embodied in popular public discourse on climate change.

To facilitate interpretation of audience segments, we incorporated auxiliary measures of several potentially relevant psychological characteristics that may help explain differences between segments. In particular, we consider mental models—internalised representations of a phenomenon that individuals use to generate descriptions, explanations, and predictions (Granger et al., 2002; Jones et al., 2011; Rouse & Morris, 1986). Different mental models can generate different predictions (Gentner & Gentner, 1983). To illustrate, consider two mental models identified by previous research: the first model features greenhouse gas emissions as the predominant cause of climate change, whereas the second model features toxic air pollution as the predominant cause (Kempton et al., 1995; Reynolds et al., 2010). Individuals with the second model may be most likely to suggest the ineffective strategy of mitigating climate change by additional filtering of factory smokestacks (Kempton et al., 1995). Thus,
knowledge of segments’ mental models provide insight into the logic by which trusted information will be transformed into action or knowledge (Granger et al., 2002), and which policies may be endorsed (Bostrom et al., 2012).

In addition to mental models, climate change views are influenced by other psychological characteristics (Swim et al., 2009). For example, individuals may be motivated to reject anthropogenic climate change because they: engage in conspiracist ideation (Lewandowsky, Oberauer et al., 2013); have a worldview that the environment is elastic and resilient to change (Price et al., 2014); are politically conservative (Leiserowitz, 2006); sceptical of societies’ capacity to avert climate change (Capstick & Pidgeon, 2014); exhibit justification for the status-quo (Feygina et al., 2010); and have more conservation values (e.g., tradition; Corner et al., 2014). In contrast, individuals who value self-transcendence, are worried about climate change, and have a worldview that the environment is ductile and sensitive to change are more likely to support climate change mitigation (Corner et al., 2014; Price et al., 2014; N. Smith & Leiserowitz, 2014). Other potentially relevant factors include personality (Yu & Yu, 2017), consideration of future consequences (Wang, 2017), self-perceived level of climate change knowledge (Stoutenborough & Vedlitz, 2014), and need for cognition (Sinatra et al., 2014). The current chapter examined segment differences in these psychological characteristics.

### 4.3.1 The Current Chapter

We carried out two studies using representative samples of the Australian public. Study 1 sought to derive audience segments using the Q methodology with statements from social media, followed by measures of the previously mentioned psychological characteristics. The study provided evidence for three different segments: Acceptors, Fencesitters, and Sceptics. Auxiliary variable analysis revealed segments differed in their mental models, climate change concern and scepticism, political ideology, and environmental worldviews. In Study 2, we replicated the three segments and checked if these differed in their receptivity to climate science information. Participants completed a belief-updating task in which they were asked their beliefs about the contribution of different causes to climate change, the likelihood climate change will have specific impacts, and the
effectiveness of Australia’s mitigation policy. They were then given the actual scientific estimates for each event before submitting their revised belief estimates. We found considerable heterogeneity across segments in their belief-updating tendencies. These results provide insights into the effectiveness of communicating scientific information to each segment.

4.4 Study 1

This study aimed to segment the audience using a bottom-up approach and examine segment differences in a range of psychological characteristics. The psychological characteristics—and the scales used to tap them—were selected using three criteria: (1) sampling psychological characteristics from as much theoretical space as possible; (2) sampling scales with good psychometric properties (reliability and validity); and (3) pragmatic constraints that lead us to minimise conceptual overlap of psychological characteristics and select short-form scales when possible. Our literature search yielded 28 psychological characteristics, described next.

4.4.1 Method

This study was pre-registered using the Open Science Framework (https://osf.io/e7zhx/). For both studies, the materials, data, and analysis scripts are available at https://github.com/AndreottaM/audience-segmentation-thesis. The studies were approved by the University of Western Australia Human Research Ethics Office (RA/4/20/5104) and the Commonwealth Scientific and Industrial Research Organisation Human Research Ethics Committee (026/19).

4.4.1.1 Participants

Four-hundred and thirty-five Australian adults were recruited online by Qualtrics to complete the entire study. A targeted and stratified sampling process was used, whereby
the age ($M = 46.71, SD = 17.77$) and gender (female = 50.34%) were matched to the general population of Australian adults reported in the national 2016 census.

### 4.4.1.2 Materials and Procedure

Before beginning the study, participants were warned of the general complexity of the Q sort and received the option to exit the study with a small reimbursement for their time. Participants who continued then completed the Q sort followed by an inventory of psychological characteristics. Administration of survey scales was counterbalanced to control order effects (see Appendix B). Data from extremely fast participants were discarded (less than 873 seconds, a preregistered criterion based on pilot testing).

**Q sort** The Q sort requires a set of statements capturing the breadth of conversational possibilities of an issue (Stephenson, 1986). Previous work has used an inductive process to identify the structure of climate change commentary of Australian tweets (Andreotta et al., 2019). This research revealed five enduring themes of public discourse on climate change: climate change action, climate change consequences, climate change conversations, climate change denial, and the legitimacy of climate science and climate change. For each theme, we selected six tweets that captured the heterogeneity of the theme (see Appendix B). The resulting 30 tweets were transcribed as statements that could be understood without the social context of the original tweet. Where possible, language, sentiment, and tone were preserved. Statements included: “it is important to vote for leaders who will combat climate change” (climate change action), “climate change is a threat to the health and safety of our children” (climate change consequences), “it is shameful that climate change, the greatest problem of our time, is barely discussed in the media” (climate change conversations), “climate change sceptics ignore basic climate science facts” (climate change denial), and “scientists should stop falsely claiming that climate change is a settled science” (legitimacy of climate science and climate change).

The Q sort comprised three phases. In phase one, participants read each statement and assigned it to one of three categories: (1) like their point of view; (2) unlike their point of view; or (3) neutral or unsure. This initial phase familiarised
participants with the statements. Phase two required participants to rank statements from “most unlike my point of view” (-4) to “most like my point of view” (+4). The number of statements that could be placed at each rank was predetermined, such that more statements could be placed at the midpoint than more extreme ranks (Figure 4.1). Thus, participants had to be selective in the statements used to represent their most extreme views. In phase 3, participants responded to open-ended questions prompting them to justify their placement of the statements ranked most extreme.
Figure 4.1. Schematic of the Q sort task. Participants progressed through a stack of unsorted statements (A) by dragging the top-most statement into the grey box that best corresponded to their point of view (B), as indicated by the blue solid line. Participants could re-arrange statements at any time during the task. To facilitate this process, statements could be placed in the orange temporary holding area (C), as indicated by the pink dashed line.
Scales  Twenty eight scales were used to measure various psychological characteristics. For brevity, the scales are summarised in Table 4.1. These scales have been developed in previous literature to have high internal consistency, justifying their use here. When required, scales were adapted to refer to Australia instead of America. Next, we summarise each scale.

**Personality**  The Big Five personality traits of agreeableness (kindness, generosity, warmth), conscientiousness (reliable, organised), extraversion (sociability, assertiveness), neuroticism (anxious, intense), and openness (imaginative, curious) were measured. Personality has been demonstrated to mediate effects of risk perceptions, values, social norms, and environmental concerns on pro-environmental attitudes (Yu & Yu, 2017). The low internal consistency reported is likely due to the small number of items. Earlier research has demonstrated the retest reliability, structural validity, convergent validity, and external validity of each scale (Rammstedt & John, 2007).

**Consideration of future consequences**  Consideration of future consequences is the propensity to orient oneself to long-term goals over short-term goals (Strathman et al., 1994). We measured an orientation towards future goals and an orientation towards immediate goals. Greater consideration of long-term goals and reduced consideration of short-term goals can lead to higher support for mitigative policy (Wang, 2017).

**Conspracist ideation**  Conspracist ideation is the general tendency to endorse conspiracy theories (Lewandowsky, Gignac et al., 2013). Greater conspiracist ideation is associated with stronger denial of anthropogenic climate change (Lewandowsky, Oberauer et al., 2013).

**Environmental worldviews**  Environmental worldviews are patterns of culturally shared values and beliefs about the environment (Douglas & Wildavsky, 1983; Price et al., 2014; Thompson et al., 1990). We measured two environmental worldviews: *environment as ductile* worldviews posit the environment is unable to recover from the effects of humanity activity, whereas *environment as elastic* worldviews posit the
environment is able to easily recover from the effects of human activity. Individuals with greater environment as ductile worldviews or reduced environment as elastic worldviews demonstrate greater belief in anthropogenic climate change, environmental concerns, and pro-environmental behaviour (Price et al., 2014).

**Knowledge volume** Knowledge volume here is self-perceived knowledge of climate change. When controlling for assessed knowledge of climate change, high perceptions of self-perceived knowledge may lead individuals to overestimate their understanding of climate change and to become more reluctant to seek information (Stoutenborough & Vedlitz, 2014).

**Mental models** Mental models are representations of climate change states, processes, and predictions. We measured several mental model characteristics, including: perceived anthropogenic influence on climate change; perceived causes of climate change, the perceived consequences of climate change; and perceived effectiveness of mitigative policies.

**Need for cognition** Need for cognition is the tendency for individuals to engage in, and enjoy, effortful thinking (Cacioppo & Petty, 1982). Those high in need for cognition tend to think openly and critically about issues, potentially leading to greater acceptance of scientific perspectives on climate change (Sinatra et al., 2014).

**Political ideology** Political ideology is a broad psychological characteristic encompassing competing, but socially shared, philosophies on the proper order of life and society (Jost et al., 2009). Ideological differences in assumptions, assertions, and interpretation of climate change can result in a negative association between right-wingness and risk perceptions, and concern, about climate change (Leiserowitz, 2006; Zia & Todd, 2010).

**System justification** System justification is a tendency to perceive the prevailing social system as fair, legitimate, and justifiable (Kay & Jost, 2003). As climate change mitigative
policies can challenge the status quo, individuals with high system justification are motivated to deny the risks of climate change (Feygina et al., 2010; van der Linden, 2017).

**Scepticism** Climate change scepticism is the tendency of individuals to generally dismiss anthropogenic climate change as a threat. We measured two forms of scepticism: *epistemic scepticism*, which involves doubting climate science; and *response scepticism*, which involves doubting mitigation is possible (Capstick & Pidgeon, 2014). Although the mental model measures share a conceptual space with scepticism, we specifically included this scale to disentangle the effects of general scepticism and specific mental model components (e.g., specific belief in greenhouse gases causing climate change).

**Values** Values are beliefs that refer to desirable goals or motivations (S. H. Schwartz, 2012). We measure two values of importance to climate change perceptions: *conservation*, the motivation to preserve the past, respect order, and resist change; and *self-transcendence*, the motivation to protect the welfare of others. Individuals greater in conservation values may be motivated to engage in climate change denial, whereas individuals greater in self-transcendence values may be more likely to engage with climate change issues (Corner et al., 2014).

**Worry** We measured participant’s general worry about climate change, an affective motivator for policy support (N. Smith & Leiserowitz, 2014).
Table 4.1. Summary of survey measures used in Study 1.

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Scale</th>
<th>Psychological characteristic</th>
<th>Items</th>
<th>Cronbach’s $\alpha$</th>
<th>Range</th>
<th>Example item</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFI_A</td>
<td>Big Five Inventory-10 (Rammstedt &amp; John, 2007)</td>
<td>Agreeableness</td>
<td>2</td>
<td>0.26</td>
<td>1-5</td>
<td>I see myself as someone who is generally trusting</td>
</tr>
<tr>
<td>BFI_C</td>
<td>Big Five Inventory-10 (Rammstedt &amp; John, 2007)</td>
<td>Conscientiousness</td>
<td>2</td>
<td>0.55</td>
<td>1-5</td>
<td>I see myself as someone who does a thorough job</td>
</tr>
<tr>
<td>BFI_E</td>
<td>Big Five Inventory-10 (Rammstedt &amp; John, 2007)</td>
<td>Extraversion</td>
<td>2</td>
<td>0.50</td>
<td>1-5</td>
<td>I see myself as someone who is outgoing, sociable</td>
</tr>
<tr>
<td>BFI_N</td>
<td>Big Five Inventory-10 (Rammstedt &amp; John, 2007)</td>
<td>Neuroticism</td>
<td>2</td>
<td>0.66</td>
<td>1-5</td>
<td>I see myself as someone who gets nervous easily</td>
</tr>
<tr>
<td>BFI_O</td>
<td>Big Five Inventory-10 (Rammstedt &amp; John, 2007)</td>
<td>Openness</td>
<td>2</td>
<td>0.21</td>
<td>1-5</td>
<td>I see myself as someone who has an active imagination</td>
</tr>
<tr>
<td>CFC_F</td>
<td>Consideration of Future Consequences (Enzler, 2015)</td>
<td>Orientation to future goals</td>
<td>4</td>
<td>0.71</td>
<td>1-5</td>
<td>I consider how things might be in the future</td>
</tr>
</tbody>
</table>
Table 4.1. Summary of survey measures used in Study 1. (continued)

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Scale</th>
<th>Psychological characteristic</th>
<th>Items</th>
<th>Cronbach’s $\alpha$</th>
<th>Range</th>
<th>Example item</th>
</tr>
</thead>
<tbody>
<tr>
<td>CFC_1</td>
<td>Consideration of Future Consequences</td>
<td>Orientation to immediate goals</td>
<td>5</td>
<td>0.86</td>
<td>1-5</td>
<td>I mainly act to satisfy my immediate concerns, figuring the future will take care of itself</td>
</tr>
<tr>
<td>CI</td>
<td>Conspiracist Ideation</td>
<td>Conspiracist Ideation</td>
<td>6</td>
<td>0.88</td>
<td>1-5</td>
<td>The Apollo moon landings never happened and were staged in a Hollywood film studio</td>
</tr>
<tr>
<td>EWS_D</td>
<td>Environmental Worldview Scale</td>
<td>Environment as Ductile Worldview</td>
<td>6</td>
<td>0.81</td>
<td>1-5</td>
<td>If the balance of the natural environment is upset the whole system will collapse</td>
</tr>
<tr>
<td>EWS_E</td>
<td>Environmental Worldview Scale</td>
<td>Environment as Elastic Worldview</td>
<td>6</td>
<td>0.85</td>
<td>1-5</td>
<td>The natural environment is capable of recovering from any damage humans may cause</td>
</tr>
<tr>
<td>KV</td>
<td>Knowledge Volume</td>
<td>Knowledge Volume</td>
<td>1</td>
<td>na</td>
<td>1-4</td>
<td>How much do you feel you know about climate change?</td>
</tr>
<tr>
<td>MMS_CAU_C</td>
<td>Based on Mental Model Scale</td>
<td>Perceptions of Carbon Emission Causes of Climate Change</td>
<td>7</td>
<td>0.92</td>
<td>1-7</td>
<td>Please indicate to what extent each of the following is a cause of climate change, to the best of your knowledge: people driving their cars</td>
</tr>
</tbody>
</table>
### Table 4.1. Summary of survey measures used in Study 1. (continued)

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Scale</th>
<th>Psychological characteristic</th>
<th>Items</th>
<th>Cronbach’s $\alpha$</th>
<th>Range</th>
<th>Example item</th>
</tr>
</thead>
<tbody>
<tr>
<td>MMS_CAU_E</td>
<td>Based on Mental Model Scale (Subscale: Perceived Causes of Climate Change; Bostrom et al., 2012)</td>
<td>Perceptions of Environmental Harm Causes of Climate Change</td>
<td>4</td>
<td>0.87</td>
<td>1-7</td>
<td>Please indicate to what extent each of the following is a cause of climate change, to the best of your knowledge: air pollution from toxic chemicals</td>
</tr>
<tr>
<td>MMS_CAU_N</td>
<td>Based on Mental Model Scale (Subscale: Perceived Causes of Climate Change; Bostrom et al., 2012)</td>
<td>Perceptions of Natural Causes of Climate Change</td>
<td>2</td>
<td>0.77</td>
<td>1-7</td>
<td>Please indicate to what extent each of the following is a cause of climate change, to the best of your knowledge: volcanic eruptions</td>
</tr>
<tr>
<td>MMS_CON_P</td>
<td>Mental Model Scale (Subscale: Perceived Consequences of Climate Change; Bostrom et al., 2012)</td>
<td>Perceived Personal Consequences of Climate Change</td>
<td>3</td>
<td>0.89</td>
<td>1-7</td>
<td>Please rate for each of the following how likely it is as a consequence of climate change by the year 2050: food shortages where you live</td>
</tr>
<tr>
<td>MMS_CON_S</td>
<td>Mental Model Scale (Subscale: Perceived Consequences of Climate Change; Bostrom et al., 2012)</td>
<td>Perceived Societal Consequences of Climate Change</td>
<td>8</td>
<td>0.96</td>
<td>1-7</td>
<td>Please rate for each of the following how likely it is as a consequence of climate change by the year 2050: food shortages in many parts of the world</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Scale</td>
<td>Psychological characteristic</td>
<td>Items</td>
<td>Cronbach’s $\alpha$</td>
<td>Range</td>
<td>Example item</td>
</tr>
<tr>
<td>--------------</td>
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</tr>
<tr>
<td>MMS_HUM</td>
<td>Mental Model Scale (Subscale: Human Contribution; Bostrom et al., 2012)</td>
<td>Perceived Human Contribution to Climate Change</td>
<td>1</td>
<td>na</td>
<td>1-7</td>
<td>How likely do you think it is that human actions have changed global climate?</td>
</tr>
<tr>
<td>MMS_MIT_C</td>
<td>Mental Model Scale (Subscale: Perceived Effectiveness of Mitigative Action Policies; Bostrom et al., 2012)</td>
<td>Perceived Effectiveness of Carbon Policies</td>
<td>3</td>
<td>0.74</td>
<td>1-7</td>
<td>Please rate for each step what effect you think it would have on climate change: requiring cars and trucks to have higher fuel efficiency (1 = Reduce or Stop Climate Change, 4 = Neither Reduce nor Increase, 7 = Increase Climate Change)</td>
</tr>
<tr>
<td>MMS_MIT_E</td>
<td>Mental Model Scale (Subscale: Perceived Effectiveness of Mitigative Action Policies; Bostrom et al., 2012)</td>
<td>Perceived Effectiveness of Green Policies</td>
<td>5</td>
<td>0.40</td>
<td>1-7</td>
<td>Please rate for each step what effect you think it would have on climate change: planting trees (1 = Reduce or Stop Climate Change, 4 = Neither Reduce nor Increase, 7 = Increase Climate Change)</td>
</tr>
<tr>
<td>MMS_MIT_G</td>
<td>Mental Model Scale (Subscale: Perceived Effectiveness of Mitigative Action Policies; Bostrom et al., 2012)</td>
<td>Perceived Effectiveness of Engineering Policies</td>
<td>3</td>
<td>0.91</td>
<td>1-7</td>
<td>Please rate for each step what effect you think it would have on climate change: putting more dust in the atmosphere (1 = Reduce or Stop Climate Change, 4 = Neither Reduce nor Increase, 7 = Increase Climate Change)</td>
</tr>
<tr>
<td>Abbreviation</td>
<td>Scale</td>
<td>Psychological characteristic</td>
<td>Items</td>
<td>Cronbach’s ( \alpha )</td>
<td>Range</td>
<td>Example item</td>
</tr>
<tr>
<td>--------------</td>
<td>--------</td>
<td>-------------------------------</td>
<td>-------</td>
<td>-----------------</td>
<td>-------</td>
<td>--------------</td>
</tr>
<tr>
<td>NCS</td>
<td>Need for Cognition Scale (NCS-6) (Lins de Holanda Coelho et al., 2018)</td>
<td>Need for Cognition</td>
<td>6</td>
<td>0.80</td>
<td>1-5</td>
<td>I would prefer complex to simple problems</td>
</tr>
<tr>
<td>PI</td>
<td>na</td>
<td>Political Ideology</td>
<td>1</td>
<td>na</td>
<td>1-7</td>
<td>Please indicate the extent to which you identify yourself as politically left-wing or right-wing (1 = Very Left-Wing, 7 = Very Right-Wing)</td>
</tr>
<tr>
<td>SJ</td>
<td>System Justification Scale (Kay &amp; Jost, 2003)</td>
<td>System Justification</td>
<td>8</td>
<td>0.86</td>
<td>1-9</td>
<td>Everyone has a fair shot at wealth and happiness</td>
</tr>
<tr>
<td>SS_E</td>
<td>Items from Capstick and Pidgeon (2014)</td>
<td>Epistemic Scepticism</td>
<td>8</td>
<td>0.91</td>
<td>1-5</td>
<td>Climate change is just a natural fluctuation in Earth’s temperatures</td>
</tr>
<tr>
<td>SS_R</td>
<td>Items from Capstick and Pidgeon (2014)</td>
<td>Response Scepticism</td>
<td>7</td>
<td>0.89</td>
<td>1-5</td>
<td>There is no point in me doing anything about climate change because no-one else is</td>
</tr>
<tr>
<td>SVSS_C</td>
<td>Short Schwartz Value Scale (Lindeman &amp; Verkasalo, 2005)</td>
<td>Conservation Values</td>
<td>10</td>
<td>0.63</td>
<td>-2.94-5.54</td>
<td>Please, rate the importance of the following values as a life-guiding principle for you: CONFORMITY (obedience, honouring parents and elders, self-discipline, politeness)</td>
</tr>
<tr>
<td>SVSS_ST</td>
<td>Short Schwartz Value Scale (Lindeman &amp; Verkasalo, 2005)</td>
<td>Self-Transcendence Values</td>
<td>10</td>
<td>0.69</td>
<td>-4.84-2.52</td>
<td>Please, rate the importance of the following values as a life-guiding principle for you: BENEVOLENCE (helpfulness, honesty, forgiveness, loyalty, responsibility)</td>
</tr>
</tbody>
</table>
### Table 4.1. Summary of survey measures used in Study 1. (continued)

