Technische Universiteit Delft

The Power of Trust

How patterns of trust in flood information influence the intention to take flood adaptation measures

E.M. Arts

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by

E.M. Arts

to obtain the degree of Master of Science
at the Delft University of Technology,
to be defended publicly on Tuesday August 26, 2025 at 10:45 AM.

Student number:	4780396	
Project duration:	February 17, 2025 – August 26, 2025	
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This thesis uses survey data collected within the European Research Council (ERC) under the European Union’s Horizon 2020 Research and Innovation Program (grant agreement number: 758014)

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TU Delft

Preface

During my bachelor studies at TU Delft, I had already developed a keen interest in both data analysis and climate change. I had this urge to understand how and why people behave in certain ways regarding a changing climate. These viewpoints might differ to what I and many other students at TU Delft think. We live in a bubble of pro-climate resilience, and I wanted to understand how people outside this bubble experience and protect themselves against climate change. This interest was also visible in my bachelor thesis on the topic of the perspectives of people on open climate data to challenge disinformation on climate change.

At the beginning of my master studies Engineering and Policy Analysis, I developed a strong liking for the course Spatial Data Science. The ability to visualise and have insight on data using maps was a new concept to me, and soon I knew I wanted to use elements from this course for my thesis. When I saw the project of Tatiana and Thorid on the Graduation Portal, I knew I could combine both spatial data elements and my interest regarding people's behaviours in climate change adaptation. Hence, I started my thesis on the topic of trust in flood information and its influence on individual flood adaptation measures.

I chose to combine my thesis with training for an Ironman 70.3. Combining this with my thesis was more doable than I thought it would be, as good planning and organising got me a long way. This was the perfect way to balance the study load, and I would not have done it another way. I enjoyed combing my thesis with training for a half distance triathlon.

The smooth thesis process was possible due to the great supervision of my two supervisors, Tatiana and Nazli, and the corresponding PhD student, Thorid. I would like to thank Tatiana Filatova for the support and communication as my first supervisor during my thesis, but also during my capita selecta. I greatly appreciate the fact that she thought along with me when I was still missing 2.5 ECTS, and therefore provided me with a very interesting project on climate vulnerability. This support was also visible during the thesis process, as I felt comfortable enough to ask her for feedback any time and I could always bring up any issues if there were some. Furthermore, I would like to thank Nazli Aydin for being my second supervisor on this topic. I always appreciated her advice and insights on data analysis techniques, particularly for clustering the data. Moreover, I would like to thank Thorid Wagenblast as well. Not only could I share my triathlon passion with her, but I could also always ask her for advice on both my data-analysis techniques and my thesis writing.

I enjoyed researching this topic and I hope this thesis can contribute to ongoing research in this field. I have a lot of gratitude for everyone who supported me during the thesis journey.

E.M. Arts
Delft, July 2025

Executive Summary

Trust is key to the success of climate adaptation strategies. In particular, trust in organisations, whose flood adaptations policies are impacting vulnerable communities, is important for individual climate adaptation. Communication efforts in those policies are important to raise the level of concern on flood risks and to increase the level of support for flood adaptation. However, the level of trust in different information sources varies and without trust in the source, policy and information could be disregarded.

Notably, human elements such as trust have often been ignored in adaptation research and climate resilience policies. Research addresses the differences in trust in information from various entities, but the impact of trust in different information sources remains unknown. Moreover, when assessing the influence of trust, the kind of climate adaptive measures is often not defined.

This gap is assessed by analysing trust in flood information from various sources and its influence on private flood adaptation strategies. The private flood adaptation measures are categorised into incremental adaptation and transformational adaptation measures. This thesis provides insight into the effectiveness of both local and national policies concerning incremental and transformational adaptation measures, in particular if those policies pertain to the communication on flood risks and flood adaptation. It is important to note trust differences between areas and assessing the need for communication strategies to be tailored to specific areas. Furthermore, the influence of trust can be determined to assess if raising trust in information is needed to increase the implementation of either incremental or transformational flood adaptation strategies.

The analysis for this thesis is based on a case study on three areas in the United Kingdom: Norfolk/-Suffolk coast, Somerset and Greater London. By using quantitative data analysis methods, an insight is given into trust levels. Furthermore, the influence of trust on adaptation strategies is assessed whilst taking other motivational factors into account. The descriptive and regression results show that rural areas tend to have less trust in flood information than urban areas, except if the flood information originates from family and friends. Moreover, in all areas social media and the prime minister are deemed as the most untrustworthy regarding flood information, whereas friends and family are most trusted regarding flood information.

However, trust in sources of information is not always associated with the intent to take flood adaptation measures. An increase in trust in flood information from family and friends and social media is associated with an increase in the likeliness of taking incremental adaptation measures. Moreover, an increase in trust in the prime minister and social media is associated with an increase in the likeliness of planning to take incremental measures in the near future. Nevertheless, an increase in trust in a government representative shows a different trend, as it is associated with a decrease of the likeliness of planning to take incremental measures in the near future.

The clustering method identified five distinct groups of respondents within the survey data based on trust in flood information, hazard experience and socio-demographics. The differences amongst these clusters showed the importance of local policies, as there are substantial differences in trust levels, flood adaptation and economic welfare between the regions. Depending on the area, policies should either cultivate trust or provide financial support to increase the implementation of private flood adaptation measures, or both.

While the findings provide valuable insights, several limitations need to be mentioned. This study mostly considered incremental measures as transformational measures were not implemented by the respondents. A lack of transformational adaptation policies and measures creates difficulty in including these type of measures in research. If possible, transformational adaptation measures should be included in future research. Moreover, it is advised to conduct longitudinal studies to further establish the relationships between trust and the intent to take flood adaptation measures. Furthermore, the results are based on the UK dataset and are therefore not generalisable. However, the methods and framework are transferable if the data are properly cleaned and similar variables are used.

To conclude, trust in information on floods and flood adaptation is context- and area-specific and its influence depends on the type of adaptation measure. National and regional flood adaptation policies concerning communication on flood risks and adaptation have to consider the possibility of lower efficacy due to low trust in the policy or in information sources. Acknowledging the power of trust in flood information sources is fundamental for designing successful flood adaptation policies.

Contents

1 Introduction

Global temperatures are rising. The speed and intensity of climate change are increasing to levels that have never been experienced before (van der Plank, 2024). Flooding and other natural hazards are becoming more frequent and extreme (IPCC, 2021). Flood-prone areas experience more extreme sea level events, rainfall or river flow than ever before (IPCC, 2021). These increasing pressures lead to new and greater adaptation challenges for both governments and local communities (Sayers et al., 2022).

There is a greater recognition for the necessity of climate adaptation measures within policy frameworks (Bonfanti et al., 2024). However, a fully adapted and resilient country is not achievable purely with actions from the government. Climate change is context- and location-specific, hence action from the entire society is crucial (DEFRA, 2023; Ministry of Housing et al., 2022). Residents and stakeholders residing in flood-prone areas are expected to support government strategies and contribute to risk management processes, but engaging them in flood adaptation strategies and receiving their support in this process remains an issue (Nye et al., 2011). Locals express concerns about the integration of their interest in flood adaptation strategies, particularly when adaptation disrupts the status quo or when adaptation requires the relocation of residents (van der Plank, 2024).

Adaptation is any adjusting done to increase the capability to respond to an external event and should give communities a greater ability to deal with uncertainties and unpredictability (Carmen et al., 2022; IPCC, 2007). Flood adaptation is needed in both public and private spaces to address the risk of floods (Uittenbroek et al., 2022). In turn this also implies that, next to government and company initiatives, individuals play an important role in successful adaptation to climate change (IPCC, 2022).

Researchers have stated that large scale interventions against climate change are necessary but often not implemented in reality (Suckall et al., 2019). Large scale interventions often change lives and livelihoods, making them very unpopular as they disrupt the status quo (Pot et al., 2024). These type of adaptation strategies are often categorised as transformational adaptation strategies. Whereas transformational adaptation measures radically change society, incremental adaptation maintain systems and consider minor changes in livelihoods (IPCC, 2022; Kates et al., 2012). Incremental adaptation is often supported by existing structures and easier to implement (Sayers et al., 2022). However, incremental adaptation is often not sufficient enough to combat climate change impacts.

1.1. Problem statement

The adaptation to climate change is not happening at the speed and magnitude required to measure up to the climate resilience needed against the increasing climate risks (van Valkengoed & Steg, 2019). As mainly governments have taken responsibility of assuring the implementation of measures (Mees, 2017), more must be done to engage private stakeholders to adapt. Moreover, governments have restricted capacity when it comes down to fully protecting citizens against floods (Klein et al., 2017). It is of utmost importance that households also take action themselves to adapt to flood risks.

Governance processes need to include much greater community involvement if authorities want to reduce the risk of encountering resistance against climate adaptation policies (Clarke & Murphy, 2023). Households often willingly take small adaptation efforts, but are more reluctant to proactive and larger adaptations (Porter et al., 2014). Long-term household adaptations are not likely to happen autonomously. Transformational adaptation measures take more time and investment, thus also need more incentives.

Trust plays an important role when related to the success of government-driven climate change implementation and adaptation strategies (Bonfanti et al., 2024). Trust may enhance adaptation measures (Adger, 2003). However, mutual trust between different stakeholders, such as residents and institutions, is not always observable regarding flood adaptation strategies (van der Plank, 2024). Furthermore, it is also possible to over-trust government entities or policies regarding adaptation measures (Smith & Mayer, 2018). When this happens, people trust other entities too much in taking adaptive measures, and therefore people do not implement any private adaptation measures themselves.

The role of trust in the intention of implementing different type of adaptation strategies remains unknown. It is therefore important to analyse what trust does to the intention of taking adaptation measures, specifically assessing if trust levels differentiate between various type of flood adaptation measures. This is important to analyse in research, as the inclusion of human elements and their influence on climate change adaptation remains neglected (Birchall & Kehler, 2023). Moreover, actor perceptions such as trust have also been neglected in designing policies (Kehler & Birchall, 2021).

In this research, trust is defined as trust in information as risk communication and information improves people's motivation to take preventive measure and to be ready for emergency cases (Hagemeier-Klose & Wagner, 2009). When there is high uncertainty and low knowledge, people are reliant on information provided by flood risk information sources (Paton, 2008). It is essential when receiving information on risks and adaptive measures, to trust the source (Hagen et al., 2016). However, trust in different sources varies, hence it is essential to assess which sources are most trusted by people to be able to successfully implement adaptation strategies (Cologna & Siegrist, 2020). This thesis therefore analyses the relationship between trust in information on floods and flood adaptation and the intention to take different flood adaptation strategies by using a case study method on three areas in United Kingdom: Norfolk/Suffolk coast, Somerset and Greater London. This leads to the following research question:

How does trust in information on floods and flood adaptation influence the intention to take private flood adaptation measures in flood-prone areas in the United Kingdom?

The objective of this thesis is to analyse the influence of trust in information on floods and flood adaptation on private adaptation strategies to address the effectiveness of current policy practices. To achieve this objective, quantitative data analysis methods are used based on a case study. A case study is used to explain or explore complex issues in a real-life setting (Yin, 2009). This case study generates insights into flood policy application within England in specific socio-economic, environmental and policy contexts (Hollweck, 2016).

Trust is vital for the acceptance of public policies (Cologna & Siegrist, 2020). Citizens with higher trust in public institutions are likely to support policies more that result in significant change (Myatt & Lester, 2003). Furthermore, there is a need to promote trust at community and institutional levels for the development of useful adaptation policies and to determine effective decision-making processes in the context of climate change (Bonfanti et al., 2024). However, trusting institutions too much in terms of taking flood adaptation measures could lead to inaction on private flood adaptation. The insight on the influence of trust in information on floods and flood adaptation on private flood adaptation is therefore important to give advice on current flood adaptation strategies and policy frameworks in the UK. To achieve full climate resilience and to be prepared for frequent flood events, all stakeholders must be ready to prevent damages and to avoid the negative influences of floods on livelihoods.

1.2. EPA relevance

This thesis is written for the Engineering and Policy Analysis (EPA) master. The EPA master focuses on model-based and data-driven decision-making with respect to international societal grand challenges. This thesis must therefore assess the quality of decision-making in societal challenges, considering the socio-economic and political context in which these challenges reside.

Climate change is a grand societal challenge from which the consequences are felt all around the world. With rising global temperatures, flooding events and coastal erosion are becoming more frequent. Numerous stakeholders are involved in applying flood adaptation strategies, from private households to public governmental bodies. Achieving full-system flood resilience necessitates all individual stakeholders to engage and cooperate in adapting to floods. Flood adaptation policies must therefore consider the complexity of different stakeholders in a multi-actor perspective to assess the quality of their decision-making and strategies.

The objective of this thesis is to analyse the influence of trust in flood information on different flood adaptation strategies for policy-oriented advice. This thesis aims to inform decision-makers on the role trust plays in adapting to floods and its significance when designing communication-oriented policies. It is essential to adjust policies to cultivate trust and to assess the effectiveness of current flood communication strategies. This thesis focuses on flood adaptation in the United Kingdom as a case study.

The methods used for this thesis are data-driven methods based on the material from the course EPA122A Spatial Data Science. Methods such as descriptives, regression and clustering analysis are used to assess relationships between variables and to visualise and group variables on maps based on the characteristics of the survey data from the respondents. As a result, area-specific policy advice can be given on the UK's flood adaptation strategies, with the potential to improve the effectiveness of the strategies.

1.3. Thesis structure

The thesis has the following structure. In the next chapter, a literature review is performed to assess existing studies and definitions and to establish the theoretical framework for this research. Then in chapter 3, a case study description is given on the three regions in the United Kingdom containing information on national flood policies and strategies, local flood characteristics and local flood management policies. Chapter 4 then discusses the data preparation, research approach and method limitations for each sub-question. This is followed by the results with relevant discussions and limitations in chapters 5, 6 and 7. The thesis concludes in chapter 8 with the general discussion and future recommendations.

2

Literature Review

Following the introduction, a literature review is done to identify previous research, important concepts and theories for further analysis. The literature review is based on specified searches in the databases Scopus and Google Scholar. The key terms used for the literature search are stated in Appendix A. Furthermore, the review is based on sources that were already given by my supervisor, the Ph.D. student on this topic and contacts that have an expertise on this topic. After the initial search, the Backward Snowballing method has been applied to further identify relevant sources (Wohlin, 2014). After establishing the existing studies and frameworks, a conceptual model is created and sub-questions are defined.

2.1. Definitions

Households play a crucial role in successful climate adaptation (van Valkengoed & Steg, 2019). To design effective approaches to motivate household adaptation behaviour, insight is needed in factors that influence that behaviour. Many studies have been done to research the different factors influencing adaptive behaviour. Trust was amongst the thirteen factors van Valkengoed and Steg (2019) determined as a motivating influence on adaptation behaviour. In this thesis, trust has been chosen to be analysed as a motivational factor for flood adaptive behaviour.

Individual behavioural climate adaptation requires trusting others to do the same (Smith & Mayer, 2018). However, many studies often assess and define trust differently (van Valkengoed & Steg, 2019). Moreover, different dimensions of trust can be identified, such as social trust and trust in institutions (Khodyakov, 2007; Smith & Mayer, 2018). Nevertheless, all definitions mainly converge to the notion that trust involves other people and institutions acting in a mutually beneficial way according to broadly defined social norms (Smith & Mayer, 2018).

The discrepancy when assessing trust is not only seen in the definitions of trust. The level of trust can also differ with respect to certain entities. Examples of such entities are local government officials, national government representatives, first responders, and relatives (Aldrich & Meyer, 2015).

Moreover, it is important to note that trust is conceptually related to knowledge (Kellens et al., 2013). Without trust in information from a certain source, any information or policy from that source is potentially disregarded (Hagen et al., 2016). This supports the view that trust influences the degree of success of climate change policies and the willingness of people to adjust to climate change (Hagen et al., 2016).

Trust is specifically crucial to organisations and entities whose risk management policies impact communities to create social cooperation (Cvetkovich & Lofstedt, 1999). In this thesis, trust is therefore defined as trust in information from different entities. In particular, more emphasis is placed on the role of trust in flood information from different sources and its influence and flood adaptation behaviour.

Incremental vs Transformational adaptation

As briefly mentioned in chapter 1, this thesis considers two different types of flood adaptation strategies: transformational and incremental flood adaptation strategies.

Incremental adaptation

Incremental adaptation maintains existing systems and involves minor changes in public, private and institutional approaches (IPCC, 2022). Incremental adaptation often has high public visibility and is easy to demonstrate to residents (Novalia & Malekpour, 2020). Furthermore, incremental changes are supported by existing government structures (Sayers et al., 2022). An example of incremental flood adaptation is the installation of higher flood barriers or elevating houses. However, incremental adaptation may be insufficient to increase resilience against floods in some situations. Therefore, fundamental systems could remain vulnerable (Clarke & Murphy, 2023).

Transformational adaptation

Transformational adaptation measures encompass making radical changes in society by massively expanding current practices, introducing new measures or shifting the geographic locations of activities (Kates et al., 2012). Transformational adaptation disrupts the status quo, thus remains unpopular to implement. Other issues are costs, low social acceptance and infrastructural lock-ins (Pot et al., 2024). It includes institutional reforms or cultural changes. Transformational adaptation strategies often have a long-term impact on or alter social-ecological systems (Kates et al., 2012; O'Brien, 2012). An example of a transformational flood adaptation strategy is the relocation of communities (Sayers et al., 2022).

Often, government led initiatives lead to transformational adaptation (Kates et al., 2012; O'Brien, 2012). On a local level, little to no guidance is offered when considering transformational change or how this would be sustained when it is required (Sayers et al., 2022). This absence of clarity seen in local strategies and the uncertainty in the climate are often excuses to focus more on short-term adaptation measures. Nevertheless, transformational adaptation can also be driven by individual actions. When individuals independently take innovative actions or show innovative behaviour, it could lead to changes that impact an entire natural system and therefore lead to transformational adaptation (Wilson et al., 2020).

2.2. Existing studies

Several meta-analyses have been conducted to look into the relationship between motivational factors and climate adaptive behaviour. Two meta-analysis studies are highlighted in this section. Both studies show varying results on the influence of trust on climate adaptive behaviour.

The meta-analyses from van Valkengoed and Steg (2019) examine how 13 different motivational factors relate to adaptive behaviour. The comprehensive overview of different motivational factors suggests different results regarding trust. On the one hand, trust in government measures is not significantly correlated with adaptive behaviour. On the other hand, stronger trust in the government itself is correlated with more adaptive behaviour. This study suggests that the defined type of trust might influence the effect size of the variable on adaptive behaviour. This establishes the importance of defining trust well. In this study it was also noted that not much is known on how different motivational factors are linked to each other and collectively lead to adaptation (van Valkengoed & Steg, 2019). Most studies on adaptation behaviour consider a limited number of variables.

The research by Bonfanti et al. (2024) also performed a review on articles focussed on the trust dynamics in the Climate Change Adaptation Cycle. The review concludes that community, institutional and scientific-technological trust do facilitate climate change adaptation in communities and serve as an important component in climate change decision-making. Furthermore, trust contributes to the support of initiatives for climate change adaptation (Choon et al., 2019). In addition, trust arose as one of the most relevant factors affecting public acceptance regarding climate change adaptation measures (Le et al., 2022). There is a need to cultivate trust at both community and institutional levels to develop effective adaptation strategies and to shape decision-making in the climate change context (Bonfanti et al., 2024). However, the study by Bonfanti et al. (2024) also mentioned the challenge imposed by differences in definition of and the assessment of trust.

These mixed outcomes suggest further research into trust on climate adaptive behaviour. When doing so, defining trust is of utmost importance for the interpretation of results. It is apparent that varying definitions and aspects of trust pose challenges in assessing the influence of this motivational factor on climate adaptive behaviour. Therefore, the following sections specify different studies done on different aspects of trust to refine the purpose of this thesis. The following aspects are discussed: individual trust, trust relative to different entities, trust in flood information and trust and adaptation measures.

Individual trust

This thesis considers private flood adaptation measures. As individuals each have different needs and different levels of trust, it is important to assess trust on an individual level. The following studies assess trust from individuals.