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Scale</th>
<th>Psychological characteristic</th>
<th>Items</th>
<th>Cronbach’s $\alpha$</th>
<th>Range</th>
<th>Example item</th>
</tr>
</thead>
<tbody>
<tr>
<td>W</td>
<td>Item from Emotion Scale (N. Smith &amp; Leiserowitz, 2014)</td>
<td>Worry about Climate Change</td>
<td>1</td>
<td>na</td>
<td>1-4</td>
<td>How strongly do you feel worry when you think about the issue of climate change?</td>
</tr>
</tbody>
</table>

*Note:*

Pilot testing indicated the Perceived Causes of Climate Change subscale of Bostrom et al. (2012) required an additional item to capture perceptions of natural causes (see Supplementary Material). All items of the Perceived Effectiveness of Mitigative Action subscales were reverse scored. Conservation and Self-Transcendence Value scores are composite scores of the same ten values (each of which was rated along a nine-point scale), with each item weighted differently to account for the spatial relationship between dimensions.
4.4.2 Results and Discussion

4.4.2.1 Segments

To identify segments, we conducted a factor analysis on the Q sort data. Unlike traditional survey approaches which characterise factors of statements that generate common response patterns across people, the Q methodology reverses this statistical procedure to identify factors of people with common sorting styles (Brown, 1980; McKeown & Thomas, 2013; Watts & Stenner, 2012). We conducted a principal components analysis using varimax rotation. We extracted a single factor, as the scree plot (Figure B.7) indicated the first component accounted for a large proportion of variance (34.06% after rotation). Broadly, this extracted factor represents a dimension of acceptance of anthropogenic climate change. We conceptualised this factor as bipolar, thereby clustering participants into one of three segments: (1) Acceptors whose positive load onto the factor was statistically significant \( n = 281; 64.60\% \); (2) Sceptics whose negative load onto the factor was statistically significant \( n = 36; 8.28\% \); and (3) Fencesitters whose loading onto the factor was not statistically significant \( n = 118; 27.13\% \). Fencesitters are necessarily less homogeneous in their climate change views than Acceptors and Sceptics, otherwise Fencesitters would have emerged as a second factor. However, the segment is included for further analysis, as insight into Fencesitters could improve psychological theory and communication practices.

To understand each segment’s perspective, we constructed a ‘representative’ Q sort (Brown, 1980; Watts & Stenner, 2012). For each segment, the average ranking assigned to each statement by participants, weighted by participants’ factor loading, was calculated. The weighted-averages of statements were then mapped onto the rankings enforced by the structure of the Q sort, known as factor scores (Table B.6). Factor scores were not calculated for Fencesitters, as the segment’s sorting style was necessarily heterogeneous. Next, we report the representative Q sorts for Acceptors and Sceptics further elaborated on with the participants’ text justification of their rankings.
Figure 4.2. Eigenvalues extracted from the first fifteen factors of the Q sort data. Hatched line indicates the break in the scree.
### Table 4.2. Q sort factor scores.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Acceptor</th>
<th>Sceptic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. It is important to vote for leaders who will combat climate change.</td>
<td>4</td>
<td>-4</td>
</tr>
<tr>
<td>2. Climate change is a hoax perpetrated by the United Nations.</td>
<td>-4</td>
<td>3</td>
</tr>
<tr>
<td>3. Scientists should stop falsely claiming that climate change is a settled science.</td>
<td>-2</td>
<td>4</td>
</tr>
<tr>
<td>4. Climate change is a threat to the health and safety of our children.</td>
<td>3</td>
<td>-3</td>
</tr>
<tr>
<td>5. They changed the name from “global warming” to “climate change” because the planet isn’t warming.</td>
<td>-2</td>
<td>3</td>
</tr>
<tr>
<td>6. The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.</td>
<td>-3</td>
<td>2</td>
</tr>
<tr>
<td>7. The Great Barrier Reef is at risk from climate change.</td>
<td>3</td>
<td>-2</td>
</tr>
<tr>
<td>8. The threat of climate change is much worse than climate scientists originally thought.</td>
<td>2</td>
<td>-3</td>
</tr>
<tr>
<td>9. Australian agriculture is thriving so climate change can’t be real.</td>
<td>-3</td>
<td>2</td>
</tr>
<tr>
<td>10. The increased occurrence of extreme weather events is a clear sign that climate change is real.</td>
<td>2</td>
<td>-2</td>
</tr>
<tr>
<td>11. Australia is experiencing more extreme weather and hotter days due to climate change.</td>
<td>2</td>
<td>-2</td>
</tr>
<tr>
<td>12. Those who demand climate action are the usual “torch-and-pitchfork” crowd.</td>
<td>-2</td>
<td>2</td>
</tr>
<tr>
<td>13. Cow farts cause more ‘climate change’ than human activity.</td>
<td>-2</td>
<td>1</td>
</tr>
<tr>
<td>Statement</td>
<td>Acceptor</td>
<td>Sceptic</td>
</tr>
<tr>
<td>--------------------------------------------------------------------------</td>
<td>----------</td>
<td>---------</td>
</tr>
<tr>
<td>14. Through cutting science funding, we damage Australia’s ability to respond to climate change.</td>
<td>1</td>
<td>-2</td>
</tr>
<tr>
<td>15. Climate change policy and renewable energy (e.g., solar power) should be a major focus of Australian political elections.</td>
<td>2</td>
<td>-1</td>
</tr>
<tr>
<td>16. Oil and gas companies could not care less about climate change.</td>
<td>-1</td>
<td>2</td>
</tr>
<tr>
<td>17. Climate change sceptics ignore basic climate science facts.</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>18. Politicians who refuse to tackle climate change are just as bad as those who deny climate science.</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>19. No political party can say they have a climate change action plan when they favour coal, oil, and gas companies.</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>20. Countries must fulfil their Paris Climate Agreement goals.</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>21. Poor people will be impacted the worst by climate change.</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>22. Politicians and the mass media are ignorant about the risks of climate change.</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>23. People who deny the science of climate change should not hold public office.</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>24. It is shameful that climate change, the greatest problem of our time, is barely discussed in the media.</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>25. Regardless of who is elected, the reality is that climate change is going to destroy everything.</td>
<td>-1</td>
<td>0</td>
</tr>
</tbody>
</table>
Table 4.2. Q sort factor scores. (continued)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Acceptor</th>
<th>Sceptic</th>
</tr>
</thead>
<tbody>
<tr>
<td>26. Australian politicians need to wake up to the emergency of tackling climate change.</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>27. We must start working together for real solutions on climate change.</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>28. Climate change and human burning of fossil fuels are strongly linked.</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>29. We need to keep coal, oil, and gas in the ground and adopt more renewable energy sources, like solar and wind power.</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30. Climate sceptics, with no genuine expertise, cannot know better than climate scientists.</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Note. The difference between Acceptors and Sceptics in the weighted-averages of italicised statements are not statistically significant.

Acceptors believe anthropogenic climate change is occurring (statements: 3, 10, 11, 13, 28), as indicated by an increased frequency of extreme weather and hotter days (statements: 5, 10, 11). Acceptors reject the notion climate change is a hoax (statements: 2, 6). Acceptors claim climate change will cause widespread changes: physical changes in weather (statements: 9, 10, 11); biological changes to ecosystems, such as damage to the Great Barrier Reef (statement: 4); and changes to human systems, threatening agriculture (statement: 6), future generations (statement: 4), and to a lesser degree, the poor (statement: 21). According to Acceptors, these impacts are worse than scientists initially thought (statement: 8), though there are still opportunities to mitigate and adapt (statements: 12, 15, 25, 26). Although Acceptors believe action partly rests on collective society (statement: 27), they believe leaders must take charge (statement: 1, 25) as “there are too many weak and idiot politicians in parliament. we need to vote in people who will take action” otherwise “climate change will spiral out of control”.
Sceptics reject the concept of anthropogenic climate change (statements: 3, 10, 11, 13, 28). According to Sceptics, there is conclusive evidence human activities do not influence climate. Scientists who say otherwise are viewed by Sceptics to rely on “dodgy modelling” and “bullshit thought up by some brain dead idiots in university”. Thus, Sceptics claim climate scientists have overestimated the frequency and intensity of current extreme weather events (statements: 10, 11), and will be incorrect in their projections for the future (statements: 4, 7, 8). Consequently, Sceptics agree that scientists changed the name of their area of study from “global warming” to “climate change”, as the world is not warming (statement: 5). As anthropogenic climate change “has nothing to do with science and reality”, Sceptics question the motives of institutions that endorse mitigative action (statements: 2, 5). For example, one Sceptic claimed “the United Nations is hiding behind climate change to acquire money”. Similarly, Sceptics argue against voting for leaders who will combat climate change (statements: 1) as such leaders are only concerned “about what they can get”. These leaders are “going to bankrupt Australia” by “chasing ghosts” as there is no way to “tame mother nature, money can’t”. Citizens who demand solutions for climate change are the usual ‘torch-and-pitchfork’ crowd (statement: 12).

4.4.2.2 Predictors of Segment Membership

Segments differed in their psychological attributes (Table 4.3). As observed from the Q sort profiles, segments sit along a dimension of climate change scepticism and belief in anthropogenic climate change. Additionally, we found many psychological characteristics were correlated with scepticism and belief in anthropogenic climate change (Figure 4.3). Namely, belief in anthropogenic climate change was moderately positively correlated \((r > 0.30)\) with environment as ductile worldviews, worry about climate change, consideration of future consequences (orientation towards future goals), and mental models of perceived causes (carbon emissions, environmental harms) and consequences (societal and personal). Moreover, belief in anthropogenic climate change was moderately negatively correlated with epistemic scepticism, response scepticism, right-wingness, environment as elastic worldviews, and conservation values. Interestingly, mental models
of cause and consequence were well correlated (median $|r| = 0.63$), but both generally poorly correlated with the perceived effectiveness of mitigative policies (median $|r| = 0.08$). Thus, mental models of cause and consequence may differ from mental models of mitigation.

To explore statistical differences in the psychological characteristics of segments, we constructed a regression model that predicted segment membership as a function of psychological characteristics. One complication in interpreting this model is the degree of multicollinearity between predictors. Multicollinearity reduces the reliability of coefficients—the estimated coefficient of one predictor will depend on the inclusion (or exclusion) of other correlated predictors. As many psychological characteristics are correlated with belief in anthropogenic climate change and scepticism, a least squares regression model would generate coefficients that do not reflect the relationship between a single psychological characteristic and segment membership.

To cope with the multicollinearity of the data, we could have combined or discarded highly-correlated terms from further analysis. However, the purpose of the study is to understand which specific psychological characteristics predict membership, despite their association with other characteristics. Thus, we maintained all psychological variables and built a multinomial logistic ridge regression model. A ridge regression penalises the estimates of highly-correlated terms to achieve greater reliability (a bias-variance tradeoff). For each level of the penalty placed on highly-correlated terms (corresponding to a shrinkage parameter $\lambda$), different coefficients are estimated. When $\lambda = 0$, coefficients are identical to a least squares regression. As $\lambda$ increases, coefficients are reduced towards zero. A cross-validation process ($k$-fold) was used to determine the ideal shrinkage penalty ($\lambda$).

To calculate confidence intervals of the coefficient, we used a bootstrap procedure (Efron & Tibshirani, 1994). One thousand samples were created by sampling participants (with replacement) from the study data. For each sample, the aforementioned ridge regression and cross-validation processes were used to estimate coefficients. From the distributions of each coefficient, 95% confidence intervals were identified.
The estimated coefficients are presented in Figure 4.4. Acceptors (Sceptics) were characterised by lower (greater) epistemic and response scepticism, greater (lower) belief in anthropogenic climate change, greater (lower) worry about climate change, lower (greater) endorsement of environment-as-elastic worldviews, less (more) conservative political ideology, and greater (lower) belief carbon-emitting human activities cause climate change. Belief in societal consequences of climate change was a reliable predictor of Acceptors only, and belief environmental harms cause climate change and self-reported levels of climate change knowledge reliably predicted Sceptics, but not other segments. Fencesitters were only distinguished by greater levels of conspiratorial ideation and greater belief in the efficacy of climate engineering solutions. Personality, need for cognition, consideration of future consequences, system justification, and values were not reliable predictors of segment membership. Thus, each segment was associated with a unique pattern of psychological characteristics.
### Table 4.3. Scale means (and standard deviations) for the data overall and for each segment.

<table>
<thead>
<tr>
<th>Scale</th>
<th>Overall</th>
<th>Acceptor</th>
<th>Fencesitter</th>
<th>Sceptic</th>
</tr>
</thead>
<tbody>
<tr>
<td>BFI_A</td>
<td>3.62 (0.84)</td>
<td>3.67 (0.83)</td>
<td>3.56 (0.82)</td>
<td>3.43 (0.99)</td>
</tr>
<tr>
<td>BFI_C</td>
<td>3.76 (0.89)</td>
<td>3.77 (0.85)</td>
<td>3.64 (0.98)</td>
<td>4.07 (0.79)</td>
</tr>
<tr>
<td>BFI_E</td>
<td>2.85 (0.96)</td>
<td>2.85 (0.99)</td>
<td>2.88 (0.93)</td>
<td>2.79 (0.88)</td>
</tr>
<tr>
<td>BFI_N</td>
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<td>2.89 (1.07)</td>
<td>2.64 (0.99)</td>
<td>2.26 (0.96)</td>
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<td>BFI_O</td>
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<td>3.36 (0.89)</td>
<td>3.24 (0.69)</td>
<td>3.31 (0.86)</td>
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<td>CFC_F</td>
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<td>3.88 (0.60)</td>
<td>3.58 (0.71)</td>
<td>3.22 (0.80)</td>
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<td>CFC_I</td>
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<td>2.36 (0.85)</td>
<td>2.95 (0.92)</td>
<td>2.95 (0.78)</td>
</tr>
<tr>
<td>CI</td>
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<td>2.22 (0.95)</td>
<td>2.60 (1.11)</td>
<td>2.20 (1.07)</td>
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<tr>
<td>EWS_D</td>
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<td>3.40 (0.71)</td>
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<td>EWS_E</td>
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<td>2.06 (0.69)</td>
<td>3.00 (0.83)</td>
<td>3.58 (0.94)</td>
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<td>KV</td>
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<tr>
<td>MMS_CAU_C</td>
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<td>5.56 (0.84)</td>
<td>4.59 (1.27)</td>
<td>2.69 (1.51)</td>
</tr>
<tr>
<td>MMS_CAU_E</td>
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<td>5.00 (1.22)</td>
<td>4.33 (1.45)</td>
<td>2.42 (1.46)</td>
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<tr>
<td>MMS_CAU_N</td>
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<td>4.15 (1.41)</td>
<td>4.49 (1.54)</td>
<td>3.99 (2.01)</td>
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<tr>
<td>MMS_CON_P</td>
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<td>5.11 (1.28)</td>
<td>4.06 (1.56)</td>
<td>2.35 (1.19)</td>
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<td>MMS_CON_S</td>
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<td>5.73 (1.00)</td>
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<td>MMS_HUM</td>
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<tr>
<td>MMS_MIT_C</td>
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<td>4.33 (1.30)</td>
<td>3.89 (1.26)</td>
<td>4.06 (0.75)</td>
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<tr>
<td>MMS_MIT_E</td>
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<td>4.03 (1.04)</td>
<td>3.98 (1.19)</td>
<td>4.25 (0.72)</td>
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<td>MMS_MIT_G</td>
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<td>4.91 (1.55)</td>
<td>4.27 (1.52)</td>
<td>4.40 (0.81)</td>
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<td>NCS</td>
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<td>3.36 (0.77)</td>
<td>3.33 (0.78)</td>
<td>3.45 (0.91)</td>
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<tr>
<td>PI</td>
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<td>3.11 (1.45)</td>
<td>4.38 (1.36)</td>
<td>5.17 (1.34)</td>
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<td>SJ</td>
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<td>5.49 (1.48)</td>
<td>4.99 (2.24)</td>
</tr>
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<td>SS_E</td>
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<td>2.51 (0.80)</td>
<td>3.60 (0.74)</td>
<td>4.42 (0.46)</td>
</tr>
<tr>
<td>SS_R</td>
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<td>1.90 (0.73)</td>
<td>3.04 (0.87)</td>
<td>3.84 (0.54)</td>
</tr>
<tr>
<td>SVSS_C</td>
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<td>1.26 (0.93)</td>
<td>1.67 (0.67)</td>
<td>2.05 (0.95)</td>
</tr>
</tbody>
</table>
Table 4.3. Scale means (and standard deviations) for the data overall and for each segment. (continued)

<table>
<thead>
<tr>
<th>Scale</th>
<th>Overall</th>
<th>Acceptor</th>
<th>Fencesitter</th>
<th>Sceptic</th>
</tr>
</thead>
<tbody>
<tr>
<td>SVSS_ST</td>
<td>-0.48 (0.97)</td>
<td>-0.40 (0.95)</td>
<td>-0.74 (0.99)</td>
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<td>W</td>
<td>2.72 (1.01)</td>
<td>3.10 (0.82)</td>
<td>2.30 (0.94)</td>
<td>1.17 (0.38)</td>
</tr>
</tbody>
</table>

*Note.* See Table 4.1 for meaning of scale abbreviations.
Figure 4.3. Pearson correlations of psychological characteristics. See Table 4.1 for meaning of characteristic abbreviations.
Chapter 4. Evidence for Three Distinct Climate Change Audience Segments

Figure 4.4. Regression coefficients for each predictor of segment membership. The coefficients (dot) and 95% confidence intervals (error bars) are presented for Acceptors (blue), Fencesitters (yellow), and Sceptics (purple). The coefficients were calculated for the z-scores of each predictor. The grey background highlights when the confidence intervals for a predictor contains zero for all segments. See Table 4.1 for meaning of predictor abbreviations.