The case study by Ekoh et al. (2023) explores climate migration as a flood adaptation strategy by assessing future mobility intentions. A key insight from this study is that individuals are not open to government aided relocation as a result of low trust. Policy makers therefore must identify and respect the needs of individuals to build this trust. Moreover, active participation of concerned individuals should be encouraged and mandated in decision-making to ensure just and proper outcomes, and to build trust.

The importance of individual trust is also apparent when considering the consequences of losing trust between different parties. The study by Clarke and Murphy (2023), on place-based values and trust in governance when adapting, concludes that when trust between different parties is lost due to poor governance the negative consequences are still noticeable long after the initial adaptation efforts. Governance processes need to incorporate more public involvement to avoid encountering resistance to adaptation. If trust has already been lost, repairing it is essential to avoid unnecessary and costly adaptation. It is therefore essential to consider individual trust in both government institutions and other entities regarding climate change and climate adaptive behaviour.

Many studies concern individual trust in government or governmental institutions. The research on managed realignment policy by Bax et al. (2025) also mentions that relying on government is very important for complex adaptation policies. People are often not able to fully inform themselves about the risks of floods and effects of adaptation. They need to be able to trust government's information and capacity to make well-informed decisions. Governments can create a feeling of trustworthiness when providing transparent and fair information (Kaasa & Andriani, 2022).

In addition, the study by Bax et al. (2025) found that there is a positive association between trust in government institutions and support for MR policy. Furthermore, the results from the study mention that the mistrust of the government may be attributed to the perception that government's do not prioritise the best interests of the communities. This divide is caused by the difference of what people expect from the government and the interventions themselves, and actual government actions.

The research from Smith and Mayer (2018) has also found that individual trust has a positive effect on climate adaptive behaviours and creates an increased support for climate change policies. When people have high institutional trust, especially in governmental institutions, citizens become accepting of increased risks and believe that the institutions will take necessary actions to protect them (Smith & Mayer, 2018). Another interesting result was that people residing in nations with high levels of trust are far more inclined to support climate policy.

Nevertheless, the study by Smith and Mayer (2018) also concludes that trust may behave in a non-linear fashion and that it is not clear if promoting trust can lead to a more social and political response to climate change. Moreover, this study is one of few studies that mentions the possibility of over-trust. Over-trust can lead to less adaptive behaviour.

The aforementioned studies conclude that individual trust has an influence on adaptation measures. However, the studies show that it is essential to address the possibility of different trust levels when considering different entities. Many studies consider governmental or institutional trust, however, it is also important to consider trust in other entities. Notably, it is unclear if trust behaves in a non-linear fashion and what role over-trust plays in climate adaptive behaviour. This thesis addresses the gap by analysing the variations of trust levels in different entities and their influence on adaptive behaviour.

Trust relative to different entities

Governmental trust is often assessed, but it is important to look at the level of trust with respect to different entities. Cologna and Siegrist (2020) suggest that determining which experts are most trusted by people to offer information and to act on climate change is crucial as these experts possess to capacity to influence adaptation behaviour. Successful climate change adaptation is dependent on people's trust in experts. This study found that trust in institutions and trust in industry are weakly associated with climate-friendly behaviour, whereas trust in environmental groups and scientists correlate strong with climate-friendly behaviours.

Moreover, the study by Smith and Mayer (2018) outlines three different dimensions of trust. These three dimensions are social trust, particular trust and trust in institutions. Results from this study show that the type of trust matters when assessing the influence on trust on risk perception, and in turn the risk perception's effect on climate policy. Results showed that for example, social trust is a more influential and reliable predictor than institutional trust.

Often, research only takes governmental institutions or climate experts into account, rather than including more accessible sources of information such as mainstream media outlets or acquaintances. Whereas previous literature notes that there are perceived differences in trust levels when regarding different entities, it does not compare trust levels between a wide range of entities and their influence on private adaptation. This thesis therefore outlines the differences in trust in a variety of entities, in particular the information they provide on climate risks and adaptation.

Trust in flood information

The study by van Valkengoed and Steg (2019) concluded that offering information on adaptive measures could be essential to motivate people to protect themselves against the consequences and risks of climate change. Deliberate conversations and communication with individuals on their responsibilities regarding climate adaptation may be crucial for effective risk management strategies. For this reason, previous literature on the importance of trust in information is outlined in this section.

When receiving information on risks and adaptive measures, trusting the source is essential. This is corroborated by the results from Hagen et al. (2016). This study exhibits results from a multi-country study focussed on public perceptions on climate change and adaptation policies. Results from this study show significant results between trust in information and public's support for mitigation policies. In addition, information from environmental organisations is the strongest predictor for support for mitigation policies. The more trust there is in information from environmental organisations, the more people support mitigation policies. The study concludes that communication efforts can raise the level of concern and can increase the level of support for mitigation and adaptation policies.

According to Hagen et al. (2016), trust in organisations whose polices impact communities is crucial to reduce uncertainty and create community resilience. Moreover, it is not enough to provide all individuals the same message about risks as they all perceive the message differently and act on it differently (Kellens et al., 2013; Martens et al., 2009). More research must be done on individual's information preferences (Lindell & Hwang, 2008).

The importance of information and communication in policies is clear, however, the levels of trust regarding that information and the different entities, where the information originates from, remains unknown. Previous research stated that individuals do not perceive information the same way, hence more research must be done regarding information preferences. This thesis aims to fill that gap, by comparing trust levels in information from various sources. Moreover, this study determines what kind of influence trust in information from different entities has on private adaptation behaviour.

Trust and adaptation measures

Not only is there a difference in trust levels in different trustees, but also is there a difference in the types of adaptation behaviour when regarding trust (Cologna & Siegrist, 2020; Paul et al., 2016). Research by Paul et al. (2016) shows that trust has different influences on different types of adaptation strategies, such as public activities and private household adaptation. However, it is unclear what role trust plays when defining adaptation as either incremental or transformational adaptation.

When taking previous literature and the knowledge gaps identified in each section into account, the following main gap can be identified. Trust has been researched often, but previous studies neglect to identify the importance of considering different trust levels regarding a wider variety of entities. Moreover, it remains unknown what type of influence trust in information from different entities has and what kind of influence trust has on different adaptation measures. Therefore, this thesis aims to identify the influential differences of the level of trust in information on floods and flood adaptation on the intention to take either incremental or transformational flood adaptation strategies. To assess this gap, a combined theoretical framework in section 2.3 has been created to be able to combine both trust and other motivational factors in analysing flood adaptive behaviour.

2.3. Theoretical Framework

Two theoretical models are used in this thesis: the Risk Information Seeking and Processing (RISP) Model and the Protection Motivation Theory (PMT). The RISP model by Griffin et al. (1999) focusses on characteristics of individuals that might alter the manner of seeking and processing information. The model contains seven factors that affect the degree to which an individual will seek out information and the time and effort a person spends on analysing risk information critically. The seven factors are individual characteristics, perceived hazard characteristics, affective responses to risk, social pressures to possess relevant information, information sufficiency, the personal capacity to learn and beliefs about the usefulness of information from different channels.

The model was initially developed to understand how individuals respond to health risks. RISP proposes that researchers and practitioners must understand the underlying factors of the relationship between the information or message characteristics and the audience's processing motivations to make sense of their response to that relevant information in terms of preventive or adaptive behaviour. The output from the RISP model, the information seeking and processing behaviour, can also serve as an antecedent to the Theory of Planned Behaviour Model (TPB). This is also suggested in Figure 2 by Griffin et al. (1999). For this thesis, the RISP model serves as an antecedent to the PMT framework.

The PMT framework is widely used in climate adaptation research and is mainly focussed on flood events and flood adaptation. The PMT framework is used to determine what motivates households' adaptation decisions and what impedes them (Noll et al., 2021). It explains which factors have an influence on precautionary damage prevention by residents in flood-prone areas (Grothmann & Reusswig, 2006). There are two main features of the model. The first feature is threat appraisal, how one assesses the probability of a threat and damage potential if one does not change his or her behaviour. The second feature is coping appraisal, a person's ability to cope with the threat if harmed.

Threat appraisal has three subcomponents, perceived probability, perceived severity and fear. Perceived probability is the individual's expectation of being vulnerable to the threat, whereas perceived severity is the assumption a person makes of how damaging the threat is. Fear is an indirect component and influences the perceived severity of the threat.

Coping appraisal also has three subcomponents: perceived response efficacy, perceived self-efficacy and perceived response costs. Response efficacy relates to how effective protective actions would be according to the person. Furthermore, self-efficacy is how the person's ability to adapt to the hazard is perceived. The last component, perceived response costs, is the assumed cost of taking preventive action in terms of money and time.

The work by Noll et al. (2021) extends the original standard framework of PMT by Grothmann and Reusswig (2006), by adding preceding flood engagement with hazards, external influences, climate related beliefs and demographic background to the framework. Preceding engagement with hazards considers undergone measures and previous flood experience. Furthermore, external influences considers the influence from social media, general media and social influence. Climate related beliefs considers the belief in climate change and the belief in government measures. Then, the demographic background considers age, education and gender.

The PMT framework by Noll et al. (2021) has been merged with the RISP model from Griffin et al. (1999) to form a new combined model in Figure 2.1. The combined PMT and RISP model allows the integration of elements from both models. Not all elements from the RISP model are included, only those that overlap with the PMT model.

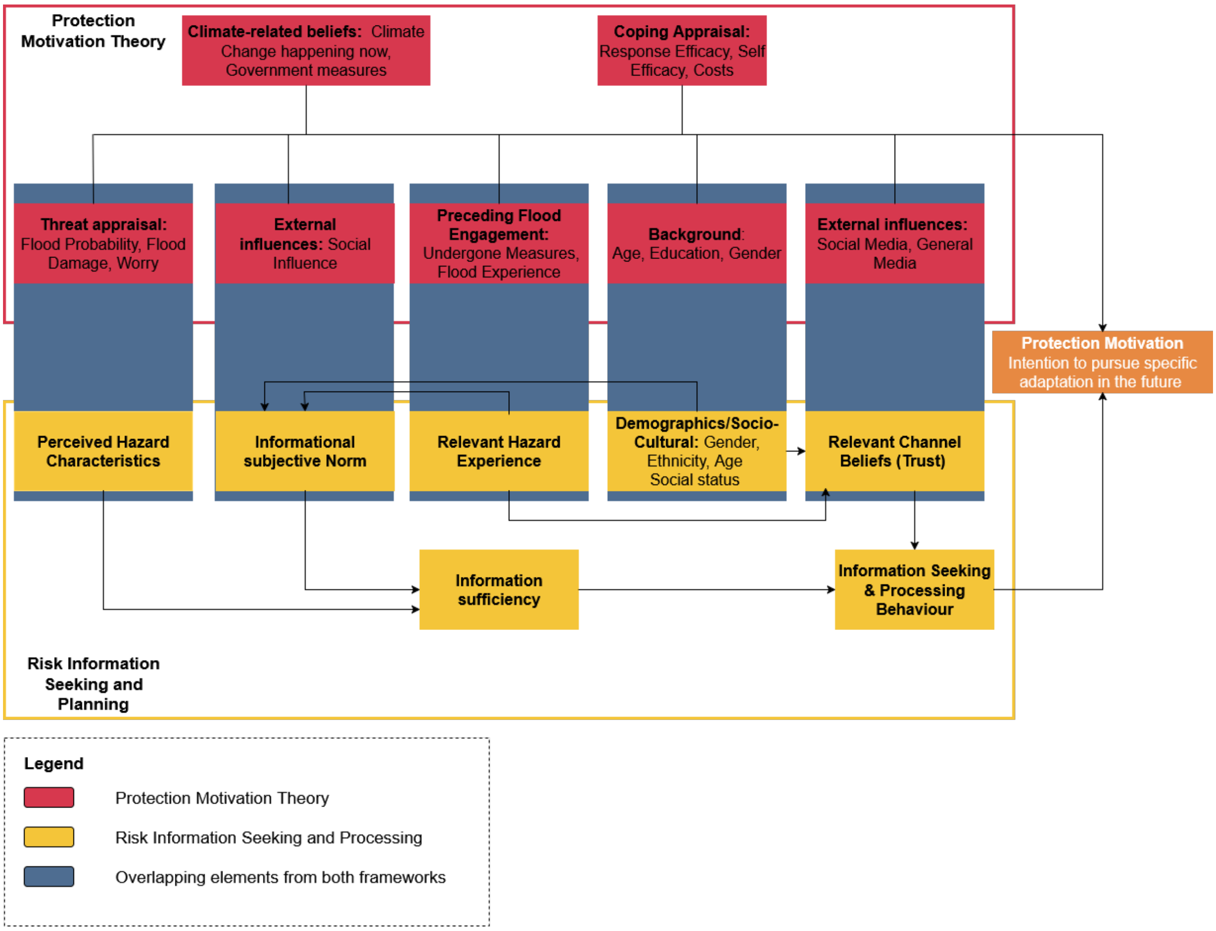

Figure 2.1: Conceptual model: Protection Motivation Theory and Risk Information Seeking and Processing combined

There are five similarities between the two frameworks, as can be seen in Figure 2.1. First, the threat appraisal from the PMT model coincides with the perceived hazard characteristics of the RISP model as they both consider the perceived properties of a hazard. In the case of the case of the PMT model, it considers specifically flood characteristics. Second, the external influences element from the PMT model is split up into two, as the informal subjective norm element from the RISP model coincides with the social influence part of the external influences, whereas relevant channel beliefs from the RISP model is similar to the social media and general media aspect of the PMT model as they both consider trust in other parties. Third, the preceding flood engagement element from the PMT model is similar to relevant hazard experience, both concerning previous experience with hazards. In the case of the PMT model, the hazard experience is specified to floods. Last, the background section from PMT is similar to the demographics and social cultural section of the RISP model. However, the RISP model does consider ethnicity and social status as additional elements, whereas the PMT model does not consider these elements.

All elements from the PMT model influence the intention to pursue specific adaptation in the future, whereas only one element from the RISP model, information seeking and processing behaviour influences that same element. Most elements from the RISP model have indirect influence on the Protection Motivation, through information seeking and processing behaviour and information sufficiency or relevant channel beliefs. By combining the two models and seeking their similarities, the direct influence of trust on the protection motivation can be assessed.

In this thesis, the focus is placed on seventh factor of the model from the RISP model from Griffin et al. (1999), relevant channel beliefs. In the RISP model, as seen in Figure 2.1, the relevant channel beliefs element is one of the final steps before information seeking/processing behaviour. This step suggests that beliefs on the trustworthiness and usefulness of different channels on risk information could affect the information seeking and processing strategies individuals undertake, and therefore also have influence on the intent to pursue specific adaptation in the future. The relevant channel beliefs element is labelled as trust in this thesis.

Figure 2.1 shows that individual characteristics, such as relevant hazard experience and demographic/socio-cultural characteristics influence trust. A study from Kosicki and McLeod (1990) already suggested that people seem to process media information more actively when they believe the information to be poor, too powerful or have negative feelings towards the content.

Based on the combined model in Figure 2.1, it is expected that trust in flood information influences the intention to take adaptation measures. According to the model in Figure 2.1, trust in flood information would be influenced by demographics and socio-cultural characteristics and relevant hazard experience. Moreover, it is expected that trust in flood information is not the sole influence on protection motivation, as important elements such as threat appraisal and coping appraisal according to the combined model, have an important influence on protection motivation as well.

2.4. Research Questions

Based on the existing studies in section 2.2 and the theoretical framework in section 2.3, the importance of researching individual trust in flood information from different entities is outlined. Furthermore, in this thesis a focus is given to private adaptation measures, subdivided in incremental and transformational adaptation in section 2.1. Moreover, the combined framework in the conceptual model shown in Figure 2.1 mentions the importance of including demographics, relevant hazard experience and undergone adaptation in analysing the intention to adapt. Therefore, the following sub-questions have been defined to answer the main research question.

- How does trust in information on floods and flood adaptation differ between urban and rural areas?
- How does trust in information on floods and flood adaptation from different sources influence the intention to take private flood adaptation measures?
- Which cluster patterns can be observed when considering trust in flood information, hazard experience and socio-demographics in Norfolk/Suffolk coast, Somerset, and Greater London?

3
Case study description

The United Kingdom is one of the world's leading economies and home to more than 69 million people (Leiserowitz et al., 2025). Similar to many other countries in the world, the UK is increasingly feeling the impacts of climate change. More extreme rainfall and increased risks of flooding are affecting communities across the country. In addition, coastal regions are experiencing more pressure as they are vulnerable to sea rise (Leiserowitz et al., 2025; Sayers et al., 2022). These changes already affect local economies, public health and infrastructure in the UK, and will disrupt communities even more if nothing is to be done to accommodate the increase in climate risks.

The UK's vision for climate adaptation is a country that successfully plans for climate change, and one that is resilient to climate risks (DEFRA, 2023). Moreover, the UK promotes policies to reduce impacts of climate change and to be resilient against climate risks (DEFRA, 2023; Leiserowitz et al., 2025).

6.3 million properties in England are in areas at risk of flooding from one or a combination of the following sources: rivers, sea, ground and/or surface water (Environment Agency, 2025a). The number of properties at risk of flooding could increase to around 8 million by 2050, which is 1 in 4 properties in England being at risk of flooding. The UK government has stated that it will spend more than £2.6 billion over the next two years to protect more homes and businesses in England from flooding. Not to mention that the UK government has already spent £1 billion on flood defences between 2021 and 2024 (Fisher, 2025).

Due to the UK's ambitions to be climate resilient whilst also facing many flood risks, the country is selected to analyse the effect of trust in flood information on flood adaptation. In this chapter, a detailed case study description is given on flood events and flood adaptation policies in England. A general overview of different flood types is given first, followed by a description of the national policies implemented to adapt to floods. Then, a closer look is taken into the areas Norfolk/Suffolk coast, Somerset and Greater London to identify local flood events and policies.

3.1. Flood types in the UK

The UK has a maritime and moist climate (World Bank, 2024). There are a variety of regional flood risks in the UK. Flooding comes from the following sources (Environment Agency, 2025a):

- Rivers (Fluvial flooding): Heavy and increased rainfall leads to overflowing of river embankments.
- Sea: High tides and storm surges lead to coastal flooding;
- Surface Water (Pluvial flooding): Heavy and increased rainfall overwhelms drainage systems, which causes flash flooding. There are more than 4.6 million properties at risk for surface flooding in England (Environment Agency, 2025b);
- Ground water: the water under the ground rises to the surface causing flooding, which can last for weeks or even months after heavy rainfall.

The UK also experiences coastal erosion (Environment Agency, 2025a). Coastal erosion causes a loss or displacement of land or the sustained removal of sediment and rocks along the coastline. The following events lead to coastal erosion: waves, currents, tides, and storms. 3500 properties in England are at risk of coastal erosion in the period up to 2055 (Environment Agency, 2025a). Coastal erosion will increase with climate change.

3.2. National Flood and Coastal Erosion Risk Management Strategy

The National Flood and Coastal Erosion Risk Management Strategy (FCERM) is the overarching national policy framework for coping with flood risks and coastal change in England. It sets out to create climate resilient places and to create a nation that is ready to respond and adapt to flooding and coastal change (Environment Agency, 2020). It was published in 2020. The strategy is part of the statutory responsibility of the Environment Agency under the Flood and Water Management Act 2010 (DEFRA, 2023). The strategy provides a framework to steer the activities of flood and coastal erosion risk management authorities and asset authorities in FCERM. It outlines both short-term practical measures and long-term delivery objectives the nation should achieve for the next 10 to 30 years (Environment Agency, 2020).

The Environment Agency also developed a roadmap to help locals by protecting, preparing and training them for flooding and coastal change. In addition, the roadmap guides policy makers and practitioners with the correct information on future flood risks. The FCERM Strategy Roadmap includes practical actions that an extensive range of organisations must have completed by 2026 (Environment Agency, 2022). The roadmap contains three long-term ambitions. Two of them are discussed here, as these relate to communication strategies. Furthermore, only relevant strategies to private household adaptation and information communication are discussed below.

- **Climate resilient places**: this ambition aims to bolster the resilience to flooding and coastal change by 2050. This is achieved by, amongst other things, ensuring to inform people on future approaches and investments in flood and coastal erosion risk management. Moreover, risk management authorities aim to help communities plan, transition and adapt to flooding and coastal change according to various climate change scenarios. This is achieved by, amongst other strategies, developing a new online portal called Shoreline Management Plan Explorer to show the Shoreline Management Plan information on a map that can be used easily.