4.5 Study 2

Study 1 provided evidence for three audience segments that differ in terms of psychological characteristics that transcend climate change (conspiratorial ideation, environmental worldviews, and political ideology) and specific climate change beliefs and mental models that may be more easily changed. Moreover, mental models,
environmental worldviews, and political ideology were correlated, suggesting some mental model components may be resistant to revision because of motivated reasoning (Bayes & Druckman, 2021). For example, our observed association between belief in anthropogenic climate change and right-leaning ideology may be due to the belief itself becoming a symbol of in-group membership for some conservative groups—a process known as identity-protective cognition (Kahan et al., 2013). If so, conservatives may be motivated to reject opposing beliefs as these would threaten the material and emotional benefits gained from in-group membership. Thus, segments may differ in their receptivity to climate science information.

To test this idea, in Study 2 we examined whether revision of mental model beliefs differed across segments. We used a belief-updating paradigm where participants first provided numerical estimates for a set of climate change drivers or outcomes. Next, they were shown corresponding scientific estimates, and asked to provide another set of estimates. The dependent measure of interest was the direction and degree of belief updating following receipt of scientific estimates. We assessed updating across three mental model domains: climate change causes, climate change consequences, and effective mitigation of climate change.

Additionally, we explored two cognitive mechanisms which may account for a relationship between segment membership and belief revision. The first is trust in the source of incoming information. Acceptors may be more likely to trust scientific institutions than Sceptics, due to observed differences in political ideology, environmental worldviews, and climate change scepticism (Cook & Lewandowsky, 2016; Sunstein et al., 2017). The second mechanism is optimism bias, where individuals tend to revise their beliefs to a greater degree when receiving good news (e.g., initially overestimating an event perceived as bad) than when receiving bad news (e.g., initially overestimating an event perceived as good; Garrett & Sharot, 2017; Ma et al., 2016). Sunstein et al. (2017) demonstrated that segments differ in their optimism bias—when revising future-warming estimates, Sceptics updated optimistically, whereas Acceptors updated pessimistically. Accordingly, we explored the possibility segment differences in belief-updating can be explained by group differences in an optimism bias. To determine which events were
good or bad news, we included a sentiment inventory for participants to indicate their feelings towards each climate change outcome.

Finally, Study 2 was an opportunity to replicate the three segment solution from Study 1. However, the length of the belief-updating paradigm meant it was not practical to include the psychological scales from Study 1.

### 4.5.1 Method

#### 4.5.1.1 Participants

Qualtrics was used to recruit Australian adults \( N = 413 \) full completes using the same targeted and stratified sampling process focused on age \( M = 46.82, SD = 18.04 \) and gender (female = 47.94%). Along these characteristics, the sample was representative of the Australian population.

#### 4.5.1.2 Materials and Procedure

All materials were presented to participants on a computer screen via a web browser. After providing informed consent and demographic data, participants were warned of the general complexity of the Q sort task, and received the option to exit the survey with some reimbursement. Those who continued completed the Q sort task used in Study 1. Next, participants completed the trust inventory, belief-updating tasks (administered in a counterbalanced order, see Appendix B), and sentiment inventory. Data from extremely fast participants were discarded (less than 664 seconds, a preregistered criterion based on pilot testing).

**Trust inventory**  Participants were informed they would be shown information from two sources: the peer-reviewed climate science literature and Climate Action Tracker (an organization that provides scientific analysis of government climate action). For each source, participants read a lay description and indicated their trust of the source on a seven-point Likert scale, ranging from “strongly distrust” (1) to “strongly trust” (7).
Belief-updating tasks  We tested belief updating across three domains with five belief-updating tasks: (1) belief in causes of climate change (three tasks); (2) belief in consequences of climate change (one task); and (3) belief in effectiveness of mitigative policies (one task). Each belief-updating task contained two stages. Firstly, participants provided estimates for climate change drivers or outcomes (see Appendix B for more detail), by entering values from 0 to 100 into text boxes. Secondly, participants were shown their initial estimates alongside the estimates according to a relevant and specified authority (climate scientists or Climate Action Tracker). Participants then provided a new estimate. The presentation of belief-updating tasks was counterbalanced across participants (see Appendix B).

The first three belief-updating tasks concerned causal beliefs. For the first task, participants estimated the percentage of human-driven and nature-driven causes of climate change between 1980–2011. For this task, there were two beliefs: human-driven climate change and nature-driven climate change. For the second task, participants estimated the percentage of climate change caused by each of six mechanisms (e.g., “carbon dioxide emissions” and “changes in solar activity”) between 1750–2011. For the third task, participants estimated the percentage of warming caused by greenhouse gas emissions from six human activities (e.g., “electricity use in residential buildings”). Before supplying their estimates, participants were informed greenhouse gas emissions drive most climate change.

Another belief-updating task concerned consequence beliefs. Participants estimated the degree to which nine climate events (e.g., “the number of hot days globally between 1901–2005”) occurred because of anthropogenic climate change.

The final belief-updating task concerned mitigation beliefs. Participants were given information about the Paris Agreement and the Emissions Reduction Fund, Australia’s central climate policy. Then, participants predicted the change in Australia’s carbon dioxide emissions by the year 2030 (compared to 2005 levels) under Australia’s current climate policies. Unlike other tasks, participants indicated the direction of change of emissions by using a drop-down menu (options: increase, decrease, no change) and the amount of change by entering a percentage (participants who indicated there would be no
change had to enter “0”). Alongside both their initial and revised estimates, participants indicated their approval of the Emissions Reduction Fund on a seven-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7); their level of approval of Australia’s climate policies on the same seven-point Likert scale; and the likelihood Australia will meet the Paris Agreement (as a percentage, from 0 to 100).

**Sentiment inventory** Participants indicated their feelings towards each climate change event presented in the belief-updating tasks, on a five-point Likert scale, ranging from “very negative” (1) to “very positive” (5). On the same scale, participants were asked “If Australia met its commitment to the Paris Agreement, how positive or negative would you feel about that?” Participants were not asked about their sentiment towards climate change causes, as responses would be difficult to interpret.

### 4.5.2 Results and Discussion

#### 4.5.2.1 Segmentation Solution

We identified a near-identical segmentation solution as in Study 1 (see Appendix B for factor scores). Of the sample, 256 participants were Acceptors (61.99%), 114 were Fencesitters (27.60%), and 43 were Sceptics (10.41%).

#### 4.5.2.2 Belief Updating

The dependent variable of interest is *update*—the degree to which a participant revised their estimate following exposure to scientific information, as a proportion of their initial error. An update score was calculated for each participant and for each belief. The magnitude of an update score is the difference between the initial and revised estimate, divided by the magnitude of difference between the initial and scientific estimate. The sign of the update score conveys whether the update was towards (positive) or away (negative) from the scientific estimate. Thus, an update score of one indicates a revision to match the scientific estimate. Using this formula, update scores could not be defined
when the initial estimate equalled the scientific estimate (293 of 9888 updates; 2.96%) and such cases were therefore excluded from further analysis.

Linear mixed-effects modelling was used to determine whether update varied as a function of segment, trust in source information, or an optimism bias. Each domain of belief (cause, consequence, and mitigation) was modelled separately. The general strategy involved constructing several models, each with a different combination of predictors (as fixed effects). We then compared the consistency between the data and each model, operationalised as the Akaike Information Criterion (AIC), to determine the best fitting models. The fixed effects and relative AIC of each model is reported in Appendix B. For models of cause and consequence beliefs, predictor coefficients were assumed to randomly vary across participants, belief items, and task administration orders (known as random effects). For mitigation beliefs, intercepts were assumed to randomly vary across only task administration orders; as only a single belief was measured, within-unit and between-unit variability cannot be partitioned. All models were fit using maximum likelihood estimation. Predictor coefficients are reported with a 95% confidence interval (CI), estimated using the Wald method. One participant was excluded from analysis, as their data prevented model convergence due to a belief update score several magnitudes higher than other participants.

Updating varied as a function of segment (Figure 4.5). Models with a main effect of segment (and no other predictors) had better fit than models with no main effects. For cause beliefs, Acceptors updated more than Fencesitters (difference = 0.25, CI = [0.12, 0.38]), and Fencesitters updated more than Sceptics (difference = 0.39, CI = [0.19, 0.59]). For consequence beliefs, Acceptors again updated more than Fencesitters (difference = 0.25, CI = [0.15, 0.34]), who again updated more than Sceptics (difference = 0.24, CI = [0.09, 0.40]). For mitigation beliefs, Fencesitters updated the most, although they did not statistically differ from Acceptors (difference = 0.07, CI = [−0.20, 0.34]). However, Acceptors updated more than Sceptics (difference = 0.53, CI = [0.13, 0.92]). Thus, the patterns of segment updating for cause and consequence beliefs are not reflected in mitigation beliefs.
Segments may have differed in belief updating solely due to differences in trust in the source of information. However, this is not well supported by the evidence. For all domains, models with only a main effect of segment had considerably better fit than models with only a main effect of trust. Thus, trust alone cannot account for the effect of segment on belief update.

Generally, the best fitting models for update of cause and consequence beliefs were those including effects for both trust and segment membership. Additionally, there was substantial evidence for interactions. For cause beliefs, greater trust was associated with greater update for Acceptors (0.09 more update per point of trust, $CI = [0.01, 0.16]$) and Sceptics (0.18 more update per point of trust, $CI = [0.08, 0.28]$), but not for Fencesitters (0.02 less update per point of trust, $CI = [-0.06, 0.10]$). For consequence beliefs, greater trust was associated with greater update for Acceptors (0.10 more update per point of trust, $CI = [0.04, 0.16]$), but not for Sceptics (0.04 more update per point of trust, $CI = [-0.04, 0.12]$) or Fencesitters (0.04 more update per point of trust, $CI = [-0.02, 0.10]$). For mitigation beliefs, there was little evidence for an interaction.
Segment differences in updating may be due to differences in optimistic revisions. To explore this possibility, we determined which scientific messages were good news and bad news on the basis of participants' emotional appraisals of events and their first estimates. For example, if a participant indicated an event was negative and was exposed to a scientific estimate greater than their first estimate, the event is bad news; conversely, if this scientific estimate was instead less than a participant's first estimate, the event is good news. Combinations of effects for segment and news type (coded as good or bad) were entered into mixed-effects models. We did not model participant update of neutral belief/news, which included 1420 of 3708 consequence belief updates (38.30%) and 90 of 412 mitigation belief updates (21.84%). Of note, we did not model optimistic updating for cause beliefs as we did not collect sentiment data for causes.

For consequence and mitigation beliefs, the best fitting models were those containing main effects for segment and news type, but no interactions. There was a tendency towards a pessimistic updating for all segments, such that updating is larger for bad news than good news (Figure 4.6). As the best fitting models contained an effect for segment, segment differences in update could not be solely accounted for by differences in an optimism or pessimism bias.

### 4.5.2.3 Change in Policy Support

Additionally, we identified the predictors of changes in policy support. To do so, we determined the fit of linear mixed-effects models with combinations of main effects and interactions of: segment; change in perceived mitigation effectiveness (positively-signed when policy perceived to be more effective); and change in perceived likelihood of Australia satisfying the Paris Agreement (positively-signed change when the Paris Agreement is perceived to be more likely to be satisfied).

For both support in the Emissions Reduction Fund and support in Australia's policy, two models had considerably better fit. The first model contained a main effect of segment, a main effect of perceived likelihood Australia will satisfy Paris Agreement commitment, and an interaction between these two variables. The second model contains the same effects as the first, with an additional main effect of change in perceived
Figure 4.6. Mean update for (a) consequence beliefs and (b) mitigation belief, as a function of news and segment: Acceptor (blue), Fencesitter (yellow), and Sceptic (purple). Error bars represent one between-participants standard error of the mean.

mitigation effectiveness. For these models, the coefficient for the interaction between segment and perceived likelihood of meeting the Paris Agreement was only reliability signed (positive) for Acceptors (that is, the confidence interval did not intersect zero). Additionally, participants who updated towards greater perceived effectiveness of the Emissions Reduction Fund increased their support for it (0.00378 change on the scale per 1% increment of carbon dioxide reduction, $CI = [0.00065, 0.00692]$), and their support for Australia’s mitigation policies, although not reliably (0.00185 change on the scale per 1% increment of carbon dioxide reduction, $CI = [−0.00172, 0.00542]$).

Overall, these models indicate participants of all segments who reduce their belief in a policy’s effectiveness also reduce their support for that specific policy, but not general policy action. Additionally, Acceptors lowered their support for specific policy to the degree that it harmed Australia’s likelihood of meeting the Paris Agreement. Though, detrimental impacts on the Paris Agreement were unrelated to changes in policy support of Fencesitters and Sceptics.
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4.6 General Discussion

We used a novel bottom-up approach to segment climate change views. Across two studies, we find consistent evidence for three distinct audience segments: Acceptors, Fencesitters, and Sceptics. In Study 1, we combined our bottom-up approach to segmentation based on the Q sort with a top-down approach to segment interpretation by incorporating auxiliary measures of potentially relevant psychological characteristics. Importantly, these auxiliary measures were used to help interpret the segments once they had been derived—they did not contribute to the segmentation process itself. This combination of approaches revealed the three segments differ in their mental models of climate change and other psychological characteristics. Study 2 demonstrated segments differ in their belief-updating tendencies when exposed to scientific information. Overall, our studies indicate the Australian public are divisible into three audience segments with unique psychological characteristics and belief-updating tendencies. In the remainder of this discussion, we summarise the characteristic differences between segments, how these can inform communication strategies, and how our segmentation solution differs from previous research.

4.6.1 Characteristic Differences Between Segments

Differences between segments can be understood by recourse to their sorting behaviour in the Q sort task, responses on the psychological characteristics measures, and updating tendencies in the belief-updating paradigm. From the Q sorts, it is apparent Acceptors strongly believe in the urgency and reality of climate change. They recognise climate change will have wide ranging impacts on environment and society, and these impacts may be worse than climate scientists expect. They reject conspiratorial notions of climate change as a hoax, and they want to see political leadership and climate action. By contrast, Sceptics have an alternative perception of reality—one where the science suggests human actions are not influencing climate. Instead, climate change is a hoax manufactured to serve a hidden agenda. Accordingly, climate scientists are thought to use questionable research practices to create the illusion climate change is occurring. They
think climate scientists’ forecasts of global warming have been proved wrong and that, because of this, they deliberately changed the name of their field of study from “global warming” to “climate change”. We cannot say anything specific about Fencesitters other than that their sorting responses are more heterogeneous than the other two segments.

Turning to psychological characteristics measures, Acceptors strongly believe climate change is occurring and that carbon-emitting human activities cause climatic changes. They are more worried about the issue than other segments and strongly support climate action. This segment is politically liberal with an environment-as-ductile worldview, meaning they think the natural environment has a limited capacity to recover from damage. By contrast, Sceptics are less likely to believe climate change is occurring and that carbon-emitting human activities cause climatic changes; yet, Sceptics have the greatest self-confidence in their knowledge about climate change. They are therefore sceptical of the need for climate action. This segment is politically conservative with an environment-as-elastic worldview, meaning they think the environment easily recovers from damage. Surprisingly, Sceptics did not show the highest levels of dispositional conspiratorial ideation of all segments, despite their strong endorsement of climate-conspiracy related items in the Q sort. Instead, Fencesitters were the highest in dispositional conspiratorial ideation. The only other characteristic that distinguishing Fencesitters was their relatively high belief in the efficacy of engineering solutions to climate change.

Our finding that dispositional conspiratorial ideation was elevated in Fencesitters, but not Sceptics, seemingly contradicts an extensive literature showing conspiratorial ideation predicts climate change scepticism (Hornsey et al., 2018; Kaiser & Puschmann, 2017; Lewandowsky, Oberauer et al., 2013). However, Lewandowsky (2020) recently suggested individuals may deploy conspiratorial explanations for two different reasons: (1) they have a general disposition towards engaging in conspiratorial ideation; and/or (2) they seek to guard against worldview-incongruent information. In the latter case, conspiracy theories may not reflect people’s real attitudes to climate change but may instead be a pragmatic tool to indicate a person’s political stance on the issue. Consistent with this, Fencesitters showed greater general disposition toward conspiracism in the
absence of a specific tendency toward climate change conspiracy theorising, and they are moderate in terms of political ideology and worldviews. By comparison, Sceptics do not show an increased general disposition toward conspiracism, but they do show a specific tendency toward climate change conspiracy theorising, accompanied by politically conservative ideology and environment-as-elastic worldviews. Thus, unlike Fencesitters, Sceptics may be ideologically motivated to believe conspiratorial accounts of climate change.

Finally, segments differed in the degree they revised their beliefs towards scientific information. Specifically, for climate change causes and consequences, Acceptors updated their beliefs more than Fencesitters, who in turn updated their beliefs more than Sceptics. For mitigation, Acceptors and Fencesitters revised their beliefs to a comparable degree, and more so than Sceptics. The effects of segment on belief updating could not be fully accounted for by trust in information source or an optimism bias. In general, Acceptors and Fencesitters showed high degrees of willingness to revise their beliefs, whereas Sceptics were highly resistant to revising their beliefs. The willingness of Fencesitters but not Sceptics to update their beliefs in response to scientific information confers further support for the notion the two segments may deploy conspiracy theories for different reasons.

### 4.6.2 Communicating with the Different Segments

To bolster public support for mitigative policies, our findings suggest communicators should focus on Fencesitters. Acceptors already trust climate science and support strong leadership to address climate change, whereas Sceptics are few in number and politically-motivated to oppose mitigative policy, and are thereby resistant to belief updating. In contrast, Fencesitters show potential for belief change, as they update their beliefs in response to scientific findings and were not characterised by extreme environmental worldviews or political ideology. However, just as Fencesitters could be tipped towards greater climate change acceptance by exposure to scientific information, they could be tipped toward scepticism by exposure to disinformation.
To protect Fencesitters from climate change disinformation, communicators could preemptively use inoculation techniques to build psychological resistance to disinformation before it is perceived (McGuire & Papageorgis, 1961). Inoculation involves warning individuals they may be exposed to disinformation and explaining to them the deceptive strategies and rhetorical techniques used by those that seek to mislead (van der Linden, Leiserowitz, Rosenthal et al., 2017). For example, Cook et al. (2017) found climate change disinformation could be successfully inoculated by alerting individuals to the use of ‘fake experts’ by the fossil fuel industry. Such approaches are particularly promising for Fencesitters, as exposing the hidden agendas of industry leverages the segment’s elevated conspiratorial disposition. Alternatively, if disinformation has already informed belief, communicators may use various best-practice debunking strategies to correct the disinformation (Lewandowsky et al., 2020; Lewandowsky et al., 2017). For example, communicators could provide clear explanations for the established knowledge that undermines the misinformation alongside an explanation of what is true instead (Ecker et al., 2020; Lewandowsky et al., 2020; Paynter et al., 2019).