- **A nation ready to respond and adapt to flooding and coastal change**: by 2030 the objective is that people have the appropriate information and support to be able to respond to flooding and coastal change. In addition, by 2050 the objective is to have people understand what the impact is of flooding and coastal change and to make them take action to reduce that impact. Both goals are achieved by improving digital risk services to check flood risks, creating new emergency alert services, creating communication and education tools for children, working with resilience forums and creating new engagement skills courses for risk management authorities. Moreover, the National Flood Forum will support new and existing volunteer groups in managing flood resilience. Furthermore, the Environment Agency aims to improve local resilience forums.

Shoreline Management Plans

The Shoreline Management Plans (SMP) are briefly described in this section as they are often mentioned in reducing risks of coastal erosion. The SMPs are strategic approaches to tackle coastal and flood erosion risk (Sayers et al., 2022). They were developed as project-based management of coastal defences was ineffective with changes across space and time which shape the coast. SMPs contain two important elements: the implementation of management units built on physical process boundaries and three extended time horizons (short-term, medium-term and long-term). There are twenty SMPS in England, each divided into Policy Management Units (PMU). The four policy options are *hold the line*, *advance the line*, *managed realignment* and *no active intervention*.

National flood information

As a resident of England, you can check for flood risk in your area based on your postcode on national government websites (GOV.UK, n.d.). Moreover, the National Flood Forum provides some essential advice on how to deal with floods (National Flood Forum, n.d.).

For planners or local authorities, the National Flood Risk Assessment offers a single representation of current and future flood risk from rivers, sea and surface water in England (Environment Agency, 2025a). This assessment uses detailed data from local authorities. Moreover, the Environment Agency included the impact of climate change on flood risk based on the UK Climate Projections in the National Flood Risk Assessment (Environment Agency, 2025c). Furthermore, the assessment shows potential flood depths to provide more detailed information and to help people understand the potential flood hazards they face.

There are several maps to inform people on climate risks. Tools such as the Flood Map for Planning are used for retrieving flood risk information for planning applications. The flood map allows developers to find data for their flood risk assessments, usually for a new development proposal (Environment Agency, 2025a).

When regarding coastal erosion, the National Coastal Erosion Risk Map provides a national picture of coastal erosion risk (Environment Agency, 2025c). It is derived from monitoring data from the National Network of Regional Coastal Monitoring Programmes and accounts for the latest UK Climate Projections. In addition, it depicts the coastal management approaches set out in the SMPs.

Furthermore, the Risk of Flooding from Surface Water (RofsW) map is produced on behalf of the UK government and includes input from Lead Local Flood Authorites. The RofSW map is an assessment of where surface water flooding could possibly occur and uses models that account for local topography, rainfall patterns and historical data (Environment Agency, 2025b).

3.3. Case study areas

Local government has an important role in climate change adaptation through strategic planning, resilience and recovery (DEFRA, 2023). They have a crucial position in climate adaptation, as they promote adaptation actions designed to their unique local context. This is due to local authorities holding local expertise, core decision-making powers and strategic duties while they have the ability to convene local partners from communities and businesses.

In this section, a greater focus is placed upon the areas of the case study, Norfolk/Suffolk coast, Somerset and Greater London. These areas were chosen as they had major flood events in the past. Moreover, these are areas where the option of transformational adaptation has been discussed. The location of these regions can be seen on the map in Figure 4.1. Local flood types, events, adaptation and flood risk information strategies for each area are described below.

3.3.1. Norfolk/Suffolk coast

Norfolk and Suffolk lay in the region East England. Both counties are classified as largely rural (Breilmann & Day, 2023; Office for National Statistics, 2024b).

Flood Types

The types of flooding experienced by these regions are mainly coastal flooding, fluvial flooding, surface water flooding and groundwater flooding (Norfolk County Council, n.d.-c; Suffolk Joint Emergency Planning Unit, 2024). Moreover, Norfolk and Suffolk contain several of the fastest eroding coasts in Europe (Environment Agency, n.d.-b). 2500 homes in Norfolk and Suffolk are at risk from coastal erosion. The risk assessment for the region East England according to the Environment Agency (2025a), without considering the future impacts of climate change, is as follows:

- 2.2 percent of the properties in East England are at either high risk or medium risk of flooding from rivers and the sea;
- 7.6 percent of the properties in East England are at either high and medium risk surface water;
- 25 percent of the properties in East England are at high or medium risk of coastal erosion up to 2055, if the SMPs are delivered. If we look at 2105, 27 percent of the total properties in East England will be at high or medium risk if the SMPs are delivered.

One of the biggest recent flood events in Norfolk and Suffolk coast was the storm surge of 2013 (Environment Agency, 2023a). In this event, a large storm along with high tides created a coastal surge in the East coast of England. Thousands of people had to be evacuated. The damages done by the flood cost millions for locals and communities.

Local adaptation measures

The local flood risk management strategy for Norfolk area complies to the National FCERM strategy for England (Norfolk County Council, n.d.-b). When regarding incremental measures taken by individuals, the local strategy includes providing adequate flood information and emergency planning to reduce the impacts of floods. In this strategy, the lead local authority and the risk management authorities are in charge for communicating flood risk, emergency planning, prioritising resources and flood resilience and adaptation. The lead local authority also promotes local flood risk adaptation and resilience activities. Although not specifically mentioned, these adaptation measures and activities most consider incremental flood adaptation approaches to be implemented by individuals.

Suffolk also has a flood risk management partnership which produced the flood risk management strategy (Suffolk County Council, n.d.). It provides a framework for coordinated approaches to manage risk and improve resilience. It complies to the National FCERM strategy. The strategy's goal is to help communities understand the impacts of flooding and the risks, and to support them to become more resilient. To achieve protection of people, business and key infrastructure, the strategy suggests working together with partner authorities to combine knowledge and resources to provide effective projects to reduce flood risks.

Transformational adaptation is found in the strategy of the Norfolk Strategic Flood Alliance (NSFA) (Norfolk County Council, 2021). The NSFA works together to improve the safety and resilience of Norfolk communities and infrastructure. This strategy mentions establishing groups to help mitigate coastal erosion and coastal flooding corresponding to SMPs.

However, the case study by van der Plank (2024) on the East of England shows that there are very few examples of transformational adaptation measures in current policies. The results showed that coastal residents acknowledged a lack of basic incremental adaptation occurring and a lack of a policy framework to facilitate transformational adaptation. Moreover, there is often a limited use of policy tools such as SMPs to support transformational adaptation. This could be caused by a reduced impact of the SMPs, as they are often weakened by an absence of transparency or a lack of funding (Ballinger & Dodds, 2020).

Communicating flood information
Both Norfolk and Suffolk county councils are partners of their local resilience forums (Norfolk Resilience Forum, n.d.; Suffolk Prepared, n.d.). These resilience forums have information on emergency planning for floods. Moreover, they provide advice on actions to take when the emergency happens.

Next to the advice on the National Flood Forum, Suffolk also created Flood Smart Living and Guide to Riparian Ownership as part of the Suffolk Flood Risk Management Partnership to supply residents of crucial information if they are at risk of flooding (Suffolk County Council, n.d.). Norfolk also has the Norfolk Strategic Flood Alliance to improve collaboration between partners involved in mitigation flood risks and flood prevention (Norfolk County Council, n.d.-a).

3.3.2. Somerset
Somerset is located in the South West region of England. It predominantly has a rural nature (Office for National Statistics, 2024b).

Flood types
The principal flood risk source within North Somerset is tidal flood risk, which is flooding to low-lying land from the sea (Koulouri, 2020). In South Somerset the Somerset Levels are susceptible to flooding from duration rainfall and urban areas are susceptible to more intense rainfall conditions. Heavy rainfall causes surface water flooding (Meecham & Harvey, n.d.). For the South West region, the following assessment has been made not considering climate change (Environment Agency, 2025a):

- 2.5 percent of the properties in the South West region of England have high medium risk of flooding from river and sea
- 27 percent of the properties in the South West region of England have high or medium risk regarding coastal erosion from now up to 2055 if the SMPs are delivered, 18 percent have high or medium risk for coastal erosion from now up to 2105 if the SMPs are delivered
- 4.6 percent of the properties in the South West region of England have high or medium surface water risk

One of the biggest flooding events experienced in Somerset was the flood in the Somerset Levels and Moors communities in 2014. There were 100 million cubic metres of floodwater covering an area of 65 square kilometres. During this flood event, many residents had to leave their homes (Environment Agency, 2023b).

Local adaptation measures
In Somerset, homeowners, tenants in private rented houses and housing association properties and businesses hold the responsibility to protect their own property from flooding (Somerset Council, n.d.). Incremental measures such as sandbags used to be supplied by the government, but this is not done any more. The Somerset Council website does provide information on where to buy sandbags and they provide information on other incremental flood adaptation measures such as moving sentimental items upstairs, moving furniture, and preparing an emergency kit. They also suggest more extreme measures such as landscaping, walls and additional drainage which leans more towards transformational adaptation. In addition, they outline that if your land is adjacent to a watercourse, you have legal duties to sustain the watercourse.

There is no mention of transformational adaptation through policies or on an authority level. The SMPs also apply to Somerset's coast, hence the same issues occur for transformational adaptation as mentioned in section 3.3.1.

Communicating flood information
In Somerset, the Somerset Council provides extensive information on how to prepare for floods, where to find information during floods and guidance after flooding (Somerset Council, n.d.). There are no external resilience forums, and the residents of Somerset are often guided to the national government websites to check flood risks (GOV.UK, n.d.).

3.3.3. Greater London
Greater London is located in South-eastern England. Greater London is an urban area (Office for National Statistics, 2024a).

Flood types
Greater London is susceptible to six possible sources of flooding (Greater London Authority, 2018); tidal floods from the River Thames, fluvial flood risk, surface water flood risk, foul sewer flood risk due to surface water flooding and ground water flood risk. The Environment Agency (2025a) has given the following risk assessment to the region, not considering future impacts of climate change:

- 1.2 percent of the properties in the region are at high or medium risk of flooding from river and sea
- 12.6 percent of the properties in the region have a high and medium flood risk from surface water flooding

One of the biggest flood events in London history is the North Sea flood from 1953. This was a tidal surge where the Thames Estuary was affected (Environment Agency, n.d.-a). The peak of the surge was 2.5 metres above spring tide level. Along the East Coast, over 300 people died and 24500 homes were damaged. The damage in Greater London itself was lower as it is located more inland, but parts of East London were also affected gravely.

Local adaptation measures
Examples of incremental measures within Greater London are embedded in strategies such as the London Surface Water Strategy (Flood Ready London, 2022). This strategy is a vision of how Greater London is able to address the surface water risk and sets out a series of incremental actions to deliver transformational change and to rethink the urban water management system. This stepwise change includes for example, engaging community groups to monitor and maintain surface water infrastructure, engaging with the insurance sector, and promoting partnerships with organisations to ensure collaboration.

Transformational adaptation elements in Greater London can be found in the the Thames Estuary 2100 programme. The programme sets to embrace the concept of adaptation pathways to reduce the risk of flooding (Environment Agency, 2024). Established in 2012, the plan was set to use the adaptation pathway approach to confront the uncertainty of climate change. It aims to deliver great benefits for communities and to create a resilient Thames Estuary. Future flood defences can then be designed in accordance with local visions.

The Adaptation Pathway is a flexible long-term plan, that identifies sequences (pathways) of potential actions to deal with a variety of possible futures and allows monitoring to comprehend how the future unfolds itself (Environment Agency, 2024). The programme allows the investment in the right sequence of actions at the right moment. The programme has both transformational and incremental elements, as it considers long-term flexible methods involving many stakeholder. However, it considers limited systematic change.

Communicating flood information

The Greater London Authority has developed the London Risk Register (London Resilience Unit, 2025). This register provides a summary of the risks that can cause harm to people or the environment. These are risks the population of Greater London face. The register is created for use by the London Resilience Partnership and for information to members of the public. Furthermore, each local authority of London has their own webpage or assessment on how to prepare for and manage floods. For the Local Authority of City of London for example, a City of London Strategic Flood Risk Assessment is made to offer information on the risks of flooding within the local authority (City of London Corporation, 2023). Some of the local authority websites suggest the use of media or weather apps to check for flood risks (City of London, 2025)

4 Research Approach

To answer the main research question, three quantitative data-analysis methods are conducted using Python version 3.11.11 in JupyterLab. This chapter describes the data sets and data preparation first, followed by a description of the different steps used to answer the main research question, as defined in section 2.4. The code can be found here: https://github.com/elisa1801/Thesis-FloodAdaptation.

4.1. Datasets

The following datasets have been used for the analysis.

Survey data

The data used for the case study are survey data collected by the SCALAR-Team within the European Research Council (ERC) project under the European Union's Horizon 2020 Research and Innovation Program (grant agreement no. 758014). This panel survey contains household data from five different countries across five different waves. The focus has been placed on the UK data from the fifth wave of the study. The UK data from the fifth wave was collected in July and August of 2023. The dataset has 743 entries from respondents, 256 from Norfolk/Suffolk coast, 129 from Somerset and 358 from Greater London. This is also seen in Table B.1.

The survey data consists of either ordinal, dichotomous, or in very few cases ratio data. Most of the variables from this survey contain ordinal data in a Likert scale form (e.g. categories 1 to 5, ranked from worst to best) or dichotomous variables with two options (either yes or no). From this dataset, both dichotomous and ordinal variables have been used. In section 4.2, the utilised variables from the survey are specified and their preparations for the analysis are described.

Furthermore, the survey data also contains MSOA codes belonging to the location of the respondents. The variable name "Q0_place_UK" contains this ID data, however, these codes seemed difficult to merge with the geodata used as mentioned in section 4.1. Thus, an additional list of MSOA names from this survey was merged belonging to the corresponding ID entries to this survey dataset. This list is present in the "msoa_names" csv file.

The plot in Figure 4.1 has been made by using the aforementioned MSOA codes and merging them with geodata to show where the respondents of the survey live. The geodata are described in section 4.1. The yellow regions show the MSOA regions where the respondents from the survey live, showing their positions relative to a map of the United Kingdom in blue.

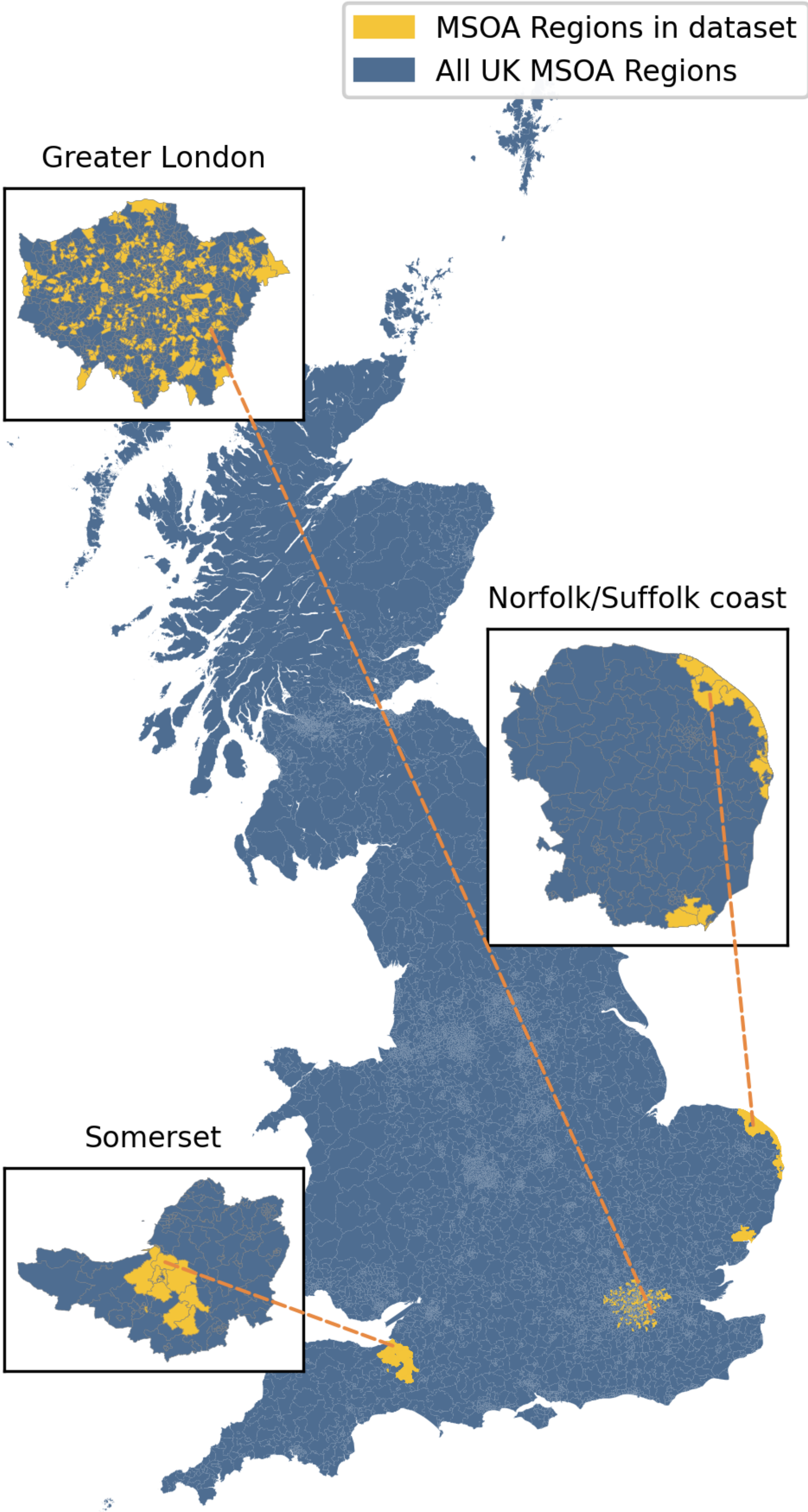

Figure 4.1: Survey data regions in the UK

MSOA and Local Authority names

As seen in Chapter 3, the three areas, Norfolk/Suffolk coast, Somerset and Greater London, are analysed separately for comparison. To compare the respondents' answers of these three regions, the survey dataset had to be split up according to the names of the MSOA regions where the respondents live. For this split, an external MSOA and Local Authority names dataset was used from the House of Commons under the Open Parliament Licence v3.0 (House of Commons Library, 2022; UK Parliament, n.d.). This dataset can be found in the "all_msoa.csv" file.

Spatial Data

To plot respondent's answers according to their MSOA codes, spatial data is used. The UK Data Service Census Support boundary dataset, under the terms of UK Open Government Licence v3, is used for geospatial vector data on Middle Super Output Area codes (Office for National Statistics et al., 2011). These MSOA codes have also been used by respondents when filling in the survey from the aforementioned SCALAR-team. This dataset can be found in the "infuse_msoa_lyr_2011.shp" file.

The choice has been made to plot the London Boroughs instead of the MSOAs of Greater London for better visibility. To be able to plot the London Boroughs, an extra dataset is needed. Statistical GIS Boundary files from the Greater London Authority have been used under the terms of the Open Government Licence (OGL) and UK Government Licensing Framework to plot the London Borough boundaries (Greater London Authority, 2014; The National Archives, n.d.-a, n.d.-b). This dataset can be found in the "London_Borough_Excluding_MHW.shp" file.

4.2. Data preparation

Preparing the dataset

First, the original survey file SCALAR_Coastal_Study_new_respondents_Wave_Five_UK.csv is uploaded into JupyterLab as a dataframe in notebook Step0DataPreperation. To be able to merge this dataframe with geodata further on in the analysis, this dataframe is merged with a names.csv which contains the MSOA names corresponding to the ID area codes of the survey dataset. This new dataframe is written to a new csv file: merged_names.csv to be used in the Step0Exploratory notebook.

After this initial merge, a new variable is created: Age Group. The age group variable is a new grouped ordinal variable based on the Q0_age variable. Five new categories have been made based on the range of ages filled in by the respondents in the survey. This is done as the data needed to be all Likert Scale type for the clustering analysis to avoid misinterpretation. This also allows consistent distance computation. Furthermore, columns are renamed. This new survey dataframe is then saved to transformed_names.csv for analysis in Step 1.