Additionally, Fencesitters are at risk of over-estimating the effectiveness of engineering solutions to climate change. Such optimism is potentially problematic, as believing that engineering can provide an ‘easy technological fix’ to the climate crisis may lead to questioning the need to cut emissions (Robock et al., 2008). Thus, communicators should use educational interventions to highlight scientific understanding of the potential role of different engineering solutions, the circumstances under which they might be deployed, and their potential risks and limitations. Simultaneously, communicators should provide education on the more effective carbon-limiting policies, as the effectiveness of these policies may be under-estimated by Fencesitters. Given Fencesitters do revise their beliefs in the face of scientific information, such education may be effective and worthwhile.

Although we emphasise Fencesitters, public support for mitigation policy can be bolstered within Acceptors and potentially Sceptics. Despite worry about climate change and having knowledge on its causes, many Acceptors fail to distinguish between effective and ineffective policies (Kempton et al., 1995; Read et al., 1994; Reynolds et al., 2010).
To reduce support for ineffective policies, communicators could encourage Acceptors to apply their causal knowledge of greenhouse gases to the policy domain. Alternatively, as demonstrated in the current work, communicators could directly highlight the ineffectiveness of a policy and the adverse impacts on international agreements. In contrast, the changes in policy support of Fencesitters and Sceptics was not associated with the perceived consequences of ineffective policy on international agreements. Lastly, messages from climate scientists could be persuasive, as climate scientists are trusted by Acceptors.

Of all segments, Sceptics were most resistant to belief revision when contradicted by science. Thus, communicators may need to deploy unique strategies to foster more positive attitudes towards climate science and policy in this segment. One approach is to leverage people’s motivations to maintain cognitive consistency in attitudes. For example, Gehlbach et al. (2019) found conservatives asked to rate the generally accepted contributions of science to society, such as discovering germs cause disease, had more positive attitudes towards climate science than conservatives asked solely about their climate science attitudes. Alternatively, communicators may avoid climate science entirely by appealing to the benefits of mitigation policy to improve policy endorsement, such as communicating the moral or economic co-benefits (Bain et al., 2015).

Lastly, for all segments, we caution communicators from assuming changing belief in the causes or consequences of climate change will necessarily change beliefs of effective mitigation. Our findings suggest mental models of cause and consequence differ from those of mitigation. For example, we found mental models of causes and consequences are strongly associated, but both are weakly associated with mental models of mitigation. Corroborating this distinction, segment updating tendencies were similar for cause and consequence beliefs, but both were different from patterns of mitigation belief updating. Thus, improving scientific literacy of climate change causes and consequences does not guarantee changes in the perceived effectiveness of policy.
4.6.3 Comparison to Previous Segmentation Research

We identified three segments, a number on the lower range of segments derived using top-down segmentation approaches (Hine et al., 2014). This finding could be accounted for by our use of a bottom-up approach, rather than a top-down approach. This distinction could be due to the differences in statistical approaches used in bottom-up and top-down approaches. When only one dimension of views exists, the Q methodology will generate at most three segments. Under the same conditions, statistics common in top-down approaches, such as latent class analysis, may produce more segments. Alternatively, the distinction could be due to the variables selected for segmentation. A potential problem with top-down approaches is they may incorporate irrelevant variables that generate spurious distinctions between segments or use statistical techniques that lead to a superfluous proliferation of segments. Thus, a segment holding similar perceptions may be divided into two segments based on another variable, empirically unrelated to perceptions but thought by researchers to be theoretically related. For example, we found conservation and self-transcending values did not predict climate change perceptions when accounting for other psychological characteristics. Accordingly, bottom-up approaches may avoid producing unnecessarily complex models.

Alternatively, the limited segments extracted may be result of political ideology constraining climate change views. Climate change is a politically polarised issue in some countries (Hornsey et al., 2018), such as the United States of America (Dunlap, 2019) and Australia (Essential Research, 2019). This polarisation is reflected in our segments, which are divided by their political affiliation, worry about climate change, and climate change scepticism. This dimension of worry and scepticism can be seen in other segmentation studies, such as the aforementioned Six Americas. This six segment solution was identified using data from 2008. However, since then Americans have become increasingly politically polarised in their climate change views (Dunlap, 2019; Kennedy, 2020; McCright & Dunlap, 2011). Similarly, studies from the earlier years of 2010-2020 found three to six segments for Australians’ climate change views (Ashworth et al., 2011; Hine et al., 2016; Morrison et al., 2013). Our current work cautiously suggests that
for Australians, and perhaps Americans, climate change views have consolidated along political lines.

Lastly, our findings could be unique to our sample. Australians may differ from people of other nations in their thinking about climate change, or how that thinking is expressed in discourse. However, the dimensions of climate change scepticism, worry, and concern about climate change that underlie our sample are reflected in other nations (Maibach et al., 2011; Metag et al., 2017). Our findings may be most relevant to nations where climate change scepticism is politically polarised, such as the United States, Canada, and Brazil (Hornsey et al., 2018).

4.6.4 Conclusion

The predominant approach to segmentation of climate change audiences has been top-down, which privileges researcher preconceptions over audience conceptions of climate change. In contrast, we used a bottom-up approach to ensure segmentation reflects lay views on climate change, as defined by the public. However, we did not disregard theory—we complimented our segmentation by examining the psychological characteristics of segments. We found the Australian public is composed of three segments—Acceptors, Fencesitters, and Sceptics—with unique psychological characteristics and belief-revision tendencies. Communication can be enhanced, our results suggest, by conceptualising the public as relatively homogeneous segments, rather than a heterogeneous whole. Yet, many communicators rely on a ‘one-size-fits-all’ approach. For these communicators, our research outlines a comprehensive profile of segments along with recommendations for communicating with each. We suggest communicators should target Fencesitters who hold moderate views and are receptive to belief revision. Care must nevertheless be taken since although Fencesitters are receptive to scientific information they are also potentially vulnerable to misinformation and conspiratorial thinking.
Effective climate change communication should account for the psychological foundations of the public's heterogeneous views. However, current understanding of climate change psychology is limited by two major shortcomings. As argued in Chapter 1, the first shortcoming is the dominance of top-down approaches used to segment the public's climate change views, which prioritises researchers' theories over participants' conceptualisations. As argued in Chapter 2, the second shortcoming is that the role of mental models of climate change in cognition is obscured by the narrow application of the mental model concept used in empirical research. To address the first shortcoming, this thesis had a descriptive aim to identify audience segments using a novel bottom-up approach. To address the second shortcoming, this thesis had an explanatory aim to identify the psychological characteristics that correspond to audience membership, with particular attention paid to mental models. In Chapter 3, I identified the discussion points of climate change salient in public discourse. In Chapter 4, I used these discussion points to create stimuli for the Q methodology, which in turn was used to derive audience segments. For each segment, I identified the climate change views, psychological characteristics, and belief updating tendencies. In this chapter, I begin by reviewing the empirical findings of this thesis. Then, I discuss the theoretical contributions to climate change cognition and the practical implications for both scientists and communicators. Lastly, I present the limitations and directions for future work.

5.1 Summary of Empirical Findings

In the first empirical chapter (Chapter 3), I reported a study that examined the common points of climate change discussions on social media. Congruent with the overarching
bottom-up approach of this thesis, I developed a novel framework for blending data
science techniques with qualitative analyses. I then applied this framework to Australian
tweets concerning climate change. Although Australians discussed a wide range of
climate change topics, the recurring topics could be conceptualised as belonging to
one of five themes. In order of prominence, the first theme, *climate change action*,
concerned coping with, preparing for, or preventing climate change. The second theme,
*consequences of climate change*, concerned discussions of a wide range of risks associated
with climate change. The third theme, *conversations of climate change*, discussed
conversation itself, particularly conversations concerning science, debates, art, media,
and podcasts. The fourth theme, *climate change deniers*, was discussions about those
perceived to deny anthropogenic climate change. The final theme, *the legitimacy of
climate change and climate science*, concerned the existence of any change in climate and
the role of anthropogenic influences. These results indicate that social commentary on
climate change is larger than climate, extending into economics, health, and society.
Furthermore, there are ‘meta’ themes that concern the beliefs about the climate change
belief (the theme of climate change deniers) and conversations about climate change
conversations (the theme of climate change conversations). Despite the prevalence of
‘meta’ conversations, such themes are rarely used in top-down approaches to segment
public views. By using the themes identified in Chapter 3 to inform the stimuli of my
bottom-up segmentation approach, I ensured the viewpoints collected were relevant to
public conceptions of climate change.

In the second empirical chapter (Chapter 4), I reported two studies that aimed
to identify audience segments in a representative Australian sample, using the Q
methodology. The first study aimed to identify segments and their psychological
characteristics. The second study aimed to identify the belief updating tendencies of
each segment. The studies featured a bottom-up approach to segmentation, using the
Q methodology (see Chapter 1) with statements representative of the social discourse
(identified in Chapter 3). Both studies suggest the Australian public can be segmented
into three unique groups along a dimension of climate scepticism: Acceptors, Fencesitters,
and Sceptics. The views of each segment are reflected in sorting behaviour in the
Q sort task. Acceptors acknowledged that human activity causes climate change,
which threatens environment and society. Acceptors wish for climate change action, particularly action driven by strong political leadership. By contrast, Sceptics rejected the notion that human activity causes climate change. To the Sceptic, climate science that supports anthropogenic climate change is the product of questionable research practices and hidden agendas. Government institutions that support climate change are either misguided or perpetuating a hoax. Fencesitter views on climate change sit between the Acceptor and Sceptic. In comparison to Acceptors and Sceptics, Fencesitters have greater heterogeneity in their perspective of climate change.

My results suggest each segment had a unique mental model of climate change accompanied by a distinct signature of other psychological attributes. I found segments differed in their mental models of climate change, self-perceived level of climate change knowledge, climate change scepticism, climate change concern, political ideology, worldviews, and conspiratorial ideation. Segments did not reliably differ in personality, need for cognition, consideration of future consequences, system justification, or values. Acceptors were unique in their prediction of severe societal consequences of climate change, and their limited belief in the effectiveness of engineering solutions to mitigate climate change. The mental models of Acceptors were accompanied by uniquely elevated worry about climate change, limited conspiratorial ideation, liberal political ideology, and ‘environment-as-ductile’ worldview, meaning that Acceptors think the environment is limited in its capacity to recover from damage. By contrast, the mental models of Sceptics neglected the influence of human activity on the climate. Despite this misconception, Sceptics had uniquely elevated confidence in their knowledge of climate change. Opposite to the Acceptors, Sceptics had limited worry about climate change, conservative political ideology, and rejected an ‘environment-as-ductile’ worldview. Lastly, the mental models of Fencesitters had uniquely high assessments of the effectiveness of engineering solutions to mitigate climate change. Accompanying this mental model were elevated levels of dispositional conspiratorial ideation. Thus, each segment was accompanied by a distinct signature of psychological attributes.

Lastly, I found segments differed in their tendencies to revise beliefs when confronted with scientific evidence. When encountering scientific claims on the causes
or consequences of climate change, Acceptors revised their beliefs to a greater degree
than Fencesitters, who revised their beliefs to a greater degree than Sceptics. However,
when this evidence concerned the effectiveness of climate change mitigation, Acceptors
and Fencesitters updated to a similar degree, with both segments updating to a greater
degree than Sceptics. These effects could not be fully accounted for by trust in the source
of information or optimistic updating. In general, Acceptors and Fencesitters were willing
to revise beliefs, whereas Sceptics were highly resistant to revising their beliefs.

Overall, this thesis provides insight for both theory and practice. Regarding
theory, my findings extend knowledge of audience segmentation, mental models of
climate change, and belief updating. Regarding practice, my work provides resources
to both scientists and communicators. I elaborate on these implications below.

5.2 Theoretical Implications

5.2.1 Comparing Bottom-Up and Top-Down Approaches to
Segmentation

Although I found the nature and number of segments of bottom-up and top-down
approaches may differ, the underlying dimension of climate change scepticism that
divides segments is present in both my and other’s segmentation solutions (Bain et al.,
2015; Hine et al., 2016; Maibach et al., 2011; Morrison et al., 2013; Myers et al., 2012).
This suggests that two segments (e.g., Accepting and Sceptical) or three segments (e.g.,
Acceptor, Fencesitter, Sceptic) are sufficient to segment lay views of climate change for
Australians, and possibly other nations where climate change is polarised (as argued in
Chapter 4). Additionally, the congruence between top-down and bottom-up approaches
indicates an association between views on different aspects of climate change. That is,
views on aspects of climate change typically omitted by top-down approaches, such as
views on climate change deniers and climate change conversations, are associated with
views on aspects of climate change typically used by top-down approaches, such as views
on climate science and climate policy. Thus, although the public discuss multiple aspects of climate change, their views are underscored by a single dimension of scepticism.

However, my findings caution researchers against assuming all theoretically relevant constructs result in differences in climate change views. I found values, personality, need for cognition, and consideration of future consequences were not diagnostic of segment membership when accounting for other psychological characteristics (e.g., political affiliation). Although a complex theory of interactions between psychological characteristics could account for this finding whilst holding values or personality as central to climate change views, the principal of parsimony wards against such a conclusion. Therefore, researchers using segments derived on values alone (e.g., ecoAmerica & Strategic Business Insights, 2014; Kahan et al., 2011) should not assume segments necessarily differ in their interpretation of climate change.

5.2.2 Segments are Underscored by Unique Mental Model Signatures

In Chapter 1, I asked whether mental models could account for differences in segment membership. In Chapter 2, I outlined empirical evidence for the association between mental models and climate change inferences. However, in the same chapter, I drew on broader cognitive theory to argue that the conceptualisation of mental models in climate change research is problematically narrow. The effect of mental models of physical climate may be overridden by other mental models or other psychological characteristics responsible for shaping mental models, such as political ideology and worldviews. Despite this, I found that each segment is indeed underscored by different mental models of climate change. Even when accounting for a range of other psychological characteristics, Sceptics were unique in their rejection of anthropogenic climate change. Acceptors were unique in their perceptions of societal climate change consequences and anthropogenic climate change. Fencesitters were unique in their perceived effectiveness of engineering mitigative policies.
Each segment is susceptible to the misconceptions of climate change that are consistent with their mental models. Sceptics rejected a range of scientific findings, such as the influence of human activity on climate, the consequences of such anthropogenic climate change, and the capacity for society to mitigate climate change through policies that reduce greenhouse gas emissions. However, as Sceptics generally reject human influences on climate, they were safeguarded against believing in inconsequential human activities as causes of climate change, such as air pollution from toxic chemicals.

Unlike Sceptics, the mental models of Acceptors and Fencesitters match the good environmental practice configuration outlined in Chapter 2, where a configuration refers to a phenomenon or mechanism represented by a mental model of climate change. That is, Acceptors and Fencesitters believe that ‘poor’ environmental practice worsens climate change and ‘good’ environmental practice can mitigate climate change. However, Fencesitters were unique in their assessment of engineering policies as effective; typically, engineering policies are perceived as citizens to be ‘poor’ environmental practice (Read et al., 1994).

The mental models of Acceptors were therefore shaped by both a greenhouse gas configuration and a good environmental practice configuration. Thus, those most likely to endorse the correct causal mechanisms of climate change, such as carbon dioxide emissions, were also most likely to endorse the incorrect causal mechanism of good environmental practice. This explains a curious finding from recent literature: that support for mitigative policy is predicted by misconceptions of good environmental practice causing climate change (Fleming et al., 2020). However, it is not clear which of the two mental model configurations drives support for general mitigation policy.

Lastly, both Fencesitters and Sceptics are less accepting of the societal consequences of climate change than Acceptors. Thus, the climate change scepticism of Fencesitters may be derived from scepticism of consequence, rather than the scepticism of cause (also referred to as epistemic scepticism) held by Sceptics. Corroborating this conclusion, I found Sceptics displayed the greatest levels of epistemic scepticism.
5.2.3 Mental Models of Effective Mitigation Differ From Mental Models of Cause and Consequence

My work suggests that the mental models used to infer causes and consequences of climate change differ from those used to infer the effectiveness of mitigation. Specifically, I found mental models of cause and mental models of consequence were strongly associated, yet both of these mental models were weakly associated with mental models of mitigation. This distinction was further reflected in patterns of associations with other psychological characteristics and patterns of belief revision. Thus, the mental models used to infer cause and consequence may not be the same mental models used to infer effective mitigation. This effect is robust, as it is observed across a range of tasks and stimuli.

The distinction between mental models of effective mitigation and mental models of cause and consequence is empirically novel. Research indicates mental models of cause, consequence, and effective mitigation are separable facets of mental models, all of which jointly determine support for specific policies (Bostrom et al., 2012). My findings contribute to this knowledge, suggesting mental models of effective mitigation are distinct from other mental models of climate change. Thus, researchers should not assume that changing an individual’s causal beliefs or risk perceptions will necessarily change an individual’s beliefs on effective mitigation strategies, and vice versa.

Despite its novelty, the distinction between mental models was anticipated by the conceptual framework of this thesis. In Chapter 2, I outlined three assumptions of the mental models of climate change literature and used broader cognitive theory to highlight how each assumption was unsound. In turn, I challenged the idea that climate change views were underpinned by a single mental model of climate change (Assumption 1) represented as a physical system (Assumption 2), that is uniformly shaped by motivation and meaning-making (Assumption 3). I will now explore how a violation of each assumption can account for my findings and the consequent implications for theory.
Mental models of cause and consequence may represent a different phenomenon than mental models of mitigation. This explanation challenges the unsound assumption that physical climate is core to mental models of climate change. One possibility is that mental models of cause and consequence are used to represent climate change, whereas mental models of effective mitigation do not. Often, the causes and consequences of climate change are embedded in the definition of the phenomenon; for example, “a change of climate which is attributed directly or indirectly to human activity that alters the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods” (pg. 7, United Nations, 1992). Further evidence is provided by my first empirical study, which identified discussions of causes and consequences in the themes of The legitimacy of climate change and climate science and consequences of climate change, respectively. In contrast, effectiveness of specific mitigation was not a prominent feature of the discourse, though discussions on the effectiveness of Australia’s climate policy featured in the theme of climate change action. Mental models of effective mitigative policies may instead represent the policy domain or general optimism for the future (Richert et al., 2017).

Alternatively, mental models of effective mitigation may be a different level of abstraction than mental models of cause and consequence. This challenges the unsound assumption that mental models exclusively represent physical structure (e.g., physical state, physical cause). Instead of physical structure, mental models may represent the intentional structures of the world. These representations are most useful when predicting the behaviour of people or a system designed by people (Rasmussen, 1986). For example, recycling may be judged as effective mitigation by virtue of the intention to help the environment, rather than by virtue of a plausible causal process. Alternatively, Acceptors and Sceptics who perceive climate change to be the product of a scientific research may have a mental model of cause that represents the intention of scientists. As there is limited research identifying the levels of abstraction of different climate change mental models, no conclusive claims can be made. Nevertheless, differences in levels of abstraction could account for the observed lack of association between mental models of effective mitigation and mental models of cause and consequence.
A final alternative is that mental models of climate change are not uniformly shaped by motivations and meaning-making. This challenges the unsound assumption that ideological and value structures are exogenous forces that influence mental models uniformly. I found that mental models of cause and consequence were associated with a range of psychological factors that determine interpretation of social issues, such as ideology, worldview, and conspiratorial ideation. Such factors were weakly associated with mental models of effective mitigation. Thus, the constraints of motivations and meaning-making devices that limit judgements on causes and consequences of climate change may not apply to judgements of the effectiveness of mitigation. Possibly, the influence of mental models in estimating causes and consequences may be overridden by motivations and meaning-making devices. In contrast, judging the effectiveness of specific mitigative policies may be a novel task, requiring participants to use their mental models in absence of strong ideological cues, useful background knowledge, or motivations to guide reasoning. This may differ from support for climate change mitigation, where political ideology can guide judgement (Kahan et al., 2013; McCright & Dunlap, 2011; Van Boven et al., 2018). Therefore, the same mental models may underlie causes, consequences, and mitigation, but the effects of ideology and meaning-making will differ depending upon the task at hand.