Then, the "msoa_all.csv" dataset was subdivided manually into three dataframes according to three regions. However, this division contains the full counties of where the MSOA codes of the respondents are located, and not only the MSOA codes of the respondents themselves. These three dataframes are then saved into new csv files with the title "...region" for use in further notebooks. This division has been carried out for plotting base maps under the relevant MSOA regions, for visualisation purposes. For the London region, the Local Authority names are kept to plot these regions for better visibility as mentioned in section 4.1.

Separate csv files are also created filtering the survey data according to three regions in the MSOA names in notebook. These csv files start with the name "filtered...". This is done so that separate analyses could be performed for the three different regions in further notebooks.

First inspection

The first inspection of the data is done in the notebook Step0Exploratory. The NaN values are first checked. All entries in the survey data have at least one missing value for any variable. When the corresponding variables of those missing values are checked, it can be deduced that those missing values belong to questions with open ended texts. These are variables containing the word "other", and are only optional to fill in when respondents do not find themselves in the other answers of the relevant question. These columns are not included in further analyses, hence nothing was done with these missing values.

134 columns in the survey data have the data type object. This was first considered to be odd as the questions corresponding to some of the columns have integer type answers. After further inspection, the answers to those questions included, next to integer type answers, empty strings.

These empty strings are due to the fact that the specific question was not asked to the respondent, as it was either not relevant to the region or it was a follow-up question to a previous question where the respondent answered ”yes” or similar. If these columns are used in further analysis, they are to be transformed to numeric columns and the NaN values are to be filled. Further explanation on the used object columns can be found in section 4.3. Other columns have type object as they were open ended questions containing string text.

Other anomalies or NaN values have not been found in the variables used for the analysis. Hence, the data is therefore ready to be used. The appropriate variables are selected in each step.

Grouping Measures

The grouping of the measures is done in notebook Step0GroupMeasures. Before the grouping of the measures takes place, alterations had to be done to the measure variables. The initial values of the measure variables are Likert scale from one, having implemented the measure, to four, not planning on implementing the measure. However, to increase the quality of the interpretation of the results, the values have been inverted. Thus, where the value of one was the option where respondents had implemented the measure, the value four is now the best option where respondents have already implemented the measure. To clarify the alteration, the switch in values is shown in Table 4.1.

Table 4.1: Inverted values of the measures

Before	After
1 - I have already implemented this measure	4
2 - I intend to implement this measure in the next 1-3 years	3
3 - I intend to implement this measure at some point in the next 3-5 years	2
4 - I do not intend to implement this measure in the foreseeable future	1

After this adjustment, the grouping of the measures could take place. Most measures in the survey, both structural and non-structural, are initially incremental measures as defined in section 2.1. The choice has been made to group the different structural and non-structural measures for a better and easier interpretation of the results. For each group measure, the assumption has been made that if a respondent implemented one of the measures, he or she would implement a similar kind of measure as well. The grouping of the measures can be seen in Table 4.2.

Table 4.2: Grouping the structural and non-structural measures

Group measure	Individual measure	Description
Informative (non-structural)	R2_implementation_NM4 R2_implementation_NM5 R2_implementation_NM8 R2_implementation_NM9	Active member of community Coordinating with neighbours Asking info on emergencies Petition for public measures
Preventive low effort (non-structural)	R2_implementation_NM1 R2_implementation_NM7 R2_implementation_NM10 R2_implementation_NM11	Keeping an emergency kit Placing possessions safely Storing emergency supplies Moving valuable assets
Preventive high effort (non-structural)	R2_implementation_NM2 R2_implementation_NM3 R2_implementation_NM6	Purchase sandbags Buy spare power generator Installing refuge zone
Elevation (structural)	R2_implementation_SM1	Elevation
Wet-proofing (structural)	R2_implementation_SM2 R2_implementation_SM3 R2_implementation_SM4	Strengthen house foundations Use water-resistant materials Raising Electricity meter
Dry-proofing (structural)	R2_implementation_SM5 R2_implementation_SM6 R2_implementation_SM7	Anti-backflow pipes Installling pump to drain Fix water barriers

Table 4.2 shows six different grouped categories of incremental measures, three based on non-structural measures, and three on structural measures. The non-structural measures are grouped on informative, preventive low effort and preventive high effort measures. The informative measures consider exchange of information between people. The preventive low effort measures are measures in preparation for floods, but they are considered to be low effort. Furthermore, the preventive high effort measures are measures in preparation for floods but require more effort than the measures grouped into the category preventive low effort. The grouping of the structural measures is based on the grouping of the Supplementary Table S1 of Taberna et al. (2023), grouping the structural measures into dry-proofing, wet-proofing and elevation.

The measure SM8 - Strengthening direct coastline privately has been left out of the analysis, as there were too few respondents that had implemented this measure, as seen in Table B.2 in the appendix. This measure is only relevant for Norfolk/Suffolk coast. This is also the only measure that could possibly be categorised as transformational.

After categorising the measures into structural and non-structural groups, another grouping took place as input for the regression analysis in Step 2. Twelve new binary variables were created out of the six as seen in Table 4.2, as each group measure is split into two: respondents who have implemented the measure (Done, value 4) and respondents who intend to implement the measure in the near future (Plan, value 3). These twelve variables then become dichotomous, with the value of one being the respondent has taken this measure/is planning on taking this measure, and zero being the respondent is not planning on taking or has not taken the measure. The overview of the twelve variables and the respondent counts of these variables can be seen in Table B.4.

The clustering analysis in Step 3 needed a different grouping of variables, going back to the division of structural and non-structural measures. The measures are grouped into four categories: Any measure done non-structural, any measure done structural, any measure plan non-structural and any measure plan structural. These groups identify if a respondent is planning to take or taking either structural or non-structural measures. The variables have the value one if any of the measures that either fall into the non-structural or structural category have been taken or are planned, zero if not.

4.3. Data-analysis methods

The set-up of the data-analysis is described in this section. This section suggests a stepwise approach to answer the main research question. For each step, the methods and the relevant variables used for each method are described.

Step 1: Descriptive analysis

To begin the analysis, a first insight is needed into the trust in information on floods and flood adaptation. Therefore, the variable on trust in information on floods and flood adaptation is compared between Norfolk/Suffolk coast, Somerset and Greater London. Five different trust variables have been chosen for this analysis. These variables signify how trustworthy the respondents think the different entities are with respect to the information they provide about floods, sea-level rise and adaptation measures. These variables are shown in Table 4.3.

Table 4.3: List of trust variables

Variables
Trustworthiness prime minister
Trustworthiness government representative
Trustworthiness family and friends
Trustworthiness general media
Trustworthiness social media

The variables in Table 4.3 are Likert scale type variables from one to five. One suggests that the respective entity is not trustworthy regarding the flood information they provide, and five is that the entity is fully trustworthy regarding the flood information they provide.

The data is then, as mentioned in section 4.2, subdivided into the three different regions to be able to analyse comparisons of the trust variables. Descriptive statistics are used to create an apprehensive overview and summary of the trust variables for further analysis (Kaliyadan & Kulkarni, 2019). The choice has been made to use a stacked (composite) bar plot with relative frequency distributions, to compare the five variables for all regions. A stacked bar plot is a common visualisation tool for comparing variables (Kaliyadan & Kulkarni, 2019). In addition to the stacked bar plot, a descriptives table has been created to specify the relative frequency distributions and to show the median, mode, mean and standard deviation of each of the variables for each region. The set-up and the results of this step can be found in Notebook Step1Descriptives.

The descriptive analysis of this step is beneficial to answering the first sub-question of this thesis: *How does trust in information on floods and flood adaptation differ between urban and rural areas?*. By using descriptives, an insight is given into the trust variables and the insight allows for comparison between the trust variables. Moreover, the combination of descriptives and a stacked bar plot of relevant frequency distributions enable comparison between the different regions.

When linking it back to the conceptual model in Figure 2.1, the Trust element (Relevant Channel Beliefs) is analysed in this section. No insight is given yet into the relationship between the aforementioned factor and the Protection Motivation variable, as this question serves as a first insight and analysis into the relevant variables. The relationship between the two elements is assessed in step 2.

Limitations of step 1

The limitations of the method used for step 1 are that descriptive statistics work best on quantitative data (Kaliyadan & Kulkarni, 2019), whereas the trust variables are ordinal five-point Likert scale data. Hence the traditional statistics such as mean and standard deviation can give misleading interpretations. Descriptives such as mean on Likert scale data often returns a number that does not belong to any category (e.g. 3.6). As ordinal data does not assume equal spacing, the variability which the standard deviation shows can be misleading. Another limitation is that descriptive statistics do not define what causes high trust levels in the three regions. The descriptive statistics only give a summary and insight on the data.

Step 2: Binary Logistic Regression

Step 2 of the data analysis focusses on analysing the relationship between the trust variables and the intention to take flood adaptation measures. This sub-question does not separate the three different regions, unlike the previous sub-question. All the entries from the three regions are considered when analysing the relationship between the trust variables, as defined in Table 4.3, and the six groups of measures, as defined seen in Table 4.2. The set-up and the results of this analysis can be found in notebook Step2Regression.

To gain an initial insight into the relationships between the trust variables and the twelve groups of measures, including the separation between having taken a measure and planning to take a measure, a Spearman correlation heatmap is created. The spearman correlation coefficient is a statistical measure that is non-parametric (Xiao et al., 2016). The spearman correlation heatmap is used to check if the input variables are highly correlated with each other, as high correlation is not beneficial for a logistic regression (Ranganathan et al., 2017). Spearman coefficients measure the strength and direction of monotonic relationships between ranked variables that do not follow a specific functional form such as linear or exponential forms. As the variables are ordinal and originate from a survey, it does not follow a normal distribution or have the same traits as continuous variables (Flora & Curran, 2004). A heatmap is created using the Python package seaborn. It is used to show the spearman correlation coefficients of the relationships between the variables.

After the spearman correlation, a binary logistic regression is performed. For the logistic regression, the choice has been made to include survey variables based on the Protection Motivation Theory and the conceptual model mentioned in section 2.3. The PMT variables such as threat appraisal and coping appraisal have an important influence on the intention to adapt as well. This is the reason why these variables are kept constant in the analysis, to solely determine the effect of trust, but not neglecting the influence of other variables. The chosen PMT variables are shown in Table 4.4.

Table 4.4: List of PMT Variables for Logistic Regression

Survey variable names	Grouped variable	Renamed PMT Variable
R02_perc_prob	No	Perceived Flood Probability
R05_worry	No	Worry Flood
Q18_flood_exp	No	Flood Experience
R03_perc_damage_UK1/2/3	Yes	Perceived Physical Damage
R1a_self_efficacy_NM4/5/8/9	Yes	Informative Self Efficacy
R1a_self_efficacy_NM1/7/10/11	Yes	Preventive-low Self Efficacy
R1a_self_efficacy_NM2/3/6	Yes	Preventive-high Self Efficacy
R1a_self_efficacy_SM1	Yes	Elevation Self Efficacy
R1a_self_efficacy_SM2/3/4	Yes	Wet-proofing Self Efficacy
R1a_self_efficacy_SM5/6/7	Yes	Dry-proofing Self Efficacy
R1b_resp_efficacy_NM4/5/8/9	Yes	Informative Respective Efficacy
R1b_resp_efficacy_NM1/7/10/11	Yes	Preventive-low Respective Efficacy
R1b_resp_efficacy_NM2/3/6	Yes	Preventive-high Respective Efficacy
R1b_resp_efficacy_SM1	Yes	Elevation Respective Efficacy
R1b_resp_efficacy_SM2/3/4	Yes	Wet-proofing Respective Efficacy
R1b_resp_efficacy_SM5/6/7	Yes	Dry-proofing Respective Efficacy
R1c_perc_cost_NM4/5/8/9	Yes	Informative Perceived cost
R1c_perc_cost_NM1/7/10/11	Yes	Preventive-low Perceived cost
R1c_perc_cost_NM2/3/6	Yes	Preventive-high Perceived cost
R1c_perc_cost_SM1	Yes	Elevation Perceived cost
R1c_perc_cost_SM2/3/4	Yes	Wet-proofing Perceived cost
R1c_perc_cost_SM5/6/7	Yes	Dry-proofing Perceived cost

In Table 4.4, the chosen PMT variables are shown. Before using them in the binary logistic regression, most variables had to be grouped. Self efficacy is if the respondent is able to take the measures themselves. Furthermore, respective efficacy relates to how effective the measures are according to the respondent. In addition, perceived cost is how the respondent perceives the price of implementing the measure. These three aforementioned variables are grouped by taking the median of the variables according to the group measures in Table 4.2. The median is taken due to the ordinal nature and slightly skewed nature of the data (Kaliyadan & Kulkarni, 2019). Perceived physical damage is also a grouped variable based on the sum of three variables, as these three variables of Likert scale type nature consider the perceived damage of three different flood events in the UK.

After grouping, selecting and scaling the necessary variables, twelve regressions are performed to understand the relationships between the predictors and the twelve outcome variables. The predictor variables are the PMT variables shown in 4.4. The outcome variables for the different regressions are the six binary 'Done' and six binary 'Plan' variables, as seen in B.4. As the preferred model for analysing binary responses is the binary logistic regression model (Harrell, 2015a), this model is used for the twelve regressions. The model is applied to predict the probability of a binary outcome. In Python, the Logit() function from the package statsmodels is used for the logistic regression, as this step has statistical modelling and inference purposes.

The results of the binary logistic regression models are reported by using the following metrics: p-value, confidence intervals and odds ratio. The first two metrics are used to determine the significant relationships. The p-value is the statistical significance, and for this research it is set to 0.05. This means that when the resulting p-value is lower than 0.05, the null hypothesis, which is the hypothesis that the relationship does not exist between the variables, can be rejected (Ranstam, 2012). Due to the many weaknesses of using the p-value in analysis strategies, confidence intervals are included as well. The confidence intervals of the odds ratio is then used to determine if the identified significant relationships are truly significant, as unlike the p-value, they show which effects are probable to exist in the population and which are not. In this case, if the confidence interval includes an odds ratio of one, it suggests that the relationship is not statistically significant.

A logistic regression measures the influence of a predictor in terms of odds ratio (Harrell, 2015a). The odds ratio is used as it is a suitable description of an effect in a probability model. A positive odds ratio yields a valid probability. Therefore, the effect of the identified significant relationships is described by using the odds ratio.

To measure the model performance, two measures are used: the Pseudo R squared and the Akaike Information Criterion (AIC). Each have their own interpretation, and are complementary to each other when determining model performance. The Pseudo R squared for the logistic regression performed in Python automatically reports a McFadden R squared. The Akaike Information Criterion assesses the balance between model complexity and model fit (Harrell, 2015b). More parameters might increase model fit, but might lead to overfitting. AIC penalizes the log likelihood based on the number of parameters the model uses. The AIC can then be compared between the models, the lower the AIC score is, the better the model.

By using these model metrics and model performance measures, an answer can be given to the second sub-question: *How does trust in flood information from different sources influence the intention to take private flood adaptation measures?* The combination of the p-value, confidence intervals and the odds ratio for each logistic regression shows the effect of the predictors, amongst which the trust variables, on the grouped measures.

To link it back to the theoretical framework in Figure 2.1, the influence of the Trust factor (Relevant Channel Beliefs) on the Protection Motivation variable is assessed by holding the following PMT variables constant: Threat Appraisal, Coping Appraisal, and Preceding Flood Engagement. It is important to note that whereas the elements from the RISP model do not have direct influence on the Protection Motivation variable, the overlapping elements from the PMT model do have direct influence. This step embraces the direct influence of the relevant variables.

Limitations of step 2

Parameters of linear models are readily interpreted (Harrell, 2015b). However, the binary logistic regression assumes non-linearity and it and predicts the probability of one or two categories, and not relationships. This must be taken into account when analysing the results. In addition, it may be that the model performance of the regression shows that the model fits poorly. This needs to be addressed when assessing the results.

Step 3: K-Medoids clustering

After the relationship has been established between the trust variables and the intention to take flood adaptation measures, geographical patterns of trust, adaptation and other motivational factors are analysed in notebook Step3Clustering. To be able to identify and visualise those patterns, clustering has been performed. By clustering trust in flood information, hazard experience and socio-demographic variables, regional patterns are identified based on the combined framework of RISP from Griffin et al. (1999) and PMT by Grothmann and Reusswig (2006) as seen in Figure 2.1. Clustering enables identification of underlying groups and potential patterns in the data. This allows identifying risk areas by analysing the results in the three regions. In addition, region-specific policy concerning the communication of flood information can be developed.

Variable selection

The variables in Table 4.5 have been chosen for the clustering analysis. All variables have been normalised manually to a scale from zero to one. For interpretation purposes, the cluster labels are then combined back again with the original scales for the variables.

The additional variables, next to the trust variables that have already been described in section 4.3, concern variables belonging to socio-economic status such as household income, household savings and multiple household incomes. Furthermore, variables such as flood experience and age group have been included as well.

Table 4.5: List of clustering variables

Variables	Original Scale
Trustworthiness prime minister	1-5
Trustworthiness government representative	1-5
Trustworthiness family and friends	1-5
Trustworthiness general media	1-5
Trustworthiness social media	1-5
Household Income	1-5
Household Savings	1-7
Multiple Incomes	0-1
Any measure done non	0-1
Any measure done struc	0-1
Any measure plan non	0-1
Any measure plan struc	0-1
Flood Experience	0-1
Age Group	1-5

K-Medoids

K-Medoids has been chosen as the clustering algorithm for this analysis. K-Medoids is a classical partitioning method of clustering and clusters n objects into k clusters (Madhulatha, 2011). K-Medoids attempts to minimize the squared error between the points in the cluster and the labelled centre of the cluster. Different to other algorithms, K-Medoids chooses actual data points as centres. The data used does not follow a normal distribution and is skewed as seen in Figure C.2, hence this method is preferable as it is more robust to outliers and to noise.

The set parameters for the K-Medoids are as follows: the Manhattan distance has been used with a k-Medoids++ initialisation. The Manhattan distance is used as it is an alternative for clustering continuos data (Murphy et al., 2024). The Manhattan distance metric calculates the absolute distance between coordinates of a pair of objects (Faisal et al., 2020). This metric is more robust against outliers as it is based on actual data points. Furthermore, a K-Medoids++ initialisation starts with a selection of random medoids that are effectively spread out. The further setup of the K-Medoids algorithm is a random state set to 0 for reproduce-ability and the maximum iterations set to 300 as a balance between performance and computational power.

The number of clusters for the K-Medoids method has to be pre-specified. To determine the number of clusters, two methods are used: the elbow method, seen in Figure C.1 and silhouette score in section C.2. The former is a graphical method for determining the optimal number of clusters, where a range of k values is usually plotted against the total within-cluster sum-of-squares (TWCSS) measure (Murphy et al., 2024). However, as this considers K-Medoids, which is a non-Euclidean distance method, an alternative dissimilarity measure has to be used. The within-cluster total distance (WTCD) is used based on the Manhattan distance, which is referred to as the total dissimilarity cost in this research. The elbow method plot shows the range of k values against the total dissimilarity cost, and the optimal point is a kink in the curve where adding more clusters would result in diminishing returns.

The latter considers the following: the higher the silhouette score, the more optimal the number of clusters (Shahapure & Nicholas, 2020). The number of clusters is set to five, as the elbow method plot shows a significant decrease of the steepness of the line at cluster five. In addition, the silhouette is 0.149 for five clusters, which is higher than the silhouette scores of higher number of clusters.

This step aims to answer the third sub-question: *Which cluster patterns can be observed when considering trust in flood information, hazard experience and socio-demographics in Norfolk/Suffolk coast, Somerset, and Greater London?* Three elements from the combined framework as seen in Figure 2.1, hazard experience, socio-demographic background and trust, are used in order to visualise patterns of these variables and to identify risk areas. This is useful for detecting areas in which adaptation is low. Moreover, if adaptation is low, it can be identified whether this relates to other characteristics such as the PMT motivational factors present in that area.

Limitations of step 3

The limitation of clustering is that it is unsupervised and therefore it is challenging to assess the output quality (Subasi, 2020). Moreover, it is never clear what the appropriate clustering is for the data or how to assess the clustering method, even if there is understanding of the underlying data distribution (Shalev-Shwartz & Ben-David, 2014). It remains just a practical way to organise the data (Subasi, 2020). This must be taken into account when analysing the results. Moreover, when Manhattan distance calculates the absolute distance between coordinates of a pair of objects, it assumes equal spacing between the categories. With Likert scale ordinal type data, equal spacing is not always assumed.

5

Results & Discussion Trust comparison

This chapter aims to answer the first sub-question *How does trust in information on floods and flood adaptation differ between urban and rural areas?* The results of the analysis are described in this section, followed by a discussion containing the interpretation and limitations of the results. As described in Chapter 3, Somerset and Norfolk/Suffolk coast are categorised as rural areas, whereas Greater London is designated as an urban area.

5.1. Results

Based on the five trust variables chosen and described in section 4.3, a bar plot has been made to compare the different regions. The bar plot, as seen in Figure 5.1, is a stacked bar plot for the five variables. The plot shows the relative frequency distribution of the respondents that have chosen a specific category for each variable and for each region. The categories for the answers range from one, the entity being not trustworthy, to five, the entity being fully trustworthy. The respondents also had a choice to either fill in do not know or prefer not to say (PNTS). The descriptives table, containing the median, mean, mode, standard deviation, and relative frequency can be found in appendix D. For further details on the results, see the tables in the appendix.

Figure 5.1 shows the results for the five different variables. All regions have very low trust regarding flood information from the prime minister, with Norfolk/Suffolk coast and Somerset having higher percentages on category one (Norfolk/Suffolk 48% and Somerset 43.4%). 36.3% of the respondents for Greater London chose category one, which is lower than Norfolk/Suffolk coast and Somerset. The mean of the variable is also lower for Norfolk/Suffolk coast (1.93) and Somerset (2.13), compared to Greater London (2.29).

In spite of the low trustworthiness for all regions, Greater London respondents find flood information from the prime minister more trustworthy than Norfolk/Suffolk coast and Somerset out of the three regions. When looking at Figure 5.1, 13.1% of the respondents from Greater London has chosen category four, and 5% has chosen category 5, which is much higher than the percentages from Norfolk/Suffolk coast (5.9% for category four and 2.3% for category 5) and Somerset (11.6% for category 4 and 3.9% for category 5).

When looking at the trustworthiness of a government representative in Figure 5.1, the overall trust in a government representative is higher than trust in the prime minister regarding flood information, as the mean for each region is much higher. There is a higher distrust in Norfolk/Suffolk coast (25.4% for category one) and Somerset (20.9% for category one) compared to Greater London (15.1% for category one). However, the respondents from Somerset find a government representative quite trustworthy (mode: four) compared to the other two regions (both regions mode: 3), but more respondents from Greater London find the government representative fully trustworthy (8.7% for category five) compared to the Norfolk/Suffolk coast (3.5% for category five) and the Somerset region (7.8% for category five).

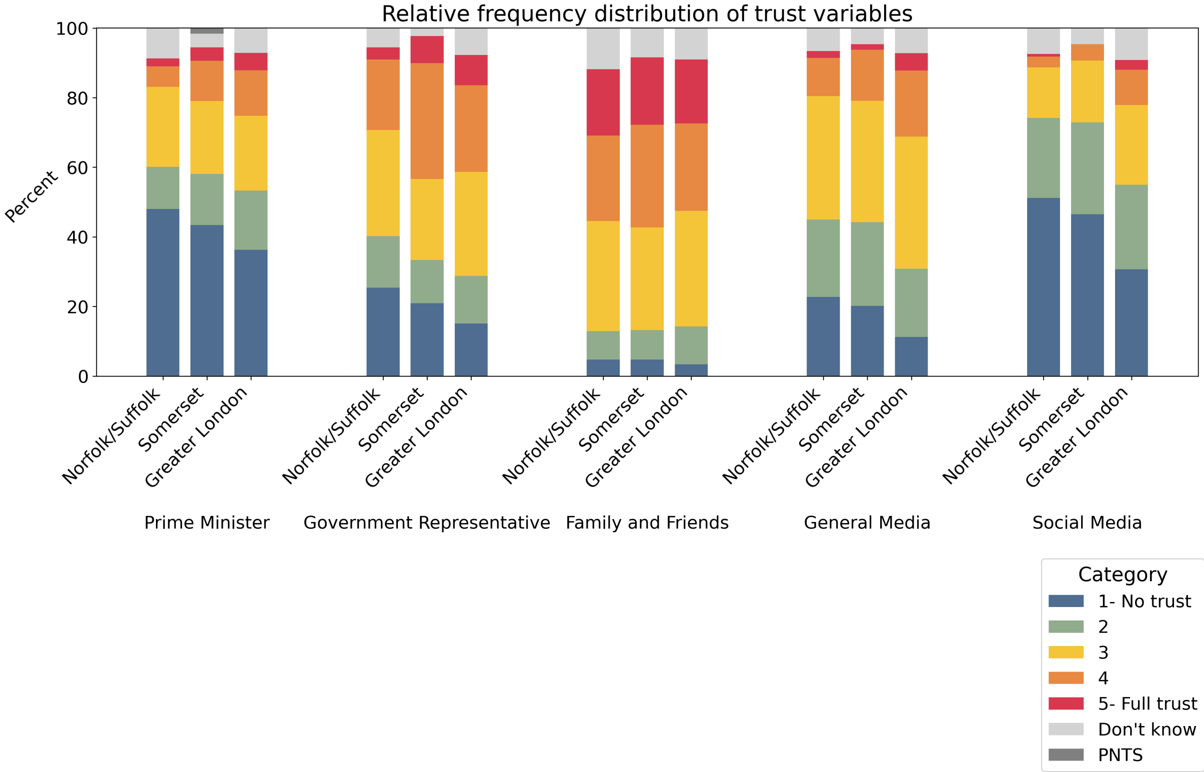

Figure 5.1: Relative frequency distribution of trust in different sources of flood information and for different regions: Categories 1 to 5, don't know and prefer not to say (PNTS)

The next variable, trustworthiness in flood information from family and friends, does not differ much between the regions. When looking at Figure 5.1, the respondents of all areas find flood information from family and friends either neutral or quite trustworthy (mode 3 for all regions). Somerset has the highest trust in family and friends (median of 4 and mean of 3.55) . When looking at the percentage distribution of the respondents for this variable, Norfolk/Suffolk coast has 19.1% and Somerset has 19.4% on category five, whereas Greater London has 18.4% on category five. Furthermore, Somerset has more respondents on category four (29.5%) compared to Norfolk/Suffolk coast (24.6%) and Greater London (25.1%).

When considering general media in Figure 5.1, it is noticeable that respondents from Norfolk/Suffolk coast (Mean: 2.44) and Somerset (Mean: 2.51) find general media less trustworthy than Greater London (mean: 2.86). Moreover, Greater London respondents also find general media more trustworthy when considering categories four (19%) and five (5%) compared to Norfolk/Suffolk coast (4-10.9%, 5-2%) and Somerset (4-14.7% and 5-1.6%).

The same is visible for the trustworthiness of social media in Figure 5.1, as Norfolk/Suffolk coast (Mean: 1.7) and Somerset (Mean: 1.8) find social media less trustworthy regarding information on flood and flood adaptation than Greater London (Mean 2.23). Greater London also has higher respondent percentages on categories four (10.1%) and five (2.8%) than the other regions. However, it must be noted that overall trust in flood information from social media is very low as the mode is category one for all regions and the mean for all regions is around 2. Furthermore, it is remarkable that none of the respondents from Somerset have selected category five for the social media variable (NaN), meaning none of the respondents find social media fully trustworthy regarding information on floods and flood adaptation.

Regarding the standard deviations, these are highest for the prime minister and government representative variables, and lowest for the social media variable. This means respondents have fairly diverse opinions concerning the prime minister and a government representative, and more similar opinions regarding the trustworthiness of flood information from social media. There is no significant difference when comparing the standard deviations from the variables between the regions.

5.2. Discussion

The results from this chapter aim to spot the differences in levels of trustworthiness in information on floods and flood adaptation from different sources between rural and urban areas. The results suggest that respondents from rural areas (Norfolk/Suffolk coast and Somerset) find that the prime minister is less trustworthy regarding information on floods and flood adaptation than urban areas. Moreover, rural areas tend to have less trust in a government representative than urban areas. Hence, people in rural areas tend to find government entities less trustworthy regarding flood information and flood adaptation than in urban areas. These insights suggest that information on floods and flood adaptation from government entities could be interpreted or acknowledged differently by residents depending on the area. In rural areas, information from government entities could possibly be seen as not trustworthy and therefore not acknowledged. Information from other entities or communication channels could therefore be more influential in rural areas.

Furthermore, people from rural areas find general media and social media less trustworthy than in urban areas. It is remarkable that there is a big difference in trustworthiness in social media regarding information on floods and adaptation between rural and urban areas. Policies including the communication of flood information via general media and social media must take into account that flood information might be acknowledged or interpreted differently depending on the area.

With regard to the trustworthiness of family and friends, all regions have rather neutral or relatively high trust. The Somerset region has the highest trust in information from family and friends. This means that for all areas, information from acquaintances is deemed trustworthy. For national policy, community groups or gatherings on flood information and adaptation could proven to be useful.

For all areas, the most trust is placed upon flood information from family and friends, followed by information from a government representative and information in general media. The prime minister and social media are the least trustworthy regarding flood information according to the survey's respondents.

When considering existing research, the differences in trust between different entities are indeed visible and important to consider (Cologna & Siegrist, 2020). It is interesting to note that, whereas research often takes government institutions as one entity to analyse trust (Bax et al., 2025; Ekoh et al., 2023; Smith & Mayer, 2018), these results suggest that the type of government entity or government representative chosen for the analysis makes a difference in assessing trust levels. These results show that there is often more trust in flood information from a government representative than in the prime minister. Moreover, it is important to consider that trust in flood information not only differs between different entities, but also between different areas. The effect of those varying trust levels in flood information on flood adaptation is not clear yet from the results for this research question, and is addressed in the next sub-question.

Research showed that without trust in the source of flood information, information or policy might be disregarded (Hagen et al., 2016). This is important to consider when implementing flood adaptation policy, as some sources of flood information, such as social media or the prime minister, are considered to be not trustworthy. Flood adaptation policy must therefore consider the source of spreading flood information. In addition, the differences in trust in flood information between urban and rural areas show that flood adaptation policies relying on the communication of information on floods and flood adaptation should be tailored specific to the area. As information is not deemed equally trustworthy from different sources and in different areas, the manner of spreading and the effectiveness of flood information matters when designing policy.

Therefore, it is advisable that the National FCERM strategy considers improving digital risk information and emergency alert services by the Environment Agency. This strategy must consider that rural areas tend to have less trust in flood information from the Environment Agency than urban areas. Therefore, using local resilience forums and volunteer groups for spreading flood information might be more influential in rural areas, as in all areas people tend to trust acquaintances or family more than flood information from a government representative.

Nevertheless, there are some limitations to be considered. As seen in Table B.1 from Appendix B, the number of respondents from Greater London is far greater than the number of respondents from Norfolk/Suffolk coast or Somerset. This could lead to skewed results. Moreover, the results do not show why there are differences in the trustworthiness of different entities between rural and urban areas. The results only show that there are differences. Furthermore, using descriptives does not show statistical inference and cannot be generalised to broader populations as it is based on the sample data available (Kaliyadan & Kulkarni, 2019). This question therefore only provides a first insight into the trustworthiness of different entities regarding flood adaptation based on the UK dataset.

6

Results & Discussion
Trust influence on adaptation

For the second research question: *How does trust in information on floods and flood adaptation from different sources influence the intention to take private flood adaptation measures?* a correlation analysis has been performed, followed by binary logistic regression. After reporting these results, the results are interpreted and discussed.

6.1. Correlations

Figures E.1 and E.2 show Spearman correlation heatmaps between the grouped measures Done and Plan and the different trust variables. Regarding the correlations, the following can be observed. The correlations between the measures and the trust variables appear to be quite low after initially examining them. Therefore, only correlations above 0.1 or below 0.1 are mentioned. Moreover, it is important to note that the correlations seen in the figure are not controlled for any other variables.

The findings show that the trustworthiness of the prime minister regarding floods and flood information has a relationship with planning to take elevation measures (0.11) and planning to take dry-proofing measures (0.13). In addition, the trustworthiness of a government representative has a relationship with planning to take dry-proofing measures (0.11), and social media has a relationship with the act of planning to take all different types of measures defined in this research (all correlations are greater than 0.1). Moreover, social media also has a positive correlation (0.12) with done dry-proofing and a negative correlation (-0.11) with done preventive low effort. The trustworthiness of family and friends does not have mentionable correlations with the measures.

These are initial insights and relationships have not been deemed significant yet. As the correlation between the input variables is low, the variables are ideal as input for a logistic regression (Ranganathan et al., 2017). To have a greater understanding of the relationships between the trust variables and the grouped measures, a binary logistic regression is performed in the following sections.

6.2. Binary Logistic Regression

The results of the binary logistic regression are structured as follows. First, the significant relationships are analysed by looking at the p-values and confidence intervals of the relationships between the variables. Second, the strength of the relationship is described by using the odds ratio. Third, the model performance is evaluated.

P-values

Figure 6.1 shows the p-values for the twelve models run by using binary logistic regression. The PMT variables, as defined in section 4.4, are kept constant. A p-value of smaller than or equal to 0.05 is taken as benchmark for significance. The following can be said about the effect of the trust variables on the grouped measures.

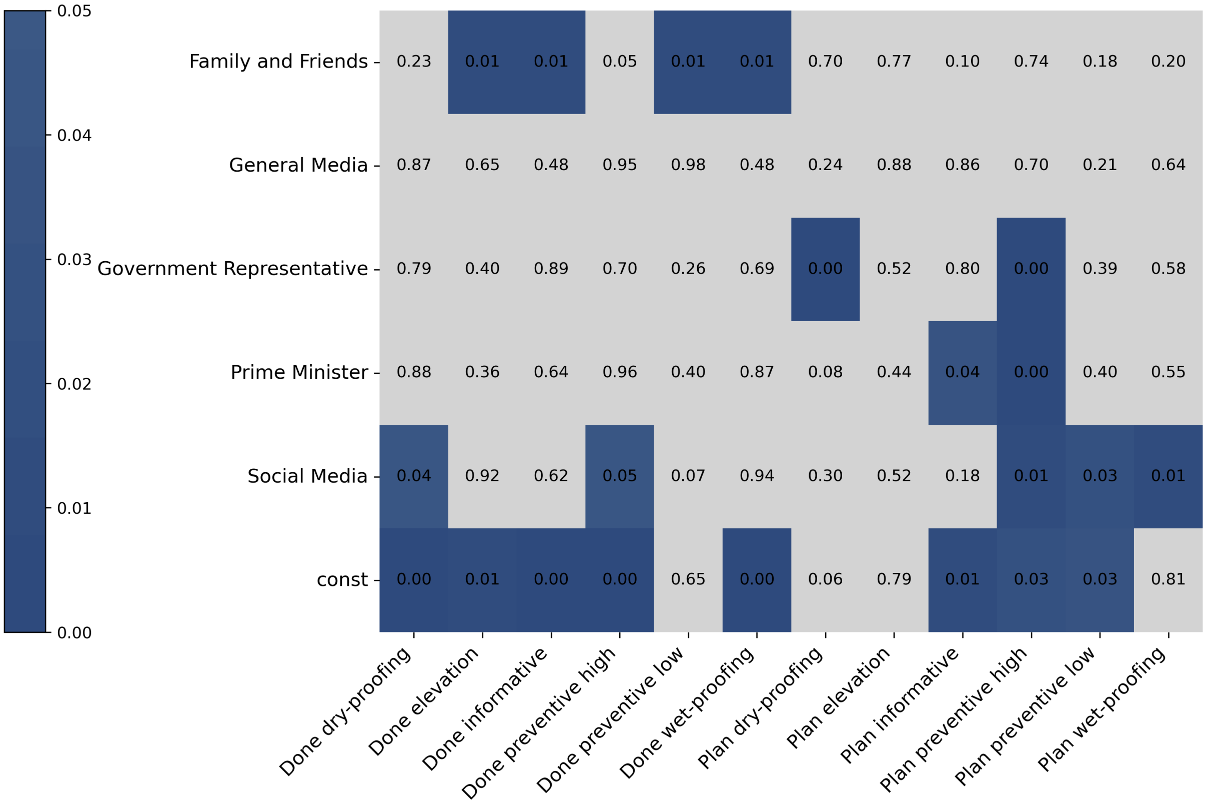

Figure 6.1: Trust variables in the binary logistic regression, p values

Figure 6.1 shows the p values of the relationships between the variables when having performed a logistic regression. Before the results have been interpreted, the results have been filtered out as all p-values above 0.05 are coloured grey, whereas values below and equal to 0.05 are dark blue.

Trustworthiness of family and friends regarding information on floods and flood adaptation has a significant effect on done elevation, done informative, done preventive low and done wet-proofing. Trustworthiness of family and friends has no effect on planning to take the measures.

Furthermore, trusting flood information from a government representative has a significant relationship with planning measures such as dry-proofing measures and preventive high effort measures, whereas trusting flood information from the prime minister has an effect on planning to take informative or preventive high effort measures.

In addition, social media has a significant relationship with planning on taking preventive high effort measures, preventive low effort measures and wet-proofing measures. Moreover, it also has a significant relationship with taking dry-proofing measures and done preventive high. It is interesting to note that general media does not have any significant relationships with the grouped measures.

Confidence intervals

Next to the p-values, the confidence intervals are analysed for identified significant relationships seen above. All twelve confidence interval plots can be seen in section E.2 in the appendix. When considering the identified relationships proven significant in section 6.2, the following relationships are significant when also considering the confidence intervals. The relationships are significant when the confidence interval does not include 1 in the interval itself.

The trustworthiness of family and friends regarding flood information has a significant relationship on taking elevation, informative, preventive low effort measures and wet-proofing measures.

Moreover, trusting information from a government representative has a significant effect on planning on taking preventive high effort measures and dry-proofing measures, whereas trusting the flood information from the prime minister has a significant effect on planning to take both informative and preventive high effort measures.

In addition, social media has a significant effect on planning to take preventive high effort, preventive low effort measures and wet-proofing measures. Moreover, social media also has a significant effect on taking dry-proofing measures and done preventive high.

Odds ratio

Several relationships have been deemed significant. To analyse the strength and direction of the aforementioned relationships, an odds ratio heatmap as been shown in Figure 6.2.