5.2.4 The Contingencies of Belief Updating

Segments differed in their revision of beliefs when confronted with scientific information. This effect could not be explained by alternative accounts, such as the trust in source of the scientific information or optimistic biases towards updating. Thus, consistent with social marketing arguments, conceptualising the audience as segments is useful in anticipating the effectiveness of climate change communication.

Trust in source information is neither sufficient nor necessary for climate change belief revision. For Fencesitters, there was minimal association between trust and belief revision. The effect may be due to Fencesitters lacking strong prior climate change beliefs or uncertainty surrounding trust in scientific institutions. Additionally, for all segments, trust had little association with revision of the perceived effectiveness of mitigation. This
could be due to uncertainty in the nature of the scientific institutions responsible for estimating policy effectiveness. Alternatively, it may be due to differences between the function of mental models for mitigation and mental models of causes and consequences. For example, if mental models of mitigation are functional purposive abstractions, then it is the intention of scientific institutions, rather than trust, that underlies belief revision.

All segments updated according to a pessimism bias. That is, individuals tended to revise their beliefs to a greater degree when confronted with bad news (e.g., underestimating the role of climate change in causing a negative event) than good news (e.g., overestimating the role of climate change in causing a negative event). This finding contradicts the optimism bias observed in belief revision of personal health events (Garrett & Sharot, 2014, 2017; Ma et al., 2016). Thus, the role of sentiment in belief updating may differ across domains of belief. The pessimism bias in climate change beliefs may be a product of the negativity of climate change discourse, rooted in inaction, doom, and negative imagery (Doulton & Brown, 2009; Leiserowitz, 2006). Given the differences between revision of health beliefs and climate change beliefs, interventions successful in targeting health misconceptions may be unsuccessful in targeting climate change misconceptions, and vice versa.

Additionally, the presence of a pessimism bias for all segments contradicts an earlier study that found an optimism bias for individuals most accepting of climate change (Sunstein et al., 2017). However, the earlier study used a fictitious scenario of scientists revising their estimates, whereas I used real estimates taken from empirical research on climate change. Additionally, the earlier study assumed all individuals viewed a global temperature increase as negative. My study allowed individuals to specify their own sentiment towards climate change consequences. Thus, my work emphasises the need to test reception to real information (rather than manufactured) and to account for individual differences in perceptions of stimuli.
5.2.5 Policy Support can be Enhanced by Improving the Perceived Effectiveness of Policy

Lastly, I found that individuals who changed their perceived effectiveness of a policy also changed their support for that policy. This effect applied for all segments, suggesting the cognitive process transcends ideological constraints. This experimental finding corroborates the results from cross-sectional research, which demonstrate that support for a specific policy is correlated with the perceived effectiveness of that policy (Bostrom et al., 2012). Although I did not directly investigate the direction of causality, exposure to information on policy effectiveness resulted in changes in support for the policy and changes in the perceived effectiveness for the policy. I tentatively suggest that improving perceptions of policy effectiveness can bolster support in a specific policy.

5.3 Practical Contributions

5.3.1 Practical Contributions for Scientists

For scientists, this thesis provides two novel frameworks. Firstly, in Chapter 3, I outlined a framework which blends data science techniques with qualitative methodologies to explore large social media data sets. Secondly, in Chapters 1 and 4, I outlined a bottom-up framework for segmenting audiences. In the empirical chapters of this thesis (Chapters 3 and 4), I demonstrated how to apply each framework. Although my applications are limited to Australian samples and the topic of climate change, each framework could be applied to other populations and topics. Both frameworks can be applied in bottom-up fashions, making them especially useful techniques for topics that lack established theories.

Secondly, I have provided open-source computer tools for scientists, such as the topic comparison algorithm of Chapter 3 (section 3.4.3.4) and the web application used to run the Q sort task of Chapter 4 (section 4.4.1.2). The Q sort tool is especially useful, given most applications used for the Q sort are prohibitively expensive or inaccessible.
In contrast, my tools are coded in the R programming language which is freely available and accessible. These tools are hosted in online repositories, allowing researchers to download them on demand.

Lastly, I have provided novel data sets to scientists. All non-sensitive data used in the empirical chapters of the thesis is hosted on online repositories. The data sets from Chapter 4, such as the data of over 400 participant scores of 28 inter-related psychological variables related to climate change perceptions, may be of particular interest for scientists. The richness of this data affords opportunities for hypothesis testing that extend beyond the scope of this thesis.

5.3.2 Practical Contributions for Science Communicators

In Chapter 3, I outlined the features of climate change most salient within the public discourse. This should be considered by science communicators, as individuals reasoning about climate change may draw incorrect inferences based on pre-existing knowledge or peripheral and irrelevant climate change topics (Sterner et al., 2019). Moreover, communicators will need to consider that climate change is rooted in discussions on political inaction, climate change sceptics, and even meta-commentary on climate change discussions. For example, the ridicule of prominent climate change sceptics, such as Malcolm Roberts, may lead to reactance within the Sceptics segment.

In Chapter 4, I provided a comprehensive profiling of three climate change segments of the Australian audience. This profiling included descriptions of the psychological characteristics of each segment, and their propensity to revise beliefs when confronted with scientific information. Based on these profiles, I proposed communication strategies for each segment. These findings are useful to those wishing to improve the effectiveness of climate change communication by tailoring messages and strategies to each segment of the public.

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1 An Australian senator who has dismissed scientific evidence of anthropogenic climate change, promoted conspiracy theories (Cook, 2016), and argued climate change mitigation threatens to reverse the "progress of civilisation" (pg. 34, Roberts, 2016).
I have argued efficient interventions to bolster policy support or communicate science should target Fencesitters. Fencesitters show potential for belief change. However, this potential is a double-edged sword—just as Fencesitters may be tipped towards revision to scientifically-congruent views, the segment may be tipped to scepticism by exposure to misinformation. Thus, communicators should intervene to guard against misinformation with inoculation or debunking strategies. Additionally, communicators may wish to temper Fencesitters’ elevated belief in the effectiveness of engineering solutions to climate change with information on the disadvantages to engineering solutions and the benefits of alternative policies.

Different techniques are required to tailor information to Acceptors and Sceptics. Acceptors support policy to mitigate climate change, but can fail to differentiate effective carbon-limiting policies from ineffective green policies. Communicators may wish to leverage Acceptors’ correct causal knowledge of greenhouse gases in communicating specific ineffective policy. Alternatively, communicators could highlight the detrimental impact of ineffective policy on international agreements (such as the Paris Agreement). Supporting this approach, I found when Acceptors (but not Fencesitters or Sceptics) viewed information on the ineffectiveness of Australia’s central climate change policy, the degree to which their support for the policy was reduced was associated with the reduction in their estimated likelihood of Australia satisfying the Paris Agreement. Turning to Sceptics, communicators will require unique strategies to foster positive attitudes towards climate science and policy. This can be achieved by drawing upon motivations of Sceptics that transcend the issue of climate change, such as their motivation to be cognitively consistent (Bain et al., 2015) or to improve society (Bain et al., 2015).

Alongside segment-specific recommendations, my work has implications for climate change communication generally. For communicators hoping to bolster policy support, I identified a mechanism to do so—improving the perceived effectiveness of that policy. I caution communicators from assuming that causal knowledge will shift perceptions of mitigation effectiveness, as there are divides between mental models of cause and consequence compared to those of effective mitigation.
5.4 Limitations and Future Directions

5.4.1 Comparing Bottom-Up and Top-Down Approaches to Segmentation

My work indicates that the segmentation results from a bottom-up approach differ from those of top-down approaches. However, I cannot conclude all differences are due to differences in approach, as I have used a statistical approach not commonly featured in top-down segmentation—the statistics of the Q methodology. For example, within the Q methodology, a single dimension of views can be split into, at most, three segments. However, that is not to suggest that our segmentation solution is purely an artefact of our design and statistical decisions. One example is the use of a forced distribution for participant rankings. Using such a forced distribution is useful for highlighting the statements most concordant with segments, but has little impact on the number of factors identified from the data (Brown, 1980).

My bottom-up approach sought to gauge climate change views, whereas some top-down approaches seek to segment individuals on their views, their behaviour, their demographics, or their motivations (for discussion, see Corner & Randall, 2011; Hine et al., 2014; Metag & Schäfer, 2018). As I only examine one bottom-up approach, the varying impacts of different statistical analysis, bottom-up versus top-down design, and the different segmentation objectives cannot be disentangled from my work alone. These effects could be further distinguished by future research that varies each analytical characteristic individually, such as the statistical approach, to quantify the effect on the resulting segmentation.

Of note, our particular implementation of the Q methodology has disadvantages. Firstly, our implementation was laborious for our research time, requiring sophisticated technologies to derive statements. This rigorous approach was optional, and not necessary for the implementation of a bottom-up approach, or even the Q methodology in general (Brown, 1980). Additionally, the Q methodology is laborious for participants, requiring participants use an unfamiliar interface and invest more time than a regular
survey inventory. For our particular research goals, the Q methodology was valuable, as it integrates nuanced quantitative and qualitative information. Future researchers may seek to forego the laborious Q methodology and instead use survey scales derived from the findings of this research (e.g., participant views on the statements that best distinguish Acceptors and Sceptics).

5.4.2 Mental Models of Effective Mitigation

My findings indicate mental models of effective mitigation differ from those of mental models of the causes and consequences of climate change. Although I have speculated on psychological accounts for the difference between mental models of effective mitigation, testing these accounts is a matter for future research. Such research could inform both mental model theory and techniques for policy communication, as mental models of effective mitigation are associated with policy support. I will now propose avenues of future research that can test my proposed accounts for mental models of effective mitigation. For each avenue of future research, researchers should identify commonalities in mental model inferences across different policy options, to ensure findings are not specific to any one policy.

My first psychological account proposed that mental models of cause and consequences represent ‘climate change’, whereas mental models of effective mitigation do not. Future research could identify the content of mental models of effective mitigation through interviews (e.g., Bostrom et al., 1994; Kempton et al., 1995). Alternatively, researchers could use a well-defined laboratory task with a known scientific solution, such as the carbon accumulation task discussed in Chapter 2. This task requires participants to balance the emissions and uptake of atmospheric carbon dioxide to stabilise carbon dioxide emissions by the year 2100. To achieve a solution consistent with physical science, individuals could resort to systems reasoning to mathematically balance the inflow and outflow of carbon dioxide. However, many participants use phenomenological reasoning, where participants draw upon ‘real world’ aspects of climate change that are irrelevant for the task at hand (Sterner et al., 2019). Carbon dioxide accumulation underpins both the cause of climate change and the effectiveness of mitigation. As such, accumulation tasks
could be constructed for historic carbon dioxide emissions (causes) and expected future carbon dioxide emissions under a specific policy (mitigative effectiveness). Participants could explain their reasoning in open-ended questions. Differences in the prevalence and content of phenomenological reasoning underpinning historic accumulation versus future accumulation should provide insight into the differences of content between mental models of causes and mental models of effective mitigation.

My second psychological account proposed that some, but not all, mental models of climate change represented an intention or function of a system. For example, Sceptics’ mental models of causes may represent the profit motive of climate scientists rather than the physical state or physical causes of the climate system. This could be explored through experimental survey studies that manipulate perceived intent. Priming or manipulating perceptions of the purposes or incentives of a scientific or political institution should have greater impact on mental models of intentional abstractions compared to those of physical processes.

My final psychological account proposed a non-uniform effect of meaning and motivation on mental models. As a result, the tendency and type of motivational reasoning used to construct or constrain mental model operations may vary depending on the task at hand. Future research could explore differences in motivational reasoning between mental models of mitigative effectiveness and mental models cause or consequence. Researchers could induce motivations concerning values, social norms, group identity, internal belief consistency, and belief accuracy to identify whether the consequent impact on beliefs of cause, consequence, and mitigative effectiveness is uniform (Bayes & Druckman, 2021; Bayes et al., 2020; Kahan, 2013, 2015; Ma et al., 2019).

5.4.3 The Measurement of Mental Models and Other Psychological Characteristics

I have attempted to measure mental models using close-ended surveys, close-ended numerical estimations of probabilities and predictions, and open-ended listing tasks.
However, I cannot conclude that responses to the mental model measurements are the content of participant mental models. As discussed in Chapter 2, my approach gauged a cross-section of participant reasoning, and as such, responses to items may indicate a mental model in long-term memory, a mental model in working memory, an inference from a mental model, or even another reasoning process that does not require mental models. Ultimately, I have assumed that responses to mental model questions correspond systematically, but not necessarily perfectly, to the mental models held by participants. Corroborating this, both my own results and the literature (as presented in Chapter 2) have reported similar mental models irrespective of tasks and sample features, such as the good environmental practice mental model configuration. However, my measures specifically aimed to gauge mental models of physical climate, as these measures have been validated by decades of research. The development of measures that gauge a broader suite of mental models (such as the inclusion of social function) are a promising area for future research.

My measurement of mental models and other psychological characteristics is also limited by a conceptual focus on individualism. Although I measured some social and cultural characteristics, such as political ideology and worldview, I neglected some environmental and social factors such as media consumption, perceived social norms, and social identity (Doherty & Webler, 2016; Kahan, 2015; Maibach et al., 2011). Despite identifying socially situated aspects of mental models in Chapter 2, I did not attempt to quantify how participants may draw on their social or physical environment to construct their mental models. My findings outlined the psychological characteristics that predict segment membership. Future research is required to integrate my insights with perceptions of social and physical environments.

### 5.4.4 Test Belief Revision in Ecologically Valid Settings

The belief updating component of the thesis was conducted in a controlled setting, with minimal competing sources of attention. Patterns of belief updating may differ within ecologically valid settings, such as television news or social media, corresponding to different presentation of information (or misinformation). Thus, my findings should
be understood within their context—participant tendency towards belief-revision, rather than belief-revising behaviour in the real world. For example, Acceptors and Fencesitters are matched in their tendency to revise mitigative effectiveness beliefs. However, in environments outside of the laboratory, information on mitigation effectiveness may be more salient for Acceptors than Fencesitters, as the former segment is more concerned about climate change. Future research should test the belief updating tendencies of segments in ecologically valid settings.

5.4.5 Segmenting Other Audiences

The thesis provides a comprehensive segmentation of an Australian audience. In Chapter 4, I argued that my results likely generalise to other nations where climate change views are politically polarised. My findings may be less relevant to societies that are not Western, Educated, Industrialized, Rich, and Democratic (WEIRD; Henrich et al., 2010). Corroborating this, mental models of climate change from non-WEIRD societies differ from those of WEIRD societies (Codjoe et al., 2014; Eisenstadt & West, 2017; Klein et al., 2014). For example, individuals from Accra (capital of Ghana) hold mental models of climate change which emphasise the deforestation and the burning of firewood and rubbish as central causes to climate change, whilst omitting the role of global fossil fuel emissions (Codjoe et al., 2014). Future research will be required to segment other audiences, particularly non-WEIRD societies and societies where climate change views are not politically polarised.

The bottom-up segmentation of this thesis is well-suited to segment audiences. Climate change discourse of the society can be gauged using the text analysis techniques of Chapter 3. This does not need involve social media data as the framework applies to any large corpus of text; though, a different topic detection algorithm would be required to model another text corpus (e.g., news articles). Although my implementation of topic modelling was laborious, requiring several human coders to select ideal parameters for the topic modelling algorithm, future implementations may not need to be as rigorous. Indeed, my approach is not typical of topic modelling practices, where the research team usually selects the ideal parameters for the algorithmn. Following a corpus analysis, the
core components of the discourse could inform the statements to be used in a Q sort task. It is critical that the Q sort includes opportunities for participants to explain their ranking of statements, to ensure the subsequent profiles are understood from the participant’s perspective, rather than the researcher’s preconceived ideas of the participant. The Q sort could be supplemented with an auxiliary analysis of psychological characteristics, allowing researchers to gauge the relevance of theory to a new sample.

5.4.6 Using Twitter as a Medium of Public Conversations

In my audience segmentation approach, I aimed to use stimuli derived bottom-up from public discourse, as described in Chapter 3. I chose to sample messages from Twitter in 2016. The choice of medium imposed restrictions that should be considered when generalising these results. For example, the Twitter users of the time were not necessarily representative of the Australian population, as they were disproportionately male and young (Essential Media Communications, 2015). Thus, the prevalence of topics reported in Chapter 3 should not be interpreted as necessarily representative of the general population. However, the primary aim of this work was to identify the diversity of concepts discussed by the public, which does not require a representative sample. For example, if an under-represented segment of the population discussed a novel climate change topic, this would be detected through the topic modelling analysis as a unique topic.

Another limitation of my analysis was sampling tweets from only the year 2016. Twitter conversations may change over time, such as in response to extreme weather events or temperature variations (Shi et al., 2020; Sisco et al., 2017; Yeo et al., 2017). My own findings indicated that many topics were confined to a small time period of the year. However, as discussed in Chapter 3, I derived climate messages from topics that were commonly discussed throughout the year, and most of these topics have been discovered in work sampling different time periods. Having said that, the topic of “conversations of climate change” is an exception, as it may be an artefact of years where a federal election takes place (as hypothesised in Chapter 3). Future research could explore this hypothesis.
Ultimately, my social media analysis derived messages from a public medium, where many tweets are available for viewing without a Twitter account. As such, users may be reluctant to share personal opinions that could result in ill consequences for family, friendship, or employment. In this instance, a user may opt to ‘protect’ their profile (which disallows many users from viewing their tweets) or delete their tweets; such tweets would not have been sampled in my study, as my approach was only way to obtain tweets programmatically (through Twitter’s Application Programming Interface) with minimal ethical concerns, whilst abiding by Twitter’s terms and conditions.

Perhaps a more pressing limitation of using a public medium is the lack of fencesitter voices. Users may not post tweets about climate change because they are disinterested or dissuaded by uncertainty or ambivalence. A semi-structured interview could include a protocol to prompt fencesitter participants. With limited tweets from fencesitters, my audience segmentation could only identify fencesitters through their rejection of Acceptor and Sceptic views. Future research that integrates messages from public and private mediums for audience segmentation could identify and distinguish different categories of fencesitters. Such research would be particularly useful for communicators, who could aim to provide information to the uncertain and emotively capture the attention of the disinterested.