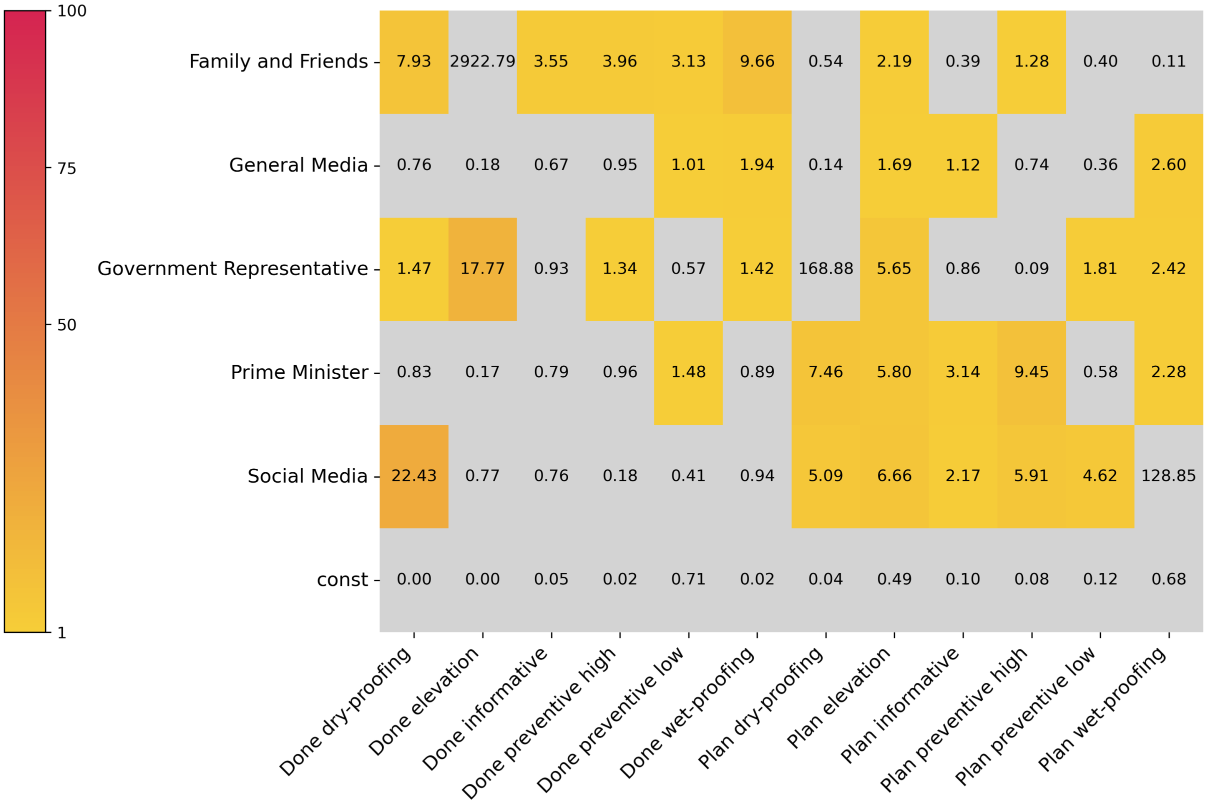

Figure 6.2: Trust variables in logistic regression, odds ratio

Figure 6.2 shows different colour codes. Grey is for relationships that are below one, whereas yellow and red and relationships above one. Relationships with an odds ratio below one are given a different colour, as the number one is the tipping point. Relationships below one decrease the likeliness of an event happening. Furthermore, other grey values that are not below one are considered to be outliers. Values above an odds ratio of 100 are set to be outliers.

When holding the PMT variables constant as mentioned in chapter 4, the following can be observed. Trusting flood information from family and friends has a strong positive effect on taking elevation (2922.79), informative (3.55), preventive low effort (3.13) and wet-proofing measures (9.66). The value of 2992.79 of family and friends on done elevation is very high and is considered an outlier, hence the effect of this relationship is not considered to be reliable. However, an increase in trustworthiness of family and friends makes it at least three times more likely to take informative and preventive low effort measures and nine times more likely to take wet-proofing measures, than not taking measures.

Furthermore, the trustworthiness of flood information from a government representative decreases the likeliness of the event of planning on taking preventive high effort measures (0.09). However, an increase in trust in information from a government representative does increase the likeliness of planning to take dry-proofing measures (168.88), compared to not taking the measure. An odds ratio of 168.88 is considered to be extremely high, hence this value is depicted as an outlier. Therefore, the effect of this relationship is considered not to be reliable.

In addition, trusting the prime minister increases the likeliness of planning on taking informative (3.14) and preventive high effort measures (9.45). The former is 3 times more likely than not planning on taking informative measures, the latter 9 times more likely than not taking any preventive high effort measures.

The trustworthiness of flood information from social media increases the likeliness to take dry-proofing measures (22.43, thus 22 times more likely to take the measures). However, it decreases the likeliness of taking preventive high effort measures (0.18). It also increases the likeliness of planning to take preventive high effort measures (5.91), preventive low effort measures (4.62) and wet-proofing measures (128.85). However, the relationship with plan wet-proofing measures with an odds ratio of 128.85 is considered to be extremely high, therefore, it is labelled as an outlier. The effect of this relationship is not considered to be reliable.

Model performance

To assess the quality of the binary logistic regressions and the relationships between the variables, the model performance is described in Table 6.1. For all twelve regression models, the Pseudo R squared (McFadden) and the Akaike Information Criterion (AIC) are assessed.

Table 6.1: Model performance

Y variable	Pseudo R2	N obs	AIC
Done informative	0.14	483	527.07
Done preventive low	0.1	483	593.58
Done preventive high	0.13	483	326.77
Done elevation	0.66	483	96.9
Done wet-proofing	0.16	483	274.93
Done dry-proofing	0.46	483	142.39
Plan informative	0.11	483	465.96
Plan preventive low	0.19	483	353.43
Plan preventive high	0.24	483	330.9
Plan elevation	0.66	483	98.94
Plan wet-proofing	0.52	483	135.95
Plan dry-proofing	0.52	483	147.4

Table 6.1 shows that the regression models on done elevation, done dry proofing, plan elevation, plan wet proofing and plan dry proofing perform the best when comparing to the other regression models. The best performing models have a high Pseudo R squared (greater than 0.45) and low AIC (below 150). This means there is a high model fit and high model quality relative to the other models. It is remarkable that for both the done and plan measures, elevation and dry-proofing prove to be the best performing models. However, plan wet-proofing is well-performing model, whereas done wet-proofing is not. Therefore, 'Plan' models overall have a better model performance than 'Done' models.

6.3. Discussion

This section aims to analyse how trust in flood information from different sources influences the intention to take different private flood adaptation measures. The results from the correlation initially measure the relationship between two variables, not controlling for other predictors. The relationships, when not controlling for other predictors, are different than the results from the binary logistic regression. This is because the identified correlations with more influential effects are not all deemed significant in the logistic regression. Social media has four identified relationships, plan preventive high effort measures, plan preventive low effort measures, plan wet-proofing measures and done dry-proofing measures, that are also significant in the logistic regression. Moreover, trust in the government representative has one relationship that is also deemed significant in the logistic regression: plan dry-proofing.

It is also interesting to note that, whereas trustworthiness of family and friends does have a relative low correlation with the measures in the correlation plots in Figure E.1 and Figure E.2, it does have several significant relationships in the regression model. This difference is possible due the non-inclusion of other predictors in the correlation heatmap. Another cause is that the significant correlations have not been identified in the correlation heatmap. The spearman correlation heatmap is purely created to provide insight into possible relationships at the start of the analysis and to identify the importance of including multiple predictors into the model. As previously mentioned, the Spearman correlation heatmap is used in this analysis to check if the correlation between the variables are not to high for the logistic regression (Ranganathan et al., 2017).

The logistic regression results show that, based on already having taken the measures (Done), an increase in trustworthiness in family and friends makes it more likely that the respondent has taken informative, preventive low effort or wet-proofing measures. Furthermore, an increase in trustworthiness of social media makes it more likely that the respondent has taken dry-proofing measures. Nevertheless, an increase in trustworthiness of social media decreases the likeliness of taking preventive high effort measures. This could be due to the presence of misinformation on social media as it is often not regulated any more. Furthermore, an increase in trust in the prime minister or in a government representative has no influence on having taken measures.

When it comes down to planning on taking measures in the near future (Plan), an increase in trustworthiness in the prime minister and a government representative do have an effect. An increase in trustworthiness of the prime minister has an influence on planning to take informative and preventive high effort measures in the near future. An increase in trustworthiness in a government representative has the opposite effect, as it decreases the likeliness of planning to take preventive high effort measures in the near future.

Trust in social media increases the likeliness of planning to take preventive high effort measures and preventive low effort measures in the near future. It is remarkable that the trustworthiness of general media does not have an influence on taking or planning to take measures.

Many of the models show low model performance. This could mean that the models are poor at predicting the outcome. Poor model performance suggests that the model does not fit the data well and that the predictors have weak explanatory power. However, it must be noted that survey data has very low R squared values and usually lower than a linear R squared, hence a low R square in this analysis does not necessarily mean bad model performance. In addition, it is interesting to note that the models done elevation and plan elevation have the highest model performance, but are not part of any of the identified significant relationships.

When considering flood adaptation policies, social media must be taken into account for spreading information and flood adaptation as it has an effect on both taking and planning to take adaptation measures. However, as seen in section 5.2, social media is not deemed trustworthy. If the quality and credibility of social media is increased regarding flood information, it leads to improved adaptation. In particular, if misinformation on flood risks and flood adaptation is being spread on social media, this should be regulated. It is important for flood information to be transparent and factual.

Moreover, the importance of family and friends must be taken account for private adaptation against floods, even if they are already deemed trustworthy (see section 5.2). Receiving information from family and friends could lead to increased adaptation as well. The National FCERM strategy (see section 3.2) could include improving the trust in flood information from social media and involve family and friends in spreading flood information to achieve the objective of people having the appropriate flood information and adaptation support by 2030. Moreover, it contributes to the objective of people understanding the risk of and reducing the impact of floods by 2050. When doing so, both trust in social media and trust in family and friends improves the intention to several incremental adaptation measures.

When planning adaptation for the future, the prime minister and a government representative play an important role as well in addition to social media and family and friends. Flood adaptation policies and strategies such as the FCERM should look into improving the trustworthiness of flood information from the prime minister as this leads to increased planning for incremental adaptation in the future. In addition, it is interesting to note that increasing trust in flood information from a government representative has the opposite effect on planning to take incremental flood adaptation measures. This could potentially be due to over-trust as mentioned by Smith and Mayer (2018), hence information from a government representative should focus on nudging people to adapt. However, it must be noted that planning on taking measures and taking measures is not the same thing, and respondents might say they would take the measure in the future but end up not implementing them.

The results on the influence of trust on adaptation corroborate with the results from other studies (Cologna & Siegrist, 2020; Hagen et al., 2016; Smith & Mayer, 2018), as trust in flood information indeed has an influence on the intention to adapt. Furthermore, the results also coincide with the conceptual model in section 2.3, as trust in flood information has influence on the protection motivation variable whilst also considering the threat and coping appraisal variables from the PMT model.

However, the presence of and the strength of the influence of trust depends on firstly, the source of information as suggested by Cologna and Siegrist (2020), and secondly, on the type of adaptation behaviour, as suggested by Paul et al. (2016). Combining these two concepts builds on previous research and it provides an overview of trust in different entities, and its influence on different six type of incremental measures. The results show which source of information is most influential on taking different incremental adaptation strategies. The implementation of the following incremental strategies can be improved by increasing trust: informative, preventive-high effort, preventive low effort, wet-proofing measures and dry-proofing measures. As Wilson et al. (2020) suggests, an increase in incremental adaptation strategies could lead to transformational adaptation on both a community and a national level.

Several limitations have to be addressed. The choice has been made to only include significant relationships with a p-value of smaller than 0.05. Harrell (2015b) mentions that p-values are problematic. Hypothesis testing is often based on arbitrary thresholds. By choosing the 0.05 threshold, other important relationships could have been left out as factors such as sample size could influence significance. Moreover, the choice has been made to only include answers of respondents regarding planning to take measures in the near future (1-3 years) and the option 3-5 years have been left out. This could influence the results as more respondents could have been considered as ”planning to take measures”. In addition, only 483 respondents out of 743 have been included in the regression due to excluding entries that contained answers such as ”don't know” or ”prefer not to say” on any of the regression variables. Therefore, many respondents have been left out of the analysis.

7

Results & Discussion
Cluster patterns of trust

For the third research question *Which cluster patterns can be observed when considering trust in flood information, hazard experience and socio-demographics in Norfolk/Suffolk coast, Somerset, and Greater London?* k-Medoids clustering has been performed. The results of the clustering analysis are described in this section.

7.1. Cluster descriptives

The findings from the k-Medoids clustering method are described in appendix F. The results are the following:

- **Cluster 0**: This cluster contains 55 respondents. Cluster 0 has **very low trust** in flood information from the **prime minister** (mean:1.09) and a **government representative** (mean:1.64). It also has **very low trust** in flood information from **general media** (mean:1.87) and **social media**(mean: 1.58). There is only **some trust** in information from **family and friends** (mean:3.27). Regarding socio-economic status, this cluster has **average income** compared to the other clusters (mean: 3), **relatively high savings** but not as high as other clusters (mean:3.98) and generally **no multiple household incomes** (mean: 0.16 and median:0).

  These people also have **barely implemented any measures**, neither structural (mean: 0.04) or non-structural (mean:0.22). This is the lowest of all clusters. However, they are **planning on implementing non-structural measures** in the near future (mean:0.65). They are **not really planning** on taking **structural measures** (mean:0.09), but the mean is higher than for other clusters. Regarding flood experience, this cluster has **barely been affected by floods** (mean: 0.13).

  The **age group** for this cluster is considered **quite average** (mean: 2.6) when comparing to the other clusters.
  When looking at the standard deviation, the standard deviation for all variables is very low except for household savings (std: 2.59). The data for this variable is more spread out around the mean than for the other variables. When considering the medians of the variables, these are usually close to the mean except for trustworthiness of government representative, social media, general media and for the age group. The median for these variables is lower than the mean. This means that the data for the aforementioned variables is right-skewed and affected by outliers.

- **Cluster 1**: This cluster has 62 respondents. Cluster 1 has **low trust** in the **prime minister** (mean: 2.13), but **neutral trust** in the **government representative** (mean:3). This cluster has quite **neutral trust** in flood information from **family and friends**(mean:3.11), this is the lowest compared to the other clusters. Moreover, there is **low trust** in flood information from **general media** (mean: 2.48) and even **lower trust** in flood information from **social media** (mean:1.81), but not the lowest out of all clusters.

Household income (mean:4.21) and **household savings** (mean:6.1) are **very high** in this cluster, as matter of fact the highest of all clusters. This clusters also does have **multiple household incomes** (mean: 0.85).

Regarding the measures, this cluster has **barely implemented any structural measures** (mean:0.13), but the mean is higher than most clusters. This cluster has **taken non-structural measures** (mean:0.84). They are also **planning** on taking **non-structural measures** (mean:0.94), but **not structural measures** (mean:0.03). The mean for planning to take structural measures is the lowest out of all clusters. This group has a **low experience of floods** (mean:0.29). **The age group** is the **highest** out of all clusters with a mean of 3.29.

The standard deviation is low or moderate for all variables, hence the data is not spread out and concentrated around the mean. The medians are for most variables also relatively close to the mean, which means that the data is not affected much by outliers. However, the medians for the variables household savings, household income and age group are higher than the mean, which means that the data is left-skewed and affected by outliers for those specific variables.

- **Cluster 2**: This cluster has 199 respondents, significantly more than the other clusters. Cluster 2 has **low trust** in flood information from the **prime minister** (mean: 2.28) and a **government representative** (mean:2.88). The respondents in this cluster have relatively **high trust** in flood information from **family and friends** (mean: 3.61). They have **low trust** in flood information from **general media** (mean:2.65) when comparing to the other clusters. Moreover, the cluster has relatively **low trust** in **social media** (mean:1.71) compared to the other clusters.

  Household income (mean:4.05) and **household savings** (mean:5.81) are **high** in this cluster. This cluster tends to have **multiple incomes** (mean:0.85).

  This cluster has **implemented** a lot of **non-structural measures** (mean:0.79), but **not many structural measures** (mean:0.08). However, the implementation of the non-structural measures tends to be higher than the other clusters. Moreover, this cluster is **not planning** on taking **non-structural measures** (mean:0.05) or **structural measures** (mean:0.04) in the near future. The mean of the variable any measure plan non-structural is lowest out of all clusters. Furthermore, this group has **not experienced floods much**. The **age group** in this cluster is **very high** compared to the other clusters (mean:3.17) meaning this cluster contains relatively older respondents.

  The standard deviation for these variables from cluster 2 is very low except for household savings, meaning the data is not spread out around the mean. The medians are very similar to the mean except for social media savings, which means that the data is symmetrical and does not contain many extreme outliers. The data for savings is left-skewed as the median is higher than the mean, meaning that there might be outliers present in this cluster pulling the mean in a lower direction. The data for trustworthiness of social media is right-skewed, as the median is lower than the mean.

- **Cluster 3**: This cluster has 46 respondents. Cluster 3 has the **highest trust** in flood information from the **prime minister**(mean:3.24) and flood information from a **government representative** (mean:3.65) compared to the other clusters. This cluster also has relatively **high trust** in flood information from **family and friends** (mean:3.72). Compared to the other clusters, it has very **high trust** in **general media** (mean:3.65) and relatively **high trust** in flood information from **social media** (mean:3.46).

  The household **income** is quite **high** (mean:3.61) and has **high savings** (mean:4.02). Households from this cluster do **not have multiple incomes**(mean:0.33).

  This cluster has **not implemented non-structural measures** compared to the other clusters (mean:0.22). It has also **not implemented structural measures** (mean:0.17). This cluster **plans on implementing non-structural** (mean:0.76) measures but **not structural measures measures** (mean:0.3), even though the mean for planning structural measures is highest out of all clusters (mean:0.3).

  People in this cluster have **not had much flood experience** (mean:0.22), but it does tend to be higher than other clusters. Regarding the age group, the people in this cluster are **relatively young** compared to the other clusters (mean: 2.22).

  The standard deviation of the variables is low except for household savings. For savings, there is more variability in the data than for the other variables. For the variables, the median is often close to the mean, which means most data is symmetrical.

- **Cluster 4**: This cluster has 106 respondents. The respondents from this cluster have **low trust** in flood information from the **prime minister** (mean:2.06) and **neutral trust** in flood information from a **government representative** (mean: 2.98). They do have relatively **high trust** in **family and friends** (mean: 3.57). However,trust in **general media** (mean:2.75) and **social media** (mean:2.27) remain **low**.

  People from this cluster have **very low household income** (mean:2.16) and **very low household savings** (mean:1.92). They do **not tend to have multiple incomes** (mean:0.05).

  However, regarding having taken measures, they have **implemented non-structural measures** (mean:0.83), but **not** really **structural measures** (mean:0.12). They are also **not planning** on taking both **non-structural measures** (mean:0.18) or **structural measures** (mean:0.09). The people in this cluster have **barely experienced any floods** (mean:0.19).

  The people in this age group are **relatively younger** than other clusters, with a mean of 2.65.

  Standard deviations for all variables are low, and medians are similar to the mean except for household savings (median:1). The median is lower than the mean, which means the data is right-skewed with a few outliers pushing the mean upwards.

7.2. Geographical cluster patterns

The spread and distribution of the clusters in each region are described in this section. For each region, the patterns of the clusters are discussed. The clusters are visualised on the region maps, showing which MSOA (Norfolk/Suffolk and Somerset) or Local Authority (Greater London) belongs to each cluster.

7.2.1. Patterns in Norfolk/Suffolk coast

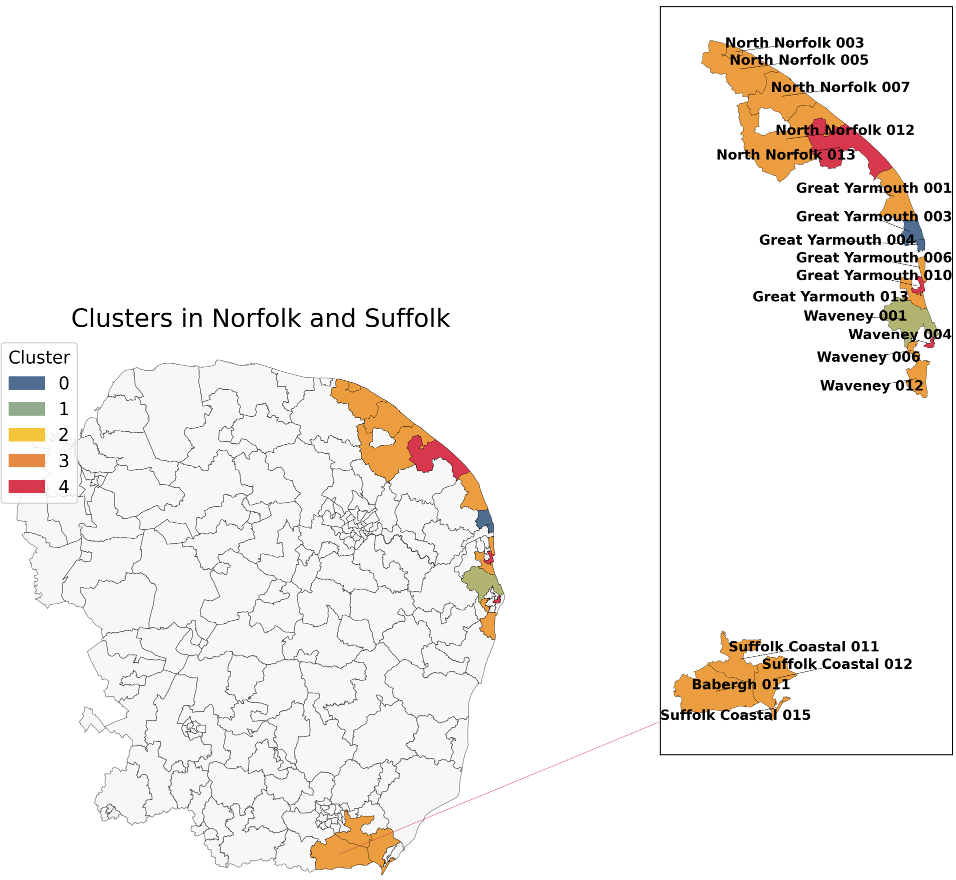

Figure 7.1: Clusters in Norfolk/Suffolk coast using the mode of region

Figure 7.1 shows the clusters in Norfolk/Suffolk coast. MSOA regions along the coast in Norfolk and Suffolk tend to belong to four of the five clusters, only cluster 2 is missing. North Norfolk mainly belongs to cluster 3, and regions in Great Yarmouth and Waveney belong to either cluster 0,1,3 or 4. It is interesting to note that Waveney 001 is the only region that belongs to cluster 1.