5.5 Concluding Remarks

There is a pressing need to bolster public support for effective climate change policies. The best communication techniques will embrace the diverse views of citizens, through tailoring messages to individuals’ informational needs and motivations. This thesis outlined a novel approach to audience segmentation that gauges lay views on lay concepts of climate change. In Chapter 3, I identified how the public discourse defined climate change. Then in Chapter 4, I used this definition to identify three audience segments—Acceptors, Fencesitters, and Sceptics—each characterised by a unique signature of ideology, worldview, climate change scepticism, and worry about climate change. Beyond this, I identified the mental model signatures of each segment. Although mental
models were constrained by stable motivators of reason, such as political ideology, I demonstrated many individuals were willing to revise their mental model beliefs in the face of contradictory information. Critically, I found changes in mental models of mitigation effectiveness corresponded to changes in policy support. Thus, there is a place for science communication in bolstering policy support to mitigate the costly dangers of a changing climate.
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References


References


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Appendix A

Supplement for Chapter 3

A.1 Preregistration

We preregistered the analysis of our study on the Open Science Framework. Typically, preregistration is used for confirmatory analyses, where hypotheses are tested. In our case, we submitted a preregistration of an exploratory analysis. However, the planned analysis failed to account for all degrees of freedom and possibilities in both quantitative and qualitative components of our study. Consequently, the planned analysis was inappropriate for our data at various stages, and we were required to frequently deviate from the preregistration.

A.2 Topic Derivation Process

To derive topics for each batch, we used the Non-Negative Matrix inter-joint Factorization (NMijF) process (Nugroho, Zhao et al., 2017). The process is described in great detail by Nugroho, Zhao et al. (2017); for our readers, we provide a brief overview of this process below.

The NMijF process requires two matrices: one containing the term co-occurrence between each tweet (tweet-to-term matrix $V$), and the other containing socio-temporal information on the relationship between each tweet (tweet-to-tweet matrix $A$). Both matrices contain information useful for topic derivation of content produced in the Twitter environment.

\(^{1}\) Examining Australian Climate Change Discourse Through a Social Media Lens 1.1. Retrieved from https://osf.io/mb8kh
A.2.1 Defining the Tweet-to-Term Matrix

The tweet-to-term matrix \( (V) \) contains the relationship between each tweet, and the set of unique terms appearing across all tweets in the batch. For each tweet \( t \) and each unique term \( s \), in the batch \( T \), the tweet-term relationship is defined by the ‘term frequency-inverse document frequency’ (Manning et al., 2008):

\[
v_{ts} = tfidf(s, t, T) = tf(s, t) \times idf(s, T)
\]

Where the term frequency \( tf(s, t) \) is the number of times term \( s \) occurs in tweet \( t \), and the inverse document frequency \( idf(s, T) \) is a measure of how common or rare the term \( s \) is across the tweet batch \( T \).

A.2.2 Defining the Tweet-to-Tweet Matrix

The tweet-to-tweet matrix \( A \) contains information on the relationship between each possible pair of tweets in the batch. To calculate each element of \( A \), the relationship \( R \) between each pair of tweets is calculated and normalized using a sigmoid function. A \( R \) value of zero indicates no similarities between two tweets, with higher values of \( R \) indicating a stronger relationship. The relationship between any two tweets \( (ti, tj) \) is composed of three components: similarities in people referenced in the tweets \( (po(ti, tj)) \), common action \( (act(ti, tj)) \), and similarity in content \( (sim(ti, tj)) \). Formally:

\[
R(ti, tj) = po(ti, tj) + act(ti, tj) + sim(ti, tj)
\]

A.2.2.1 Similarities in People Referenced in the Tweets

Terms in tweets may be references to other users on the platform, through an interactive Twitter feature called ‘mentions’. If tweet \( ti \) and tweet \( tj \) are posted at a similar time \( (ti, tj) \), mentioning the same users \( (P_{ti} \ and \ P_{tj}) \), these tweets may be similar in topic. The similarity in mention activity is expressed as:
Appendix A. Supplement for Chapter 3

\[ p_o(t_i, t_j) = \frac{|P_{t_i} \cap P_{t_j}|}{|P_{t_i} \cup P_{t_j}|} f(t_i - i_{t_j}) \]

where \[ f(t_i - i_{t_j}) = e^{\frac{-1}{a}|i_{t_i} - i_{t_j}|} \]

The function \( f(t_i - i_{t_j}) \) models the temporal aspect of the similarity of mention activity. The parameter \( a \) controls the rate of decay. Based on empirical analysis by Nugroho, Zhao et al. (2017), we set this to 1320 seconds.

A.2.2.2 Common Action

On Twitter, users can retweet a tweet and consequently re-post it. Users may also reply to tweets with a tweet. If a tweet \( t_i \) is a retweet or reply of another tweet \( t_j \) (or vice versa), or if both \( t_i \) and \( t_j \) are a retweet or reply of the same tweet, then \( act(t_i, t_j) = 1 \). Otherwise, there is no common action between the two tweets, and \( act(t_i, t_j) = 0 \). The presence of a common action (\( act(t_i, t_j) \)) can indicate a similarity in topic between two tweets.

A.2.2.3 Similarity in Content

Tweets which share content are likely to belong to the same topic. The similarity in content of tweet \( t_i \) and tweet \( t_j \) can be measured by a cosine similarity function, \( sim(t_i, t_j) \).

A.2.3 NMijF Process

Using NMijF, the tweet-to-term matrix \( V \) is factorized to the tweet-topic matrix \( W \) (base matrix) and \( W^T \) (coefficient matrix). Simultaneously, the tweet-to-tweet matrix \( A \) is factorized to the same tweet-topic matrix \( W \) (base) and the topic-term matrix \( Y \) (coefficient). From the resulting tweet-topic matrix \( W \), the topic of each tweet can be determined by extracting at the highest value from the vector of each tweet. From the resulting topic-term matrix \( Y \), the keywords of each topic can be learned by sorting the vector for each topic and extracting the top-\( n \) terms.
Appendix A. Supplement for Chapter 3


The NMijF process is used to factorize $V$ and $A$ within the same iterative update process under one cost function (see Figure A.1). This allows both information from $V$ and $A$ to inform the derivation of topics. However, the extreme sparsity of the tweet-to-term matrix $V$ (tweets contain few terms) can heavily penalize the quality of the derived tweet-topic matrix $W$ (Nugroho, Zhao et al., 2017; Nugroho et al., 2015). To reduce the effect of $V$, a parameter $\alpha$ is used to scale the effect of $V$ in every iteration of the process. As per the empirical work of Nugroho, Zhao et al. (2017), we set this to 0.1.

The cost function $I_{NMijF}$ combines the divergences of $V \approx WY$ and $A \approx WW^T$. The NMijF process aims to reduce this divergence and find the minimum of $I_{NMijF}$. After the latent matrices $W$ and $Y$ are initialized, a multiplicative update rule is applied to every element in $W$ and $Y$. These rules ensure that $I_{NMijF}$ is non-increasing in each iterative update. The process continues until the minimum of $I_{NMijF}$ is reached. The resulting tweet-topic matrix $W$ and topic-term $Y$ are then extracted and used to determine the topic of each tweet and the keywords of each topic.
Appendix A. Supplement for Chapter 3

A pairwise preference decision. Participants select the better topic based upon the criteria of coherency, meaningfulness, and interpretability. If required, participants can choose to view three tweets associated with each topic to inform their decision. All tweets shown to participants were anonymized.

Figure A.2. A pairwise preference decision. Participants select the better topic based upon the criteria of coherency, meaningfulness, and interpretability. If required, participants can choose to view three tweets associated with each topic to inform their decision. All tweets shown to participants were anonymized.

A.3 Human Assessment of the Quality of Topical Representations

To compare the relative quality of topics from the 205 and 410 topical representations, we used a pairwise preference task (adapted from Fang et al., 2016a, 2016b). In each trial of the task, participants select the better of two topics (from separate topical representations), each represented by ten keywords and three associated tweets (see Figure A.2). The task allowed us to aggregate participant responses, and discern which topical representation was preferred. In this section, we firstly explain the process for selecting topics to present to participants, then we present the procedure for collecting participant preferences.
A.3.1 Selecting Topics as Stimuli for the Task

In each trial of the pairwise preference task, participants are shown two similar topics (each from a separate topical representation). To generate a list of pairs of similar topics, we examined the topics from both topical representations. For each topic $t_1$, we identified a set of similar topics. Each topic in this set satisfied the following conditions: (1) topics belonged to a different topical representation than $t_1$, AND (2) topics belonged to the same batch as $t_1$, AND (3) topics had three or more keywords in common with $t_1$. From the set of similar topics, the topic ($t_2$) with the most keywords in common was extracted. The pair $t_1$ and $t_2$ were used for the pairwise preference task. If the set of similar topics were empty (e.g., if no topics had three or more keywords in common with $t_1$), $t_1$ was not used in the task.

Importantly, we chose to exclude 2 of 41 batches from consideration. In the 410 topical representation, these two batches contained topics that we identified as non-distinct. Non-distinct topics are topics that are too conceptually similar to be considered different. As the 410 topical representation was inappropriate for these batches, we excluded these from the task.

From the aforementioned process, we identified 445 pairs of similar topics. For each topic, we extracted three tweets belonging to that topic.

A.3.2 Procedure

The task was presented in an online survey, using Qualtrics. After reading an information form and providing informed consent, participants indicated their age and gender. Following this, participants read instructions on the task. These outlined the decision participants would make (selecting a better topic) and the criteria to be used to make the decision (shown in Figure A.3). Participants were informed about Twitter and provided a ‘Twitter Glossary’. As seen in Figure A.4, the glossary contained information on common terms and hashtags. Participants then read over two example trials, and were provided with the solutions for each of these trials.
Appendix A. Supplement for Chapter 3

Figure A.3. Instructions given to participants. Participants were instructed to base their selection of better topics on four criteria: coherency, meaningfulness, interpretability, and associated tweets.

Following this instruction phase, participants completed two practice trials. The trials contained contrived topics, with clear solutions. Participants who answered at least one trial incorrectly were asked to re-attempt the two trials. The study was terminated for participants who incorrectly answered at least one trial question in their re-attempt. The remaining participants proceeded to the topic evaluations.
Participants were given 12 pairs of topics to assess. The 12 pairs of topics were randomly selected from a possible 445, for each participant.² In each trial, participants answered three questions. Firstly, participants indicated their preference for one of two topics (see Figure A.2). Secondly, participants provided reasons for their decision through selecting up to four responses to the question “The topic is better because it:” (response options: (1) has more semantically similar keywords; (2) contains fewer discussions/events; (3) is more specific; (4) has more related tweets (only select this if you viewed tweets)). Thirdly, participants indicated the certainty of their preference (“How certain are you that the topic you have selected is better than the other topic:” (1) not at all certain, (2) only a little certain, (3) reasonably certain, (4) largely certain, and (5) completely certain). Through clicking buttons at the top of the page, participants could revisit a critical summary of the instructions or the Twitter Glossary. Through another button, participants could also view three tweets belonging to each topic. To protect the privacy of users, usernames and hyperlinks were anonymized.

²Before conducting the study, for each of the 445 pairs of topics, one of the two topics was randomly selected to be displayed on the left of the screen (the other was displayed on the right).
A.4 Calculating Proportion of Agreement and Proportion of Specific Agreement

To indicate inter-rater agreement for each theme, we provided two measures: a proportion of agreement and a proportion of specific agreement. These measurements are described at length by Fleiss et al. (2003). For our readers, we provide a brief overview.

A.4.1 Proportion of Agreement

For each theme, we calculated the proportion of occurrences where the two raters involved agreed or disagreed on the classification of tweets. Table A.1 contains the data for the theme of ‘climate change action’ in a 2 x 2 table. All classifications that are not climate change action are grouped into a single category: all others. For example, 11.4% of all inspected tweets were coded by Rater A as climate change action, and coded by Rater B as not climate change action.

The proportion of agreement, \( p_0 \), is the proportion of tweets where both raters agree the tweet either: (1) belongs to the theme in consideration, or (2) does not belong to the theme in consideration. Thus,

\[
p_0 = a + d
\]

For climate change action, the proportion of agreement is

\[
p_0 = 0.300 + 0.545 = 0.845
\]

A.4.2 Proportion of Specific Agreement

If the theme at hand is rare, \( d \) can be large and inflate the proportion of agreement. Thus, it can be useful to provide a measurement that does not depend on \( d \), such as the
Table A.1. Proportions for measuring agreement, both generally (left) and specifically for climate change action (right).

<table>
<thead>
<tr>
<th>General</th>
<th>For climate change action</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Rater A</td>
</tr>
<tr>
<td>Rater B</td>
<td>Given category</td>
</tr>
<tr>
<td></td>
<td>a</td>
</tr>
<tr>
<td>Given category</td>
<td>c</td>
</tr>
<tr>
<td>All others</td>
<td>p₂</td>
</tr>
</tbody>
</table>


The proportion of specific agreement is the conditional probability that a randomly selected rater will assign the theme to a tweet, given that the other rater did. For climate change action, the proportion of specific agreement is

\[ p_s = \frac{2a}{2a + b + c} \]

\[ p_s = \frac{2 \times 0.300}{2 \times 0.300 + 0.041 + 0.114} = 0.795 \]

A.5 References


Appendix A. Supplement for Chapter 3


B.1 Study 1

B.1.1 Preregistration

Study 1 was preregistered using the Open Science Framework (https://osf.io/tc8v6). The research questions, methods, analyses, exclusion criteria, and sample size criteria were specified before data collection. However, the preregistered analysis was impossible to perform for the current sample. Thus, we deviated from the planned analysis in three ways. Where appropriate, we maintained the same analysis decisions that were preregistered.

Firstly, we had preregistered the use of a Comparison Data technique to determine the number of factors to extract from the Q sort data (Ruscio & Roche, 2012). However, we found the algorithm was sensitive to superficial changes in the data structure, such as the ordering of participant data. Thus, we opted to use the alternative approach of examining a scree plot to inform our decision.

Secondly, the preregistered analyses implicitly assumed more than one factor would be extracted from the Q sort data. Within this framework, participants were allocated a segment that corresponded to their highest-loading factor. If we were to follow this process for the current study, only a single segment would be derived, as we extracted only one factor. Logistic regression models could not be built to predict segment membership, as all participants would belong to the same segment. Instead, we divided participants into three segments on the basis of their magnitude and sign: highly-
positive loadings, highly-negative loadings, and neither highly-positive or highly-negative loadings (see main text for more details).

Lastly, the preregistered analysis did not specify any standardisation of the data before constructing regression models. If the preregistered analysis could be followed, it would produce regression weights that depend on the coding of survey scales. Scales with a meaningful score of zero would be difficult to interpret. Thus, we standardised the data before constructing models, by converting each auxiliary variable’s raw score to a z-score. In this instance, a score of zero indicates a mean score.

We preregistered an additional analysis that is not reported in the main text. This is a regression model to predict segment membership based on only mental model characteristics, using the same modelling procedures described in the main text. We omitted the analysis from the main text, as the interpretation is similar to that of the more complex model. For completion, we report the results in Figure B.1 below.

### B.1.2 Derivation of Statements for the Q sort

The Q methodology assumes for any given issue, there exists “a universe of statements” (Stephenson, 1986, p. 44). This universe contains every conversational possibility for an issue—anything anyone could say in any situation or context. This space of conversational possibilities is called a concourse. Ideally, the set of statements used in a Q sort (hereby referred to as a Q-set) should be representative of the concourse. However, it is impossible to physically examine a climate change concourse as it is infinite. Instead, discourses of climate change must be used as an approximation of the concourse.

We derived a Q-set from the data of Andreotta et al. (2019), who explored the climate change discourse of Australian Twitter users during the year 2016. Twitter is a microblogging platform, where users share short posts (i.e., tweets). The discourse was a corpus of 201,506 tweets that contained climate change-specific terms, such as “climate change”, “global warming”, and “#climatechange”. This discourse, like all discourses, does not represent all conversational possibilities, as a minority of Australians contributed to the discourse and it is limited to a single year. In practice, if a reasonable
Figure B.1. Regression coefficients for each mental model characteristic used to predict segment membership. The coefficients (dot) and 95% confidence intervals (error bars) are presented for Acceptors (blue), Fencesitters (yellow), and Sceptics (purple). The coefficients were calculated for the z-scores of each predictor. The grey background highlights when the confidence intervals for a predictor contains zero for all segments. MMS_HUM = human contribution; MMS_CON_S = consequences: societal consequences; MMS_CAU_C = causes: carbon emissions; MMS_CAU_N = causes: natural causes; MMS_MIT_C = mitigation: carbon policies; MMS_CON_P = consequences: personal consequences; MMS_CAU_E = causes: environmental harms; MMS_MIT_G = mitigation: green policies; MMS_MIT_E = mitigation: engineering policies.
Appendix B. Supplement for Chapter 4

approach is used to obtain statements that span the breadth of a discourse, participants
will typically have enough dimensions to express a close approximation of their views
(McKeown & Thomas, 2013). Andreotta et al. inductively identified five themes in
the discourse: climate change action, climate change consequences, conversations on
climate change, climate change denial, and the legitimacy of climate science and climate
change. From each theme, we selected six tweets that best represented the heterogeneity
of the theme at hand, totalling to 30 tweets. The resulting collection was a set of tweets
that both captured the breadth of climate change views in the discourse and could be
simultaneously presented on a computer screen without scrolling.

To derive the Q-set, two members of the research team created sub-groups of
tweets to capture variability within each theme. This inductive process was repeated
until both researchers were satisfied with the sub-groupings. The researchers then
decided on the six tweets that best represent the diversity of each theme, with each
tweet being drawn from a separate sub-group. Tweets that were clear and required “little
tampering” (Brown, 1980, p. 190) were privileged in this process. Once six tweets for
each theme were selected, the tweets were transformed into plain-English statements
which preserved the original sentiment, and where possible, language, of the tweet.

B.1.3 Revisions to the Mental Model Scales

To measure mental models of climate change, we used the four mental model survey
scales validated by Bostrom et al. (2012). The scales gauge perceptions of cause of
climate change, consequence of climate change, and effectiveness of climate change
mitigation. The scales were selected for three reasons. Firstly, the items on the scale
are constructed from a long history of mental model semi-structured interviews and
survey findings (Bostrom et al., 1994; Read et al., 1994; Reynolds et al., 2010). Secondly,
these scales have been tested with a large, multinational sample (Bostrom et al., 2012).
Thirdly, scores from these scales predict policy preference above and beyond general risk
perceptions (Bostrom et al., 2012).
Initially, the scales were developed for samples from Europe and the United States. To ensure the scales adequately captured salient mental model concepts of current day Australians, we piloted the scales for a small Australian sample. In the pilot, participants provided qualitative feedback on each multi-item scale. Additionally, participants completed free listing tasks. Free listing is a qualitative technique from cognitive anthropology, used to elicit elements of cultural domains.\(^1\) More recently, the technique has been adapted to elicit mental model concepts, both in general (Jones et al., 2011), and specific to the case of climate change (Crona et al., 2013; Klein et al., 2014). The method involves asking participants to list all kinds/types/names of \(X\) that they can recall, where \(X\) is the cultural domain of interest. Through asking participants to free list concepts related to the climate change scales (i.e., causes of climate change, consequences of climate change, and effectiveness of mitigative action policies), we can elicit mental model concepts. We can then test if mental model concepts salient within our sample are well-represented within the scales.

B.1.3.1 Methods

Participants Ninety Australian adults were recruited online by Qualtrics panel services. A stratified sampling process was used, whereby the age and gender of the sample were matched to the general population of Australian adults. Participants were excluded from the study if consent was denied or if participants elected to opt-out once informed the study will require several text responses. As the study required substantial qualitative responses from participants, we piloted the study to ensure participants were responding as predicted. From the data, we calculated a minimum time to complete,\(^2\) whereby fast responders were discarded and replaced by the panel services. Likewise, participants who provided clearly irrelevant text responses (e.g., nonsensical sequences of letters, responses entirely unrelated to the question) were replaced.