7.2.2. Patterns in Somerset

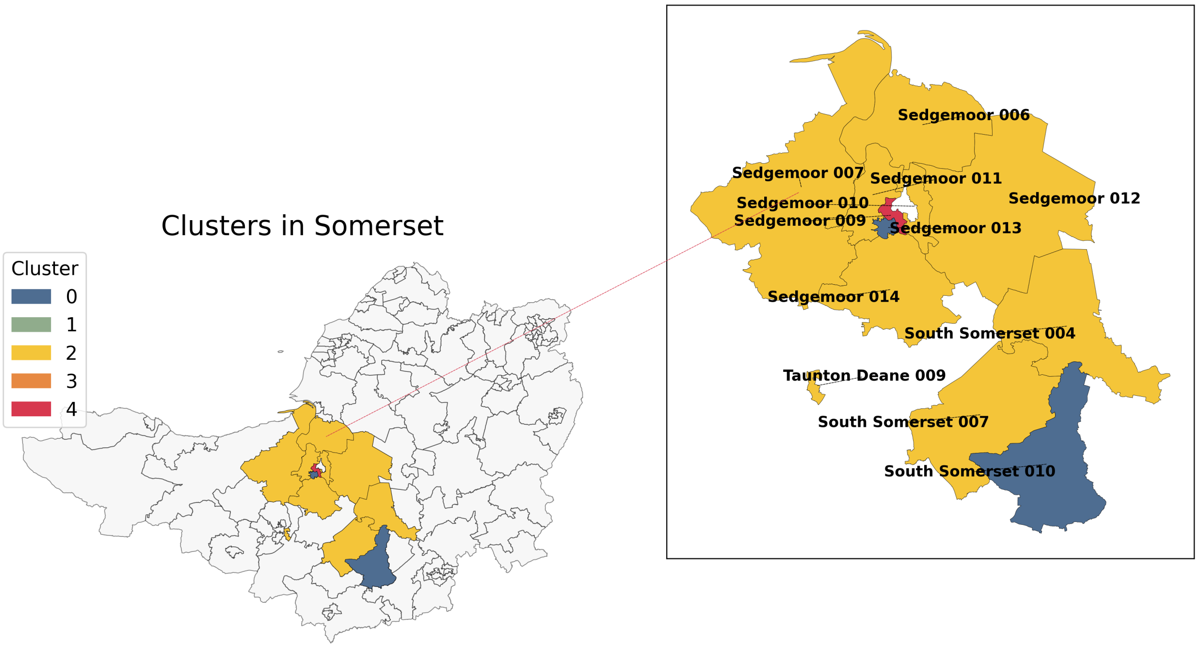

Figure 7.2: Clusters in Somerset using the mode of region

Figure 7.2 shows the clusters in Somerset. Most regions in Somerset belong to cluster 2. Only regions Sedgemoor 013 and South Somerset 010 belong to cluster 0, and Sedgemoor 009 belongs to cluster 4.

7.2.3. Patterns in Greater London

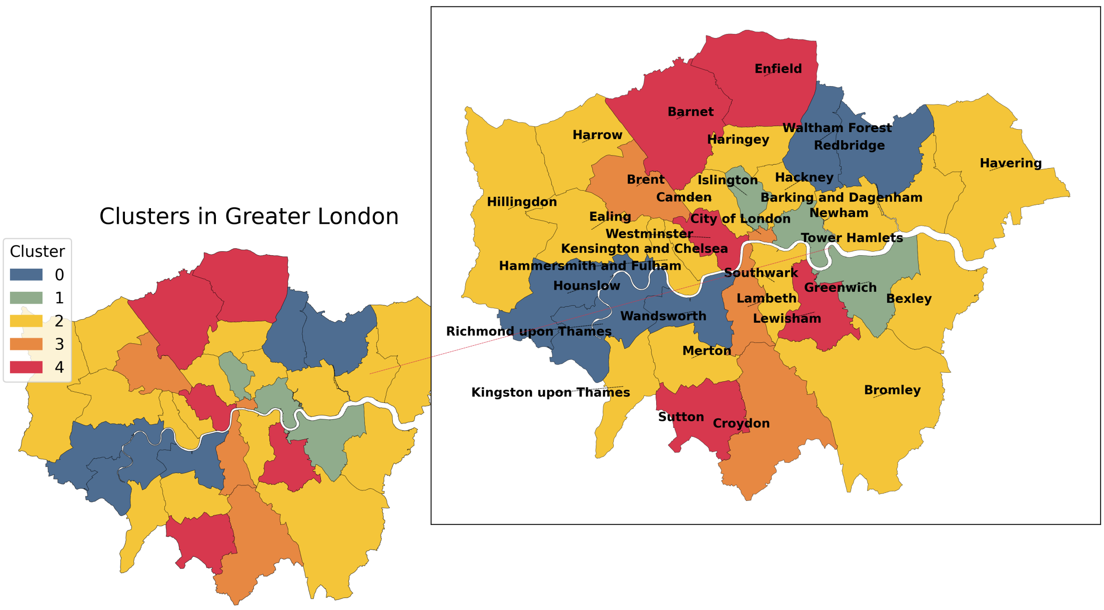

Figure 7.3: Clusters in Greater London using the mode of region

Figure 7.3 shows the clusters in Greater London. It is remarkable that only Islington, Tower Hamlets and Greenwich belong to cluster 1. The clusters are rather spread out over London, however, outer areas of London (more to the West or East) tend to belong to cluster 2. Other outer areas (North and South) belong to either cluster 0, 3 or 4.

7.3. Discussion

7.3.1. Cluster interpretations

- **Cluster 0: Cautious at-risk planners**. This middle-aged group has very low trust in flood information from any source. They only trust their family and friends regarding flood information. Due to this low trust, they may resist flood adaptation policies. They have relatively average income, no multiple incomes and low savings compared to the other clusters. They have not adapted yet and have not really experienced floods, but are planning on taking non-structural measures in the near future due to flood-risks. However, if they resist flood adaptation policy as they do not trust flood information, there might be cases of maladaptation and a false sense of security. Hence if a flood happens, this could be disastrous for this group of people with average incomes and savings, as they barely have implemented any measures.

  Cluster 0 only appears in two areas of Norfolk/Suffolk coast and in two areas in Somerset, but in multiple areas in Greater London. These areas can be identified as at-risk areas, vulnerable for the consequences of flooding.

  When looking at communicating flood information in Greater London, the people in these areas might not resort to the London Risk Register or local authority websites as they do not trust flood information from governments or media. National flood adaptation policy, such as the National FCERM strategy, must consider nudging the people in these areas via the spread of information through family and friends, as there still is some trust in those people. Only then can the consequences of flooding be reduced. As seen in the results of 6, trusting family and friends leads to an increase in taking adaptation measures. Local resilience groups or community groups could benefit flood adaptation in these areas. By communicating flood risks and flood information and sharing plans for individual flood adaptation, individual flood adaptation could increase. The local adaptation strategies in Greater London, such as the Surface Water Strategy and the Thames Estuary programme, might encounter resistance when trying to force information upon residents and trying to involve them decision-making process. Engaging them in community groups would be more beneficial. Moreover, nudging these areas in other ways, by using money incentives for example, could also be beneficial to increase both incremental and flood adaptation measures.

  The same is advised for the few areas in Norfolk/Suffolk coast and Somerset. The rurality of those areas suggests involving friends and family (acquaintances) more in spreading flood information instead of using their resilience forums, as these regions have high trust in family and friends (as seen in section 5.2). Current strategies, derived from the National FCERM strategy, would only work if other incentives are given to individuals to adapt instead of supplying them with information or if they would create more community and volunteer groups. In particular, many of the respondents have average income and no savings, hence they do not have the money to adapt. For example, bringing sandbags back in Somerset provided by the Somerset Council would be more effective than supplying these regions with flood information. For authorities, a better transformational adaptation framework would be beneficial in supporting these individual adaptation actions.

- **Cluster 1: Risk-ready sceptical adaptors**: This cluster contains relatively old people compared to other clusters. These people are often more towards age 60. They have low trust in the prime minister, but a government representative could possibly be a good source of flood information for these people. They have neutral trust in family and friends, but still find general media and social media not trustworthy. However, household income and household savings are very high for this cluster, and these households tend to have multiple incomes. These people therefore have the capability to adapt. This group of people has implemented non-structural measures but not any structural measures. They also plan on taking more non-structural measures in the future. This means that this group of people is willing to adapt, if they get the right information from an expert, such as a government representative. This group of people has experienced some floods compared to the other clusters.

This cluster is only visible in Norfolk/Suffolk coast, and only three regions in Greater London. When assessing communication strategies, the areas belonging to cluster 1 would look at a National Flood Forum or Flood maps to assess flood risks, as these are often created by the Environment Agency, a government representative. When taking a closer look into the regions, the local resilience forums and registers are beneficial to spread flood information as people tend to trust that type of information. The people in this cluster also have the ability to adapt, and have taken non-structural measures. However, as seen in chapter 6, trust in a government representative such as the Environment Agency could lead to over-trust and less adaptation. The local resilience forums should include more transparent and relevant information on all incremental measures, both structural and non-structural, to nudge these people to take more measures and not to over-trust the Environment Agency, especially if this group tends to experience floods more often than other clusters. Thus, national and local adaptation policies should promote communicating flood risks more in cluster 1 areas to increase flood resilience and adaptation. Nevertheless, those policies have to make it clear that individual incremental adaptation must be undertaken in order to achieve societal and transformational resilience. Transparency in policies is therefore key.

- **Cluster 2: Rational adapters**: This group of older adults have more of a neutral attitude towards flood information from governments and general media, but still find it not trustworthy. They have low trust in the prime minister and social media, but they do find flood information from friends and family very trust worthy. They have high income and savings, but slightly lower compared to cluster 1. They also have multiple incomes in their households. Their socio-economic status makes them financially stable and capable of adapting to floods.

  They have implemented non-structural measures but have barely implemented structural measures. The people in this group find this enough, as they do not plan to take adaptation actions in the future. They also seem to have relatively low flood experience compared to the other clusters.

  These clusters are dominantly present in Somerset and Greater London. Most areas have either neutral or no trust in flood information from various sources, but do have the income and savings to take incremental adaptation measures. Flood adaptation policy must consider that these groups would acknowledge information from government representatives and general media, but they would not necessarily find this information reliable. This group needs a nudge towards planning for adaptation for the future instead of thinking it is a ”one time only” investment, as they have implemented non-structural measures. Communication must be clear and transparent so that this group can evaluate the risks themselves and to increase trust. Somerset has resilience forums, and these provide information on how to prepare for floods. However, policies should consider a greater focus on emphasizing the increase in flood risks and being transparent on flood information. Local flood adaptation policy and the National FCERM strategy should focus on communicating the flood risks properly, by highlighting different flood risk and erosion maps as mentioned in section 3.2.

  Being more transparent in spreading flood information and building trust in the source could increase support for transformational adaptation policies and strategies. As seen in Chapter 3, there is often a lack of transparency in policy frameworks supporting transformational strategies. Programmes such as the Thames Estuary 2100 could therefore benefit from communication policies on flood information, especially as this cluster is dominantly present in Greater London.

- **Cluster 3: Influential young planners**: This cluster contains younger people, more towards an age of 30-45 years old. This group of people consider the following sources very trustworthy: a government representative, family and friends, general media and social media. These people also tend to trust flood information from the prime minister, which is rare amongst the clusters. They tend to have a reasonable household income and household savings, but no multiple incomes. The people in this cluster have not adapted yet, but are planning to take non-structural measures in the near future. With the right information, they are willing to adapt and they are able to adapt themselves. They have experienced flood events more often compared to other clusters.

This cluster is mainly found in Norfolk/Suffolk coast, and in a few regions in Greater London. This cluster is not found in Somerset. It is interesting to note that Greater London has a lower risk at flooding than the other two regions, as mentioned in section 3.3.3. This could be the reason that many of the people in this cluster have not adapted yet, but realise the necessity to do so for future flood risks. Norfolk/Suffolk coast mainly experiences coastal erosion as seen in section 3.3.1. Hence, taking incremental adaptation measures to reduce the risk from flooding from rivers or sea or from surface water is possibly not a priority.

Regarding flood policy for adaptation, these people can be nudged through various types of sources to adapt, if they receive proper flood information. As this is a younger generation, social media could potentially be more effective, as seen in the results of 6. Local resilience forums, the national flood forum and the National FCERM strategy could consider spreading flood risk and information more via social media as younger people tend to read these kind of information sources more than checking flood risk maps or registers. Local authority websites already mention the use of media for checking flood risks (as seen in section 3.3.3). Taking the results from 6 into account, trust in information from family and friends and social media have a positive effect on taking and planning to take measures. Focussing on these information sources for this cluster could prove beneficial for individual incremental adaptation, possibly leading to transformational adaptation.

- **Cluster 4: Risk ignorant and adaptation-constrained**: This relatively young cluster, compared to the other clusters, has low trust in the prime minister and social media. They have a neutral attitude to general media and a government representative, and have the highest trust in flood information from family and friends. The people in cluster 4 have low household income and savings and do not have multiple incomes. Furthermore, they have not adapted against floods and are not planning to do so in the future, even though they have experienced more floods than two other clusters in the analysis. If flood information needs to be communicated to these people, this must be done via family and friends, with a possibility of spreading the information a government representative.

  Cluster 4 is present in Norfolk/Suffolk coast, Somerset and Greater London. Flood adaptation policy must therefore concern all three areas for this cluster of people. However, Greater London contains more regions belonging to cluster 4 than Norfolk/Suffolk coast and Somerset. As Greater London faces less flood risk than Norfolk/Suffolk coast and Somerset (as seen in Chapter 3), it could be that the respondents from this cluster do not feel the necessity to adapt as they have experienced less flood events.

  For flood adaptation policy, this group needs to be nudged more as they have not adapted and do not intend to do so either. However, they would also need some financial support to be able to adapt. Hence, there must be a greater focus on being transparent about flood information and adaptation in policies. This is to be combined with money incentives. Moreover, policies should focus more on increasing support via community support groups and acquaintances, to increase individual adaptation and awareness. An example of such a community or volunteer group is supported by the National Flood Forum as part of the National FCERM strategy (see section 3.2). If the information is deemed trustworthy enough, media and the local resilience forums can be used to spread information as well.

When considering previous studies, the meta-analyses by van Valkengoed and Steg (2019) mentioned that many studies consider a limited number of variables and not much is known how different motivational factors are linked to each other to motivate adaptation. Using clustering analysis and identifying underlying patterns using multiple RISP and PMT variables, a first insight is given into the relationships between the following elements: socio-demographics, hazard experience and trust in information.

7.3.2. Limitations

Several limitations are identified for this analysis. First, the data has been assumed to be numeric for the clustering analysis and the Manhattan distance has been used as a metric. Most variables are originally ordinal data as they have a Likert scale type values, but equal spacing has been assumed between the values for this research. This could potentially alter results as the ordinal nature of the variables is not respected. Moreover, the mean has been used to compare the variables between different clusters, which is a descriptive statistic that works best on quantitative data (Kaliyadan & Kulkarni, 2019). This might lead to skewed interpretations, as all variables consider categories (e.g. a mean of 2.6 is not a category).

Moreover, the silhouette score (see section C.2) is very low for all k clusters. The values are positive but closer to zero than to one, which means that the divide between the clusters is possibly not clear and could suggest poor clustering performance. There might be some overlap in the cluster data or ambiguous boundaries.

In addition, the variable Household Savings has quite high standard deviations for all the clustering categories. This means that the Household Savings variable does not distinguish the clusters well and does not contribute to the division of the clusters as the data for this variable is still highly spread within each cluster.

As mentioned above, van Valkengoed and Steg (2019) mentioned many studies containing limited number of variables. For the clustering analysis, only a limited number of variables are chosen based on the combined RISP and PMT framework. There could potentially be other variables, such as social influence from the PMT framework, that have an influence on adapting against floods and having trust in flood information.

When considering the respondent counts per region in Appendix G, some regions have very few respondents compared to others. The clusters and cluster descriptions assigned to these regions might not be accurate, as the respondent's answers could possibly not be representative for the entire region and the results only cover a few residents of the area. In particular, the mode of the clusters available in the region is used for plotting the maps. This means other cluster labels are probably present in the region, but not shown on the maps. Moreover, the MSOA regions of the respondents for Greater London have been adjusted to London Boroughs for better visibility. However, as seen in Figure G.3, this means few respondents for very big regions. This could mean that the clusters are possibly not representative for the region.

8 Conclusion

Trust plays an important role when taking individual adaptation actions. The absence of trust results in inaction on adaptation or maladaptation. As information is essential to motivate people to protect themselves against the risks of climate change, trusting information on floods and adaptation is necessary to increase the level of support for and success of different adaptation policies. Trust and its influence on climate adaptive behaviour has been researched often, however, research often neglects the importance of clarity on the definition of trust. Not only do levels of trust differ regarding different entities, but also do different definitions of trust lead to varying results. As information is essential to motivate people to protect themselves, this thesis defines trust specifically as trust in information on floods and flood adaptation from different entities.

Moreover, trust has varying influences on different type of adaptation measures. Nonetheless, a research gap was identified concerning the assessment of trust's influence on incremental and transformational adaptation strategies. This thesis therefore explores this association considering these two types of adaptation strategies. As a case study, three regions in the UK, Norfolk/Suffolk coast, Somerset and Greater London are used to analyse this gap. The research question of this thesis is as follows: *How does trust in information on floods and flood adaptation influence the intention to take private flood adaptation measures in flood-prone areas in the United Kingdom?*

A combined framework of the Protection Motivation Theory framework (PMT) and the Risk Information Seeking and Processing (RISP) model supports the use of descriptives, binary logistic regressions and a k-Medoids clustering analysis to answer the research question. In addition, the framework provides the opportunity to consider multiple motivational factors such as coping appraisal, threat appraisal, socio-demographics and hazard experience whilst analysing the influence of trust on climate adaptive behaviour.

The findings of this study address the comparison of trust in different entities between rural and urban areas to answer the first sub-question. Rural areas tend have less trust in flood information from the government or from (social) media than urban areas, but have higher trust in flood information from family and friends. However, all regions show similar trends when assessing which sources are most and least trustworthy. For all areas, people have the least trust in flood information from social media and prime minister, and the most trust in flood information from family and friends. The rural and urban differences in trust serve as an initial insight to answer the research question as they create a more comprehensive understanding of the behaviour of trust in information from different entities. This insight shows which regions have either high or low trust in different sources of flood information. This insight is useful for policy specific advice, as the level of trust can determine the willingness to adapt to flood events.

Nevertheless, when focussing on the influence of trust on adaptation strategies, only some sources of information are deemed influential. An increase in trust in flood information from family and friends makes is more likely that the respondent has taken incremental measures. Furthermore, we see a similar trend with social media as an increase in trust in flood information from social media makes it more likely that a person has taken incremental adaptation measures, specifically structural measures. When looking at other type of incremental measures such as non-structural measures however, an increase in trust in social media is associated with a decrease in private adaptation. This could be possible due to the presence of misinformation and misleading information on social media, as this is often not regulated.