\(^1\)Weller and Romney (1988) defined a cultural domain as the subject matter of interest. However, others are less lenient when defining cultural domains. For example, Borgatti (1999) claimed cultural domains consist of a set of perceptions that, according to a culture, are all the same type.

\(^2\)Following the recommendations of the panel services, the threshold was calculated by computing the median time to complete of the first 25 responders, than dividing this number by three.
Appendix B. Supplement for Chapter 4

Figure B.2. Participant assignment to occurrence of climate change conditions (grey box). Assignment depended on responses (yellow boxes) on questions (white boxes).

**Design** This study used a between-subjects design, with two factors: 3 (occurrence of climate change) × 2 (possibility of mitigation). Participants were allocated to conditions most congruent to their survey responses. The purpose of these conditions was to provide free list tasks that were most appropriate to participant's beliefs. For example, it makes little sense to ask a participant to provide strategies for climate change mitigation when they believe climate change cannot be mitigated. The occurrence of climate change factor had three levels: climate change is occurring (occurring; \(n = 65\)), climate change could occur (can occur; \(n = 22\)), and climate change cannot occur (cannot occur; \(n = 3\)). Possibility of mitigation had two levels: mitigation is possible (possible; \(n = 80\)), mitigation is not possible (impossible; \(n = 7\)).

**Materials and procedure** Participants began the study by reading the information sheet and providing informed consent. Following this, participants provided demographic information: age, gender, and level of education. Additionally, participants were informed about the requirements of the study (“This study will require you to write out several of your responses. Are you willing to continue with this study?”), and could select to close the study. Those who opted to continue were asked to “in your own words, please describe what climate change is:”. Participants were then asked “according to your own definition of climate change, is climate change currently happening” (response options: yes, maybe, no); participants who responded with “no” were asked an additional question: “according to your own definition of climate change, could climate change ever happen?” (response options: yes, maybe, no). Based on their responses, participants were allocated to one of three occurrence of climate change conditions (shown in Figure B.2).
In the next phase of the study, participants completed free lists. Participants received a practice list (“list three animals”) before completing the lists of interest. Participants in the occurring and could occur conditions completed lists concerning the domain of climate change, whereas those in the cannot occur condition completed lists concerning the domain of scientists who claim climate change is occurring. Participants completed three free lists eliciting: (1) causes of climate change, (2) consequences of climate change, and (3) effective mitigation of climate change. Before administration of the effective mitigation strategies list, participants were asked if society could intervene in the domain at hand (response options: yes, maybe, no). Those who indicated mitigation was possible (i.e., selected ‘yes’ or ‘maybe’) were allocated to the ‘possible’ condition and received a free list eliciting effective mitigative options, whereas those who indicated mitigation was impossible (i.e., selected ‘no’) were allocated to the ‘impossible’ condition and received a free list eliciting reasons for the inability to intervene.

Following the free list phase, participants completed each of the multi-item mental model scales. Participants could also provide feedback on each scale through an open-ended text response.

**B.1.3.2 Results**

As we were interested in comparing the concepts listed by participants with the concepts featured in the mental models scales, we only examined free lists of causes and consequences for participants who believed climate change was occurring or could occur ($n = 87$). With regards to mitigation, we only examined the free lists of participants who believed climate change was occurring or could occur and who believed mitigation of climate change was possible ($n = 80$).

The concepts generated by participants in the free list task were coded with a qualitative process. Participant responses that varied slightly in spelling, construal level, or concept boundaries were coded as listing the same concept. The codebook is available in the online repository provided in the chapter text. For a concept to be salient, it must be occur at a frequency greater than chance level. The chance-level frequency was determined by creating surrogate samples (Efron & Tibshirani, 1994). One thousand
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surrogate samples were created by assuming the same number of participants from the current study listed the same number of unique concepts, but these concepts were selected by participants at random (from the set of concepts provided by participants in the current study). For each sample, the frequency of each concept was computed. From the distributions of these frequencies, a mean frequency and 95% confidence intervals were calculated for each concept, as shown in Figures B.3, B.4, and B.5. Salient concepts will occur at a frequency greater than the frequency derived using the surrogate sampling procedure.

For causes of climate change, eight concepts were listed at a frequency greater than chance level. The three most frequently listed causes were: general pollutions (listed by 28.92% of participants); the use of electricity from coal and oil (22.89% of participants); and the destruction of forests (22.89% of participants). For consequences of climate change, eight concepts were listed more frequently than expected by chance. The three most prevalent consequences of climate change were: higher temperatures (37.35% of participants), higher sea levels (34.94% of participants), and massive species extinctions (20.48% of participants). Lastly, six effective mitigative actions were listed more frequently than chance, the most frequent of which were: stopping or reducing greenhouse gas emissions/use of fossil fuels (40.79% of participants); adopting more renewable sources of energy (27.63% of participants); and reducing pollution or waste (19.74% of participants).

To examine whether collecting more data would have resulted in qualitatively different findings, we tested the saturation of each list. Saturation refers to the point in data collection where additional participants would provide little additional information. Following the advice of Weller et al. (2018), we examined whether the set of salient concepts, rather than all concepts, changed with additional participants. To test this, subsamples (five fewer participants than the sample) of randomly-selected participants were constructed for causes, consequences, and mitigation. Then, for each of these subsamples, the surrogate procedure was used to identify a set of salient concepts. The set of salient concepts from subsamples were compared to the set of salient concepts from the sample. For consequences and mitigation, no new salient concepts were identified.
Figure B.3. Proportion of participants who mention a concept in their list of causes of climate change. Dark bars (gray and black) display proportions of the sample from appropriate conditions. Light grey bars display the mean proportion generated through random sampling in the surrogate sampling process. Error bars indicate 95% confidence intervals of the frequency derived from surrogate samples. Black bars are concepts that are feature on the mental model survey scales. Only the twelve most prominent concepts are shown. Concepts are: (1) pollution, (2) use of electricity from coal and oil, (3) destruction of forests, (4) human activity, (5) fossil fuel burning, (6) carbon dioxide emissions, (7) natural causes/cycles, (8) vehicle use, (9) population growth, (10) greenhouse gas emissions, (11) livestock production, and (12) factories and industry.

for the sample compared to the subsamples. For causes of climate change, we found that one concept was salient in the full sample but not salient in the subsample—population growth. However, as seen in Figure B.3, this concept is a borderline case, whereby the upper bound of the 95% confidence interval is equal to the frequency of the concept up to at least eight decimal places. Given this, we concluded that each list had reached an acceptable level of saturation. Thus, we did not continue data collection beyond what is reported in the methods.

Few of the prevalent concepts listed by participants feature in the mental model scale (see Figures B.3, B.4, and B.5). This is due to a tendency for participants to generate concepts at a more generalised level than the specific drivers, outcomes, or mitigative actions of items from the mental model scales. Thus, we decided to consider additions
Figure B.4. Proportion of participants who mention a concept in their list of consequences of climate change. Dark bars (gray and black) display proportions of the sample from appropriate conditions. Light grey bars display the mean proportion generated through random sampling in the bootstrap process. Error bars indicate 95% confidence intervals of the frequency derived from surrogate samples. Black bars are concepts that are feature on the mental model survey scales. Only the twelve most prominent concepts are shown. Concepts are: (1) higher temperatures, (2) higher sea levels, (3) massive species extinctions, (4) more and longer droughts in many parts of the world, (5) reduction in plant life, (6) ice mass loss, (7) more and larger storms in many parts of the world, (8) flooding, (9) increased human mortality rates, (10) food shortages in many parts of the world, (11) increase in extreme weather, and (12) coastline changes.

To the scale if: (1) the addition corresponds to a salient concept from the free-list task; and (2) the concept is mentioned in the open-ended question for feedback on the mental model scale. For example, despite participants citing high temperatures as a climate change consequence (37.35%), no participant noted its omission in the mental model scale. We assumed this indicated that the general impact of increased temperature is included in the more specific items in the scale (e.g., “disappearance of island nations due to sea level rise”). Only one salient concept was recommended for inclusion into the mental model scale by participants: a non-specific natural cycle or cause (recommended by 12.05% of participants). Some participants recommended including more natural causes, indicating that the sole natural cause on the scale was insufficient (that is, volcanic
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Figure B.5. Proportion of participants who mention a concept in their list of effective mitigation strategies. Dark bars (gray and black) display proportions of the sample from appropriate conditions. Light grey bars display the mean proportion generated through random sampling in the bootstrap process. Error bars indicate 95% confidence intervals of the frequency derived from surrogate samples. Black bars are concepts that are feature on the mental model survey scales. Only the twelve most prominent concepts are shown. Concepts are: (1) reduce or stop emissions of greenhouse gases or fossil fuel use, (2) adopt more renewable energy sources, (3) reduce pollution and waste, (4) plant trees, (5) change lifestyles to reduce consumption, (6) drive less, (7) do not know, (8) change lifestyles to consume less meat, (9) reduce land clearing, (10) adopt electric vehicles, (11) limit population growth, and (12) recycle.

eruptions). Of participants advocating for natural causes of climate change, few mention specific drivers in the free list task, such as solar activity (3.61% of participants), pole shifts (1.20% of participants), magnetic flux (1.20% of participants), miscellaneous geological processes (1.20% of participants) and distance from other stars (1.20% of participants).

B.1.3.3 Conclusion

Participants tended to generate more generalised concepts than those in the mental model scales. Despite this, many items in the scale are either specific examples or inferences of the generalised concepts listed by participants. Only one concept was explicitly recommended by participants for inclusion into the scale: another natural driver
of climate change. However, no specific natural driver was identified as a salient concept. Thus, we added a single item to the causes of climate change scale: “Other natural causes (e.g., fluctuations in the sun, changes in the Earth’s axis, the Earth’s magnetic field, etc.).” This item was added to ensure participants who believed in natural causes for climate change could adequately express their beliefs in the causes scale. We maintained the abstract notion of a ‘natural cause’ listed by participants in both the freelist task and the feedback to the scale, though added exemplars drawn from the peripheral concepts generated by participants.

**B.1.4 Factor Structure of the New Mental Model Scale**

The preregistered analysis proposed to use an algorithm to identify the number of factors to extract for the revised causes of climate change scale (Ruscio & Roche, 2012). According to the algorithm, a four factor structure best explained the observed eigenvalues. However, we found the algorithm was sensitive to initial conditions. Superficial changes in the ordering of data lead to different output. Thus, we resorted to visual heuristics, such as examining the eigenvalues in a scree plot. As shown in Figure B.6, a three factor solution is acceptable. A principal components analysis with a varimax rotation was used to calculate the factor loadings seen in Table B.1. The factor of carbon emissions includes seven causes related to the emissions of carbon dioxide and accounts for 36.11%. Environmental harms includes four items capturing poor environmental practice, and accounts for 13.39% of variance. Lastly, the natural causes factor captures the only two items in the scale unrelated to human activity, accounting for a total of 22.71% of variance.
Figure B.6. Eigenvalues extracted from the thirteen factors of the perceived causes of climate change scale. Dashed line indicates the break in the scree.
### Table B.1. Factor structure of the causes of climate change scale.

<table>
<thead>
<tr>
<th>Item</th>
<th>Mean</th>
<th>Standard error</th>
<th>Factor loadings</th>
<th>Carbon emissions</th>
<th>Environmental harms</th>
<th>Natural causes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population growth</td>
<td>5.34</td>
<td>0.07</td>
<td></td>
<td>0.80</td>
<td>0.08</td>
<td>0.19</td>
</tr>
<tr>
<td>Carbon dioxide emissions</td>
<td>5.40</td>
<td>0.08</td>
<td></td>
<td>0.79</td>
<td>0.39</td>
<td>0.01</td>
</tr>
<tr>
<td>Use of electricity from coal and oil</td>
<td>5.19</td>
<td>0.09</td>
<td></td>
<td>0.77</td>
<td>0.35</td>
<td>-0.03</td>
</tr>
<tr>
<td>People heating and cooling their homes</td>
<td>4.69</td>
<td>0.08</td>
<td></td>
<td>0.76</td>
<td>0.26</td>
<td>0.23</td>
</tr>
<tr>
<td>People driving their cars</td>
<td>4.94</td>
<td>0.07</td>
<td></td>
<td>0.75</td>
<td>0.42</td>
<td>0.06</td>
</tr>
<tr>
<td>Livestock production</td>
<td>4.43</td>
<td>0.08</td>
<td></td>
<td>0.74</td>
<td>0.24</td>
<td>0.02</td>
</tr>
<tr>
<td>Destruction of tropical forests</td>
<td>5.43</td>
<td>0.08</td>
<td></td>
<td>0.67</td>
<td>0.35</td>
<td>0.12</td>
</tr>
<tr>
<td>Nuclear energy</td>
<td>4.12</td>
<td>0.10</td>
<td></td>
<td>0.15</td>
<td>0.87</td>
<td>0.09</td>
</tr>
<tr>
<td>Air pollution from toxic chemicals</td>
<td>5.14</td>
<td>0.08</td>
<td></td>
<td>0.47</td>
<td>0.74</td>
<td>0.06</td>
</tr>
<tr>
<td>The ozone hole in the upper atmosphere</td>
<td>4.78</td>
<td>0.08</td>
<td></td>
<td>0.41</td>
<td>0.71</td>
<td>0.17</td>
</tr>
<tr>
<td>The use of aerosol spray cans</td>
<td>4.39</td>
<td>0.08</td>
<td></td>
<td>0.49</td>
<td>0.64</td>
<td>0.20</td>
</tr>
<tr>
<td>Other natural causes†</td>
<td>4.36</td>
<td>0.08</td>
<td></td>
<td>-0.02</td>
<td>0.09</td>
<td>0.90</td>
</tr>
<tr>
<td>Volcanic eruptions</td>
<td>4.10</td>
<td>0.08</td>
<td></td>
<td>0.23</td>
<td>0.15</td>
<td>0.86</td>
</tr>
</tbody>
</table>

Note. The highest loading for each item is bolded. Items were responded to on a seven point scale, ranging from (1) not a cause at all, to (7) a major cause. †= item was followed by specific examples in parenthesis: “(e.g., fluctuations in the sun, changes in the Earth’s axis, the Earth’s magnetic field)”.  

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B.1.5 Order of Survey Scale Administration

The order of surveys was counterbalanced across participants, using a digram-balanced Latin square design. However, due to a variety of factors (e.g., participants prematurely exiting the study, participants completing before 873 seconds), there is a slight discrepancy in the number of each Latin squares completed (range = 25 to 44).

B.2 Study 2

B.2.1 Belief-Updating Task Stimuli

All belief-updating tasks were preceded by a short explanation demonstrating the meaning of the estimate. For example, when asked about the possible drivers of climate change, participants read: “So, if you think one driver is responsible for most of climate change, enter a high number. If you think one driver is responsible for little of climate change, enter a low number. If you think one driver is responsible for half of climate change, enter 50.” Following this, participants were provided with clarification on the range of estimates, such as: “Please note that the minimum number you can enter is 0%, and the maximum number is 100%. Do not enter a % sign after your estimate.”

The stimuli for each of the three belief-updating tasks that concerned causes of climate change are shown in Tables B.2, B.3, and B.4. The stimuli for the belief-updating task that concerned consequences of climate change are shown in Table B.5.

Only one belief was used in the belief-updating task that concerned effectiveness of mitigation. Participants began the task by reading passages about Australia’s approach to mitigation. The passage read: “In 2015, Australia committed to participating in the Paris Agreement under the United Nations Framework Convention on Climate Change (UNFCCC). Parties to the agreement have agreed to cooperate to keep global temperature increases well below 2 degrees Celsius above pre-industrial levels. Australia has committed to reducing its carbon dioxide emissions by 26-28% of 2005 levels, by the year 2030.”
The passage continued: “To meet their Paris Agreement goals, the Australian government uses an Emissions Reduction Fund. By running projects to reduce emissions, businesses, local councils, state governments, land managers and others can earn Australian carbon credit units (ACCUs). These units can be sold to the Australian Government through a carbon abatement contract, or to other businesses seeking to offset its emissions. For example, a business which plans a project to improve energy efficiency in buildings and industrial facilities by upgrading lights and equipment can earn ACCUs. So far, the government has invested $4.55 billion into the fund.”

The passage concluded with: “A safeguard mechanism applies limits to large emitters. It requires Australia's largest emitters to keep emissions within baseline levels. This is to ensure that emissions reductions purchased by the Government are not offset by significant increases in emissions above business-as-usual levels elsewhere in the economy.”

Participants were then asked to estimate: “Under current policies in place (including the Emissions Reduction Fund), what will be the change in Australia’s carbon dioxide emissions by the year 2030 (compared to 2005 levels)?” Alongside this question were other belief items, specified in the main text.

In the second session, participants are given an estimate from a scientifically respected authority: (adapted from Climate Action Tracker, 2019): “Climate Action Tracker has assessed Australia’s policies. According to their analysis, under current policies, Australia is unlikely to meet their Paris Agreement goal of reducing their carbon dioxide emissions by 26-28% of 2005 levels, by 2030. Australia’s emissions have been increasing since 2014, and the latest quarterly emissions data inventory to December 2018 (published in June 2019) shows continuing increases. Under current policies-including the Emissions Reduction Fund-Australia is predicted to increase their carbon dioxide emissions by 8% of 2005 levels by the year 2030.”
Table B.2. Stimuli for the belief-updating task (anthropogenic climate change beliefs).

<table>
<thead>
<tr>
<th>Belief</th>
<th>Scientific estimate</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caused by humans (e.g., emissions, use of land)</td>
<td>Near 100</td>
<td>(IPCC, 2013, p. 662)</td>
</tr>
<tr>
<td>Caused by nature (e.g., changes in the sun, volcanic eruptions)</td>
<td>Near 0</td>
<td>(IPCC, 2013, p. 662)</td>
</tr>
</tbody>
</table>

*Note.* Wording of the task: “Some possible causes of climate change are human-driven (e.g., emissions, use of land) whereas others are nature-driven (e.g., changes in the sun, volcanic activity). Please provide an estimate of the percentage of human-driven and nature-driven causes of climate change, over the period of 1980 to 2011”.

### B.2.2 Order of Materials Administration

Participants were administered the task as an Internet survey. After providing informed consent and demographic data, participants completed the Q sort task. Following this, participants were provided the trust inventory, the belief-updating task, and the sentiment inventory, in this order. The five belief-updating tasks were separated into four blocks: one block contained the belief-updating task concerning physical mechanisms (Table B.3), immediately followed by the belief-updating task concerning the degree each human activity causes climate change (Table B.4), as the latter contained information about the former; whereas the other three blocks each contained a single belief-updating task. The blocks were counterbalanced across participants using a digram-balanced Latin square design. However, due to survey attrition and the exclusion of extremely early completions, an uneven number of participants completed each Latin square ordering (range = 100 to 112).
Table B.3. Stimuli for the belief-updating task (physical mechanisms of climate change).

<table>
<thead>
<tr>
<th>Belief</th>
<th>Scientific estimate</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Carbon dioxide emissions</td>
<td>50</td>
<td>(IPCC, 2013, Figure SPM.5)</td>
</tr>
<tr>
<td>Halocarbon emissions (can deplete ozone)</td>
<td>5</td>
<td>(IPCC, 2013, Figure SPM.8)</td>
</tr>
<tr>
<td>Changes in solar activity</td>
<td>1</td>
<td>(IPCC, 2013, Figure SPM.10)</td>
</tr>
<tr>
<td>Methane emissions</td>
<td>29</td>
<td>(IPCC, 2013, Figure SPM.7)</td>
</tr>
<tr>
<td>Carbon monoxide emissions</td>
<td>7</td>
<td>(IPCC, 2013, Figure SPM.6)</td>
</tr>
<tr>
<td>Emissions of greenhouse gases</td>
<td>89</td>
<td>(IPCC, 2013, Figure SPM.9)</td>
</tr>
</tbody>
</table>

*Note. Wording of the task: “According to climate scientists, the world’s climate has warmed since the beginning of the industrial era (late 1700s). Scientists have researched many drivers for this warming, some of which are listed in the question below. Please provide an estimate of the percentage of climate change caused by each driver, over the period 1750 to 2011”.*

Table B.4. Stimuli for the belief-updating task (human activities that contribute to climate change).

<table>
<thead>
<tr>
<th>Belief</th>
<th>Scientific estimate</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Road transportation</td>
<td>10</td>
<td>(IPCC, 2014, Figure 1.3(b))</td>
</tr>
<tr>
<td>Other transportation (e.g., plane, ship)</td>
<td>4</td>
<td>(IPCC, 2014, Figure 1.3(b))</td>
</tr>
<tr>
<td>Agriculture, forestry, and other land use (not including fires)</td>
<td>24</td>
<td>(IPCC, 2014, Figure 1.3(b))</td>
</tr>
<tr>
<td>Bushfires, forest fires, peatland fires, etc.</td>
<td>1</td>
<td>(IPCC, 2014, p. 829)</td>
</tr>
<tr>
<td>Electricity use for residential buildings</td>
<td>7</td>
<td>(IPCC, 2014, p. 678)</td>
</tr>
<tr>
<td>Industrial activity (does not include energy production for transport, buildings, forestry, or other land use)</td>
<td>31</td>
<td>(IPCC, 2014, Figure 1.3(b))</td>
</tr>
</tbody>
</table>

*Note. Wording of the task: “According to climate scientists, the world’s climate has warmed since the beginning of the industrial era (late 1700s). This is mostly due to the emissions of greenhouse gases from various activities. Please provide an estimate of the percentage of warming caused by greenhouse gas emissions from the activities below, for the year 2010”.*
### Table B.5. Stimuli for the belief-updating task (consequences of climate change).

<table>
<thead>
<tr>
<th>Belief</th>
<th>Scientific estimate</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hot November days in Brisbane (2014)</td>
<td>20</td>
<td>(King et al., 2015)</td>
</tr>
<tr>
<td>Hot days globally (1901-2005)</td>
<td>75</td>
<td>(Fischer &amp; Knutti, 2015)</td>
</tr>
<tr>
<td>The 2015/16 Tasman Sea marine heatwave event</td>
<td>65</td>
<td>(Oliver et al., 2017)</td>
</tr>
<tr>
<td>Maximum Australian summer temperatures (1976-2005)</td>
<td>50</td>
<td>(Lewis &amp; Karoly, 2013)</td>
</tr>
<tr>
<td>Maximum intensity of heat waves in Australia (2012-2013)</td>
<td>27</td>
<td>(Perkins et al., 2014)</td>
</tr>
<tr>
<td>Heavy rainfall globally (1901-2005)</td>
<td>18</td>
<td>(Fischer &amp; Knutti, 2015)</td>
</tr>
<tr>
<td>Immediate heat stress on reefs in the Coral Sea region, which includes the Great Barrier Reef (2016)</td>
<td>85</td>
<td>(Lewis &amp; Mallela, 2018)</td>
</tr>
<tr>
<td>Average Australian temperature in September (2013)</td>
<td>82</td>
<td>(Lewis &amp; Karoly, 2014)</td>
</tr>
<tr>
<td>Dry air in Australia (2015-2016)</td>
<td>60</td>
<td>(Tett et al., 2018)</td>
</tr>
</tbody>
</table>

*Note.* Wording of the task: “For each event, provide your estimate of how likely it is that this event occurred due to human-driven climate change”.

B.2.3 Replication of Audience Segments

The Q sort data of Study 2 was analysed in an identical manner to Study 1. As per Study 1, the first factor accounted for a large portion of variance (32.78%), as shown in Figure B.7. Thus, following Study 1, we extracted a single factor and divided it into three segments. We used correspondence between the factor scores of Study 1 and Study 2 samples to determine which segments were replicated, as factor scores are used as the basis for qualitative work to synthesise the characteristics of each segment. We found that the factor scores for the segments corresponding to a positive and negative loading onto the factor closely match those of Acceptors (Spearman’s $\rho = 0.96$) and Sceptics (Spearman’s $\rho = 0.96$), respectively (see Table B.6). The replication of Acceptors and Sceptics provides evidence that Fencesitters is replicated too, given Fencesitters are characterised by not being assigned to the Acceptor or Sceptic segment. Thus, the three segments of Study 1 were replicated in Study 2.

B.2.4 Akaike Information Criterion for Mixed-Effects Models

The Akaike Information Criterion (AIC) of mixed-effects models used to analyse the Study 2 data are reported below. Table B.7 shows the AIC for different models used to examine the effects of segment and trust on relative belief update. Table B.8 shows the AIC for each model of relative belief update, when considering segment and type of news. Lastly, Table B.9 presents the AIC of each model used to identify changes in policy support. For convenience, models of policy support are presented again in order of differences in AIC compared to the best fitting model in Table B.10.
Figure B.7. Eigenvalues extracted from the first fifteen factors of the Q sort data. Dashed line indicates the break in the scree.
Table B.6. Factor scores for each statement used in the Q sort, for both Study 1 and Study 2.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Study 1</th>
<th></th>
<th>Study 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acceptor</td>
<td>Sceptic</td>
<td>Acceptor</td>
<td>Sceptic</td>
</tr>
<tr>
<td>1. It is important to vote for leaders who will combat climate change.</td>
<td>4</td>
<td>-4</td>
<td>4</td>
<td>-3</td>
</tr>
<tr>
<td>2. Climate change is a hoax perpetrated by the United Nations.</td>
<td>-4</td>
<td>3</td>
<td>-4</td>
<td>3</td>
</tr>
<tr>
<td>3. Climate change is a threat to the health and safety of our children.</td>
<td>3</td>
<td>-3</td>
<td>3</td>
<td>-4</td>
</tr>
<tr>
<td>4. Scientists should stop falsely claiming that climate change is a settled science.</td>
<td>-2</td>
<td>4</td>
<td>-2</td>
<td>4</td>
</tr>
<tr>
<td>5. They changed the name from “global warming” to “climate change” because the planet isn’t warming.</td>
<td>-2</td>
<td>3</td>
<td>-2</td>
<td>3</td>
</tr>
<tr>
<td>6. The Great Barrier Reef is at risk from climate change.</td>
<td>3</td>
<td>-2</td>
<td>3</td>
<td>-2</td>
</tr>
<tr>
<td>7. Australian agriculture is thriving so climate change can’t be real.</td>
<td>-3</td>
<td>2</td>
<td>-3</td>
<td>2</td>
</tr>
<tr>
<td>8. The concept of global warming was created by and for the Chinese in order to make U.S. manufacturing non-competitive.</td>
<td>-3</td>
<td>2</td>
<td>-3</td>
<td>1</td>
</tr>
</tbody>
</table>
## Table B.6. Factor scores for each statement used in the Q sort, for both Study 1 and Study 2. (continued)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Study 1</th>
<th></th>
<th>Study 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acceptor</td>
<td>Sceptic</td>
<td>Acceptor</td>
<td>Sceptic</td>
</tr>
<tr>
<td>9. Cow farts cause more ‘climate change’ than human activity.</td>
<td>-2</td>
<td>1</td>
<td>-2</td>
<td>2</td>
</tr>
<tr>
<td>10. The threat of climate change is much worse than climate scientists originally thought.</td>
<td>2</td>
<td>-3</td>
<td>1</td>
<td>-3</td>
</tr>
<tr>
<td>11. The increased occurrence of extreme weather events is a clear sign that climate change is real.</td>
<td>2</td>
<td>-2</td>
<td>2</td>
<td>-2</td>
</tr>
<tr>
<td>12. Those who demand climate action are the usual “torch-and-pitchfork” crowd.</td>
<td>-2</td>
<td>2</td>
<td>-2</td>
<td>2</td>
</tr>
<tr>
<td>13. Climate change sceptics ignore basic climate science facts.</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>-2</td>
</tr>
<tr>
<td>14. Through cutting science funding, we damage Australia’s ability to respond to climate change.</td>
<td>1</td>
<td>-2</td>
<td>2</td>
<td>-1</td>
</tr>
<tr>
<td>15. Politicians who refuse to tackle climate change are just as bad as those who deny climate science.</td>
<td>1</td>
<td>-1</td>
<td>1</td>
<td>-2</td>
</tr>
<tr>
<td>16. Australia is experiencing more extreme weather and hotter days due to climate change.</td>
<td>2</td>
<td>-2</td>
<td>2</td>
<td>-1</td>
</tr>
</tbody>
</table>
### Table B.6. Factor scores for each statement used in the Q sort, for both Study 1 and Study 2. (continued)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Study 1</th>
<th></th>
<th>Study 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acceptor</td>
<td>Sceptic</td>
<td>Acceptor</td>
<td>Sceptic</td>
</tr>
<tr>
<td>17. Oil and gas companies could not care less about climate change.</td>
<td>-1</td>
<td>2</td>
<td>-1</td>
<td>2</td>
</tr>
<tr>
<td>18. Climate change policy and renewable energy (e.g., solar power) should</td>
<td>2</td>
<td>-1</td>
<td>2</td>
<td>0</td>
</tr>
<tr>
<td>be a major focus of Australian political elections.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19. Climate change and human burning of fossil fuels are strongly linked.</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>-1</td>
</tr>
<tr>
<td>20. Countries must fulfil their Paris Climate Agreement goals.</td>
<td>-1</td>
<td>1</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>21. Australian politicians need to wake up to the emergency of</td>
<td>0</td>
<td>1</td>
<td>-1</td>
<td>1</td>
</tr>
<tr>
<td>tackling climate change.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>22. Politicians and the mass media are ignorant about the risks of</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>climate change.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>23. People who deny the science of climate change should not hold</td>
<td>0</td>
<td>-1</td>
<td>0</td>
<td>-1</td>
</tr>
<tr>
<td>public office.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>24. No political party can say they have a climate change action plan</td>
<td>-1</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>when they favour coal, oil, and gas companies.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table B.6. Factor scores for each statement used in the Q sort, for both Study 1 and Study 2. (continued)

<table>
<thead>
<tr>
<th>Statement</th>
<th>Study 1</th>
<th>Study 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Acceptor</td>
<td>Sceptic</td>
</tr>
<tr>
<td>25. It is shameful that climate change, the greatest problem of our time, is barely discussed in the media.</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>26. Regardless of who is elected, the reality is that climate change is going to destroy everything.</td>
<td>-1</td>
<td>0</td>
</tr>
<tr>
<td>27. We need to keep coal, oil, and gas in the ground and adopt more renewable energy sources, like solar and wind power.</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>28. Poor people will be impacted the worst by climate change.</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>29. Climate sceptics, with no genuine expertise, cannot know better than climate scientists.</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>30. We must start working together for real solutions on climate change.</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>
Table B.7. Differences in Akaike Information Criterion (AIC) compared to the best fitting model to examine the effects of segment membership and trust on relative belief update.

<table>
<thead>
<tr>
<th>Model</th>
<th>Difference in AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cause</td>
</tr>
<tr>
<td>Intercept only</td>
<td>75.69</td>
</tr>
<tr>
<td>Main effect of segment membership</td>
<td>14.42</td>
</tr>
<tr>
<td>Main effect of trust</td>
<td>23.13</td>
</tr>
<tr>
<td>Main effect of segment membership, main effect of trust</td>
<td>7.16*</td>
</tr>
<tr>
<td>Main effect of segment membership, main effect of trust, interaction between segment membership and trust</td>
<td>0.00**</td>
</tr>
</tbody>
</table>

*Note.  * = difference in AIC compared to best fitting model is less than 10 (considerably worse fit); ** = difference in AIC compared to best fitting model is less than 2 (similar fit); no marker = difference in AIC compared to best fitting model is greater than 10 (substantially worse fit).*
Table B.8. Differences in Akaike Information Criterion (AIC) compared to the best fitting model to examine the effects of segment membership and news type on relative belief update.

<table>
<thead>
<tr>
<th>Model</th>
<th>Difference in AIC</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept only</td>
<td>26.93</td>
<td>2.48*</td>
<td></td>
</tr>
<tr>
<td>Main effect of segment membership</td>
<td>0.84**</td>
<td>0.15**</td>
<td></td>
</tr>
<tr>
<td>Main effect of news type</td>
<td>25.09</td>
<td>1.40**</td>
<td></td>
</tr>
<tr>
<td>Main effect of segment membership, main effect of news type</td>
<td>0.00**</td>
<td>0.00**</td>
<td></td>
</tr>
<tr>
<td>Main effect of segment membership, main effect of news type, interaction between segment membership and news type</td>
<td>3.84*</td>
<td>3.95*</td>
<td></td>
</tr>
</tbody>
</table>

* = difference in AIC compared to best fitting model is less than 10 (considerably worse fit); ** = difference in AIC compared to best fitting model is less than 2 (similar fit); no marker = difference in AIC compared to best fitting model is greater than 10 (substantially worse fit).
## Table B.9

Differences in Akaike Information Criterion (AIC) compared to the best fitting model to examine the effects of segment membership and change in beliefs on change in policy support. Listed in order of increasing model complexity.

<table>
<thead>
<tr>
<th>Model</th>
<th>Difference in AIC</th>
<th>Change in support of the Emissions Reduction Fund</th>
<th>Change in support of Australia's climate policies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept only.</td>
<td>24.17</td>
<td>27.21</td>
<td></td>
</tr>
<tr>
<td>Main effect of S.</td>
<td>19.60</td>
<td>30.31</td>
<td></td>
</tr>
<tr>
<td>Main effect of BC1.</td>
<td>18.07</td>
<td>26.19</td>
<td></td>
</tr>
<tr>
<td>Main effect of BC2.</td>
<td>11.54</td>
<td>4.80*</td>
<td></td>
</tr>
<tr>
<td>Main effect of S and BC1.</td>
<td>13.76</td>
<td>29.31</td>
<td></td>
</tr>
<tr>
<td>Main effect of S and BC2.</td>
<td>8.18*</td>
<td>8.36*</td>
<td></td>
</tr>
<tr>
<td>Main effect of BC1 and BC2.</td>
<td>8.21*</td>
<td>5.79*</td>
<td></td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2.</td>
<td>4.96*</td>
<td>9.34*</td>
<td></td>
</tr>
<tr>
<td>Main effect of S and BC1, Interaction of S with BC1.</td>
<td>15.47</td>
<td>32.08</td>
<td></td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC1.</td>
<td>7.06*</td>
<td>12.41</td>
<td></td>
</tr>
<tr>
<td>Main effect of S and BC2, Interaction of S with BC2.</td>
<td>3.55*</td>
<td>0.00**</td>
<td></td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC2.</td>
<td>0.00**</td>
<td>0.97**</td>
<td></td>
</tr>
<tr>
<td>Main effect of BC1 and BC2, Interaction of BC1 with BC2.</td>
<td>12.93</td>
<td>20.42</td>
<td></td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of BC1 with BC2.</td>
<td>8.76*</td>
<td>23.45</td>
<td></td>
</tr>
</tbody>
</table>
Table B.9. Differences in Akaike Information Criterion compared to the best fitting model to examine the effects of segment membership and change in beliefs on change in policy support. Listed in order of increasing model complexity. *(continued)*

<table>
<thead>
<tr>
<th>Model</th>
<th>Difference in AIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change in support of the Emissions Reduction Fund</td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC1 with BC2.</td>
<td>15.53</td>
</tr>
</tbody>
</table>

*Note.* * = difference in AIC compared to best fitting model is less than 10 (considerably worse fit); ** = difference in AIC compared to best fitting model is less than 2 (similar fit); no marker = difference in AIC compared to best fitting model is greater than 10 (substantially worse fit). S = Segment; BC1 = Change in belief of effectiveness of the Emissions Reduction Fund; BC2 = Change in belief of the likelihood Australia will satisfy its committment to the Paris Agreement.
Table B.10. Differences in Akaike Information Criterion (AIC) compared to the best fitting model to examine the effects of segment membership and change in beliefs on change in policy support. Listed in order of increasing differences in AIC between the model and the best fitting model (for models predicting support of the Emissions Reduction Fund).

<table>
<thead>
<tr>
<th>Model</th>
<th>Change in support of the Emissions Reduciton Fund</th>
<th>Change in support of Australia's climate policies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC2.</td>
<td>0.00***</td>
<td>0.97***</td>
</tr>
<tr>
<td>Main effect of S and BC2, Interaction of S with BC2.</td>
<td>3.55*</td>
<td>0.00***</td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2.</td>
<td>4.96*</td>
<td>9.34*</td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC1.</td>
<td>7.06*</td>
<td>12.41</td>
</tr>
<tr>
<td>Main effect of S and BC2.</td>
<td>8.18*</td>
<td>8.36*</td>
</tr>
<tr>
<td>Main effect of BC1 and BC2.</td>
<td>8.21*</td>
<td>5.79*</td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of BC1 with BC2.</td>
<td>8.76*</td>
<td>23.45</td>
</tr>
<tr>
<td>Main effect of BC2.</td>
<td>11.54</td>
<td>4.80*</td>
</tr>
<tr>
<td>Main effect of BC1 and BC2, Interaction of BC1 with BC2.</td>
<td>12.93</td>
<td>20.42</td>
</tr>
<tr>
<td>Main effect of S and BC1.</td>
<td>13.76</td>
<td>29.31</td>
</tr>
<tr>
<td>Main effect of S and BC1, Interaction of S with BC1.</td>
<td>15.47</td>
<td>32.08</td>
</tr>
<tr>
<td>Main effect of S, BC1, and BC2, Interaction of S with BC1 with BC2.</td>
<td>15.53</td>
<td>24.69</td>
</tr>
<tr>
<td>Main effect of BC1.</td>
<td>18.07</td>
<td>26.19</td>
</tr>
</tbody>
</table>
Table B.10. Differences in Akaike Information Criterion compared to the best fitting model to examine the effects of segment membership and change in beliefs on change in policy support. Listed in order of increasing differences in Akaike Information Criterion between the model and the best fitting model (for models predicting support of the Emissions Reduction Fund). *(continued)*

<table>
<thead>
<tr>
<th>Model</th>
<th>Difference in AIC</th>
<th>Change in support of</th>
<th>Change in support of</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>the Emissions Fund</td>
<td>Australia's climate</td>
</tr>
<tr>
<td>Main effect of S.</td>
<td>19.60</td>
<td>30.31</td>
<td></td>
</tr>
<tr>
<td>Intercept only.</td>
<td>24.17</td>
<td>27.21</td>
<td></td>
</tr>
</tbody>
</table>

*Note.* * *= difference in AIC compared to best fitting model is less than 10 (considerably worse fit); ** *= difference in AIC compared to best fitting model is less than 2 (similar fit); no marker = difference in AIC compared to best fitting model is greater than 10 (substantially worse fit). S = Segment; BC1 = Change in belief of effectiveness of the Emissions Reduction Fund; BC2 = Change in belief of the likelihood Australia will satisfy its commitment to the Paris Agreement.
B.3 References


Appendix B. Supplement for Chapter 4