Planning to undertake adaptation in the future shows different trends. An increase in trust in flood information from the prime minister is associated with an increase in the likeliness that a person plans to take incremental measures in the future. Similar trends are found for social media, as an increase in trust increases the likeliness that adaptation of incremental measures is planned for the future. Trust in information from a government representative shows the opposite effect, as an increase in trust makes it more unlikely that a person plans to take certain incremental measures in the future. Over-trusting a government representative could lead to a feeling of safety. As a result, people do not undertake any adaptation measures themselves. The last source, general media, does not have an influence on either taking or planning to take private adaptation measures.

It has been established if trust in various information sources has an influence on taking incremental adaptation measures, holding other motivational factors constant. Hence, the second sub-question has contributed to analysing the influence of trust on the intention to take flood adaptation measures and answers the main research question. However, as the combined framework of the PMT and RISP models suggests, trust does not have a sole influence on the intent to adapt. Establishing the influence of trust is not enough for area-specific policy advice. Therefore, motivational factors identified in the combined PMT and RISP framework, are also included to support geographically targeted policy advice.

For the third sub-question, five clusters were created based on trust in flood information, hazard experience and socio-demographics to identify areas requiring policy intervention. The clusters revealed that there are five distinct groups amongst the respondents. Many respondents in the clusters had not implemented incremental adaptation measures, some are planning on doing so in the future. The differences in cluster characteristics and the (non-)application of flood adaptation strategies show the urgency for area-specific flood adaptation policies to either cultivate trust in flood information or to provide financial support for adaptation, or both. The results to the third sub-question therefore, complete the analysis of trust in information on floods and flood adaptation and the influence on taking private flood adaptation strategies.

The findings indicate that trust in information varies by the type of source. This variation is associated with the intention to take flood adaptation measures. The research gap is addressed by showing the association between trust in specific information sources and the adoption of particular adaptation measures, taking other area-specific motivational characteristics from the combined PMT and RISP framework into account. When revisiting the framework, only general media and social media as external influences are considered to have an influence on the protection motivation variable when taking the other motivational factors into account. This could be extended with other sources such as a government representative, the prime minister and family and friends. Moreover, the protection motivation element in the framework should be extended with several types of adaptation measures, as not all adaptation variables are equally influenced by trust.

Policy Implication

The results of this thesis question the effectiveness of policies regarding incremental adaptation measures, particularly when those policies concern the communication of flood information. The findings show that trust in flood information is context- and area-specific and its influence on flood adaptation varies between different types of incremental flood adaptation measures. This means national or regional flood adaptation policies and strategies concerning the communication of information are not equally effective in each area. Depending on trust in the source, people are willing to acknowledge the information and implement specific types of incremental measures.

To increase incremental adaptation by households, policies must consider the local trust characteristics. The Nation FCERM strategy and information platforms such as the National Flood Information Forum must consider that not all people trust the UK government or government representatives, hence spreading flood information via these sources is not always effective. However, focussing on the increase of trust in social media sources and the prime minister is associated with an increase in either taking or planning to take incremental adaptation measures. These sources can be made more credible and transparent regarding flood information.

Local policies and strategies can focus more on additional motivational factors next to trust shaping incremental adaptation in each area. The National FCERM is the main guideline for local flood risk management strategies, however, local strategies should include characteristics such as income, savings, trust and flood experience per region to increase the intention to take flood adaptation measures. Local strategies should include more insight into the demographics of the region and should acknowledge the lack of trust in information sources, in particular when local strategies are focussed on engaging citizens and creating community groups. Furthermore, depending on the socio-demographics, information spread might not be enough to reduce flood risks as low income or savings restricts the adaptation to floods. Hence, money incentives or aid in adapting is necessary in some areas combined with communicating information on floods and flood adaptation.

As previously noted, transformational adaptation is often government-led and not implemented individually by residents. On a local level, no guidance is given on implementing transformational change. Transformational adaptation strategies, such as the SMPs in both Norfolk/Suffolk coast and Somerset and the adaptation pathways in Greater London, should provide transparent policy frameworks and use existing policy tools for local implementation. Individual transformational adaptation has not been included in this thesis due to a lack of implementation. However, increasing incremental adaptation by households can lead to transformational change on a national scale. Full transformational change on a national scope is only possible when all individuals implement small incremental flood adaptation changes.

Research limitations and further research

There are several limitations related to the survey data. This study considers the grouping of measures into three categories of non-structural measures and three categories of structural measures. When grouping these measures, the assumption has been made that if a respondent takes or plans to take one of the measures, they would take the other measures within the group as well. In reality, this is not the case. For future studies, the best manner of grouping the measures should be analysed. A possibility would be aggregating the responses to the different measures into the new group variable, by using mean or median values.

Moreover, the difference between incremental and transformational adaptation was assessed in the initial phase of this study. In reality, the boundaries between the two adaptation strategies are often fuzzy. There is no uniform method in categorising household adaptation strategies (Wilson et al., 2020). Additionally, the study contained few measures that belong to the category of transformational adaptation. The only measure related to transformational adaptation, namely strengthening direct coastline privately, has been excluded from this research due to a lack of implementation by the respondents. As Norfolk/Suffolk coasts contain multiple of the fastest eroding coasts in Europe (Environment Agency, n.d.-b), important insights on private adaptation could have been missed in the results.

As steps on incremental adaptation can lead to transformational adaptation, conclusions can be made on transformational strategies and adaptation measures. However, this is not based on actual individual transformational adaptation measures. Future surveys and studies should also include transformational adaptation strategies that are possible to be implemented by households. Moreover, studies should define the boundaries between incremental and transformational adaptation properly to differentiate the influential factors on both types of strategies.

Furthermore, the data from this survey is not based on longitudinal data. van Valkengoed and Steg (2019) mention that to establish relationships between variables, experimental and longitudinal studies are essential. Future studies should include multiple survey waves to assess the long-term effect of trust on private household adaptation in the UK. It is also interesting to analyse what current respondents will do in the future if they said they would plan for future adaptation, as the question remains if the respondents actually end up doing so.

In addition, this study is based on data from specific regions in the UK. The results are therefore not generalisable to a wider population. However, the study is transferable. The methods and the combined theoretical framework can be used on survey data from other countries as the methods and framework are not country or culture-specific, provided that the dataset has been cleaned and handled properly. It is also advised for future research to use the methods and theoretical framework on survey data from other countries to compare results, but only if the survey data has the appropriate variables needed for the methods.

There are also limitations regarding the theoretical framework that need to be addressed. When combining the RISP and PMT theory, several elements of the RISP framework have been left out. Only the elements that coincided with the PMT framework have been added to discover the influences on the intention to take adaptation measures. As the RISP framework contains seven factors influencing the information seeking and processing behaviour variable, important elements possibly influencing the protection motivation theory could have been left out.

Furthermore, the original protection motivation variable from the PMT framework only considers the intent to implement adaptation in the future. In this thesis, the variable also served as a basis for having taken adaptation measures already. Future studies should have a look into expanding the combined RISP and PMT theory.

Moreover, according to the combined RISP and PMT theory in this thesis, trust in flood information would not have a direct influence on the intention to take adaptation measures in the future. According to the framework, the Information Seeking and Processing Behaviour serves as a mediator between the two variables. However, this indirect influence of the trust variable is not taken into consideration. When applying the combined framework, more research should be done into this mediator variable in the future instead of using the assumption from the PMT theory that trust has a direct influence on the intent to adapt.

The definition of trust is often ambiguous and comparing trust levels with other studies remains difficult. Nevertheless, the power of trust should never be underestimated. The effectiveness of individual flood adaptation depends on trust in various information sources, ranging from government sources to social media sources. Recognising the power of these diverse information sources is key to building effective flood adaptation policies.

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A
Key search words

In this appendix, the search terms that were used for the literature review are mentioned. As mentioned in Chapter 2, other literature has also been found via contacts or the Backward Snowballing method.

- trust AND government AND climate AND (change OR adaptation)
- trust AND climate AND adaptation AND survey
- private AND public AND institutions AND trust AND climate AND change
- private AND public AND institutions AND trust
- (trust AND government AND climate AND adaptation) AND (survey AND data)
- transformational AND flood AND adaptation
- (transformational AND flood AND adaptation) AND (survey AND data)
- ”social institutions” AND ”climate change” AND adaptation
- trust AND flood AND information
- ”survey data” AND advantages AND limitations

B
First data insights

This appendix shows respondent counts for the areas and the measures. Table B.1 shows the number of respondents per region and shows the total respondents for this survey.

Table B.1: Respondent counts per region in survey data

Region	**Respondent counts**
Norfolk/Suffolk coast	256
Somerset	129
Greater London	358
Total	743

Table B.2 shows how many respondents have chosen one of the four answers for each structural measure. The answers to the measures are the following: one considers not having implemented, two is planning to implement in the next three to five years, three is planning to implement in the next one to three years and four is having implemented the measure.

Table B.2: Initial value counts for structural measures (Inverted)

	SM1	SM2	SM3	SM4	SM5	SM6	SM7	SM8
1	677	679	679	639	654	671	679	245
2	23	25	26	38	32	37	27	4
3	25	23	22	22	39	21	26	1
4	18	16	16	44	18	14	11	6

Table B.3 shows the value counts for the inverted non-structural measures. The possible values to these variables are in the same four-point Likert scale as seen in Table B.2.

Table B.3: Initial value counts for non-structural measures (Inverted)

	NM1	NM2	NM3	NM4	NM5	NM6	NM7	NM8	NM9	M10	M11
1	182	605	622	459	427	584	283	505	538	385	357
2	58	64	68	89	101	60	68	83	75	78	61
3	122	48	27	101	128	61	125	116	92	160	113
4	381	26	26	94	87	38	267	39	38	120	212

Table B.4 shows, according to the six new grouped variables, the value counts for the respondents that have taken the type of measure (Done) and for the respondents that plan to take the measure in the near future (Plan).

Table B.4: Respondent counts for grouped measures

Measure	**Done**	**Plan**
Informative	157	138
Preventive low	462	110
Preventive high	69	84
Elevation	18	25
Wet proofing	54	32
Dry proofing	32	38
Any measure	494	260
All measures	3	3

C

Clustering set-up

The appendix elaborates the choice for the number of clusters for sub-question three. The elbow method is first shown, and then the silhouette score is shown for different number of clusters. At the end of the appendix, the distribution is shown for the variables included in the clustering analysis.

C.1. Elbow method

The elbow-method plot is seen in Figure C.1. It is interesting to note that the cost decreases steeply at first until three clusters, rises again at cluster 4 and then decreases steeply again in five. Five could be considered the kink in the plot, as the line does not decrease steeply any more after that point. There is a rise and fall after eight clusters again, but this does not change the total cost much.

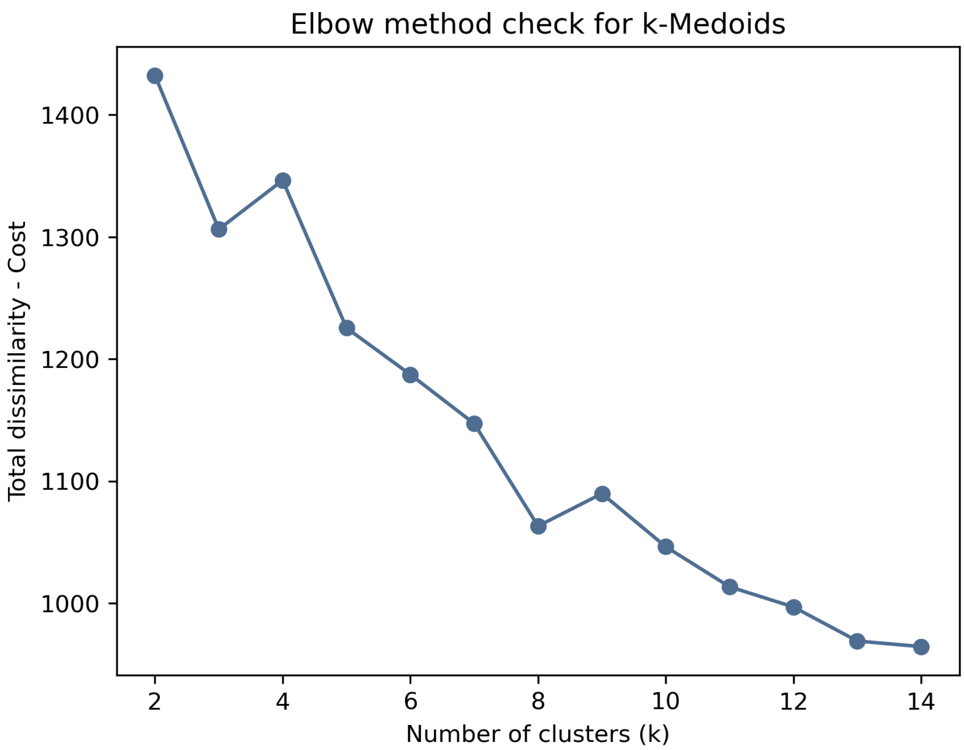


Figure C.1: Elbow method plot for determining optimal number clusters

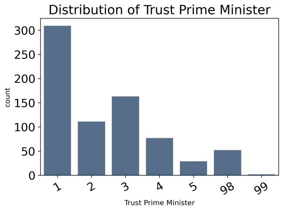
C.2. Silhouette score

The silhouette score for the clustering algorithm, as seen in section 4.3, is shown below. It can be seen that two and three have the highest silhouette scores, but these consider too few clusters. Therefore, five clusters is deemed the most appropriate for the clustering algorithm as the score is relatively higher than for the higher number clusters.

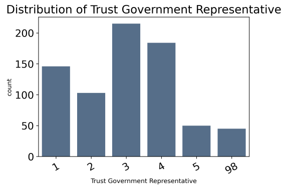
```
k = 2, The silhouette score is = 0.207
k = 3, The silhouette score is = 0.176
k = 4, The silhouette score is = 0.118
k = 5, The silhouette score is = 0.149
k = 6, The silhouette score is = 0.129
k = 7, The silhouette score is = 0.111
k = 8, The silhouette score is = 0.131
k = 9, The silhouette score is = 0.121
k = 10, The silhouette score is = 0.124
k = 11, The silhouette score is = 0.119
k = 12, The silhouette score is = 0.121
k = 13, The silhouette score is = 0.123
k = 14, The silhouette score is = 0.127
```

C.3. Distributions of the clustering variables

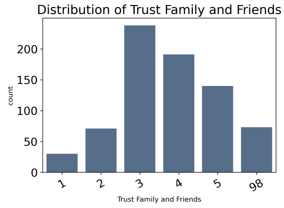
This section shows the distribution of the variables used in the clustering analysis, to support the choice of the K-Medoids clustering method.



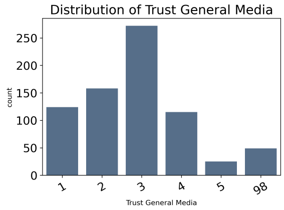
(a) Trust prime minister



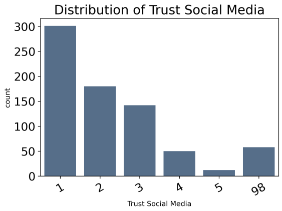
(b) Trust government representative



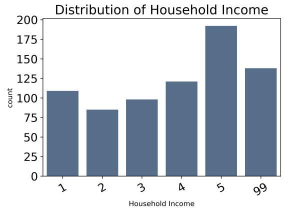
(c) Trust family and friends



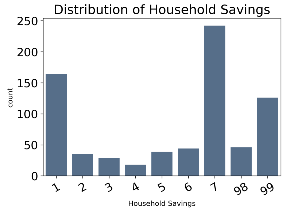
(d) Trust general media



(e) Trust social media

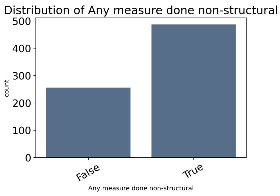


(f) Household Income

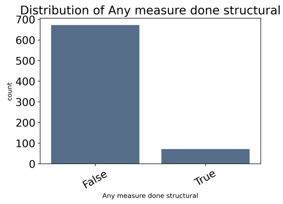


(g) Household Savings

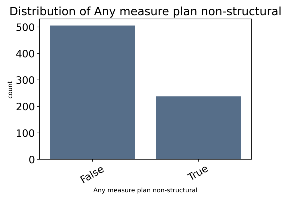
(h) Multiple Incomes



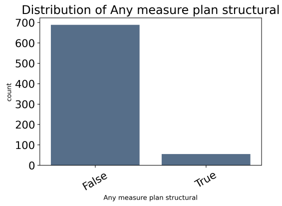
(i) Any measures taken non-structural



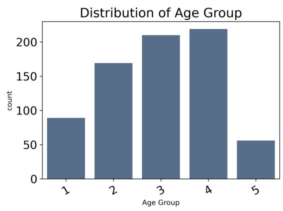
(j) Any measures taken structural



(k) Any measures planned non-structural



(l) Any measures planned structural



(m) Age Group

Figure C.2: Distribution of the clustering variables

D

Additional materials chapter 5

The descriptives of the trust variables for each region is shown in this appendix as an addition to the results in Chapter 5. The tables show the median, mode, mean, standard deviation (STD) and the relevant frequency distribution regarding the region for each possible answer in Table D.1 and Table D.2.

Table D.1: Descriptives of trust variables per region set 1

Variable	Statistic	Norfolk/Suffolk	Somerset	Greater London
Prime Minister	Median	1	2	2
Prime Minister	Mode	1	1	1
Prime Minister	Mean	1.93	2.13	2.29
Prime Minister	STD	1.13	1.24	1.26
Prime Minister	% - 1	48	43.4	36.3
Prime Minister	% - 2	12.1	14.7	17
Prime Minister	% - 3	23	20.9	21.5
Prime Minister	% - 4	5.9	11.6	13.1
Prime Minister	% - 5	2.3	3.9	5
Government Representative	Median	3	3	3
Government Representative	Mode	3	4	3
Government Representative	Mean	2.6	2.94	2.98
Government Representative	STD	1.2	1.29	1.21
Government Representative	% - 1	25.4	20.9	15.1
Government Representative	% - 2	14.8	12.4	13.7
Government Representative	% - 3	30.5	23.3	29.9
Government Representative	% - 4	20.3	33.3	24.9
Government Representative	% - 5	3.5	7.8	8.7

Table D.2: Descriptives of trust variables per region set 2

Variable	Statistic	Norfolk/Suffolk	Somerset	Greater London
Family and Friends	Median	3	4	3
Family and Friends	Mode	3	3	3
Family and Friends	Mean	3.51	3.55	3.49
Family and Friends	STD	1.09	1.08	1.06
Family and Friends	% - 1	4.7	4.7	3.4
Family and Friends	% - 2	8.2	8.5	10.9
Family and Friends	% - 3	31.6	29.5	33.2
Family and Friends	% - 4	24.6	29.5	25.1
Family and Friends	% - 5	19.1	19.4	18.4
General Media	Median	3	3	3
General Media	Mode	3	3	3
General Media	Mean	2.44	2.51	2.86
General Media	STD	1.05	1.04	1.05
General Media	% - 1	22.7	20.2	11.2
General Media	% - 2	22.3	24	19.6
General Media	% - 3	35.5	34.9	38
General Media	% - 4	10.9	14.7	19
General Media	% - 5	2	1.6	5
Social Media	Median	1	2	2
Social Media	Mode	1	1	1
Social Media	Mean	1.7	1.8	2.23
Social Media	STD	0.91	0.91	1.12
Social Media	% - 1	51.2	46.5	30.7
Social Media	% - 2	23	26.4	24.3
Social Media	% - 3	14.5	17.8	22.9
Social Media	% - 4	3.1	4.7	10.1
Social Media	% - 5	0.8	NaN	2.8

E

Additional materials chapter 6

This appendix considers the spearman heatmap correlations for two sets of measures: the correlation coefficients between the Done variables and trust variables, and the correlation coefficients between the Plan variables and the trust variables. Moreover, this appendix also shows the confidence intervals of the odds ratio for twelve binary logistic regressions.

E.1. Spearman Correlations

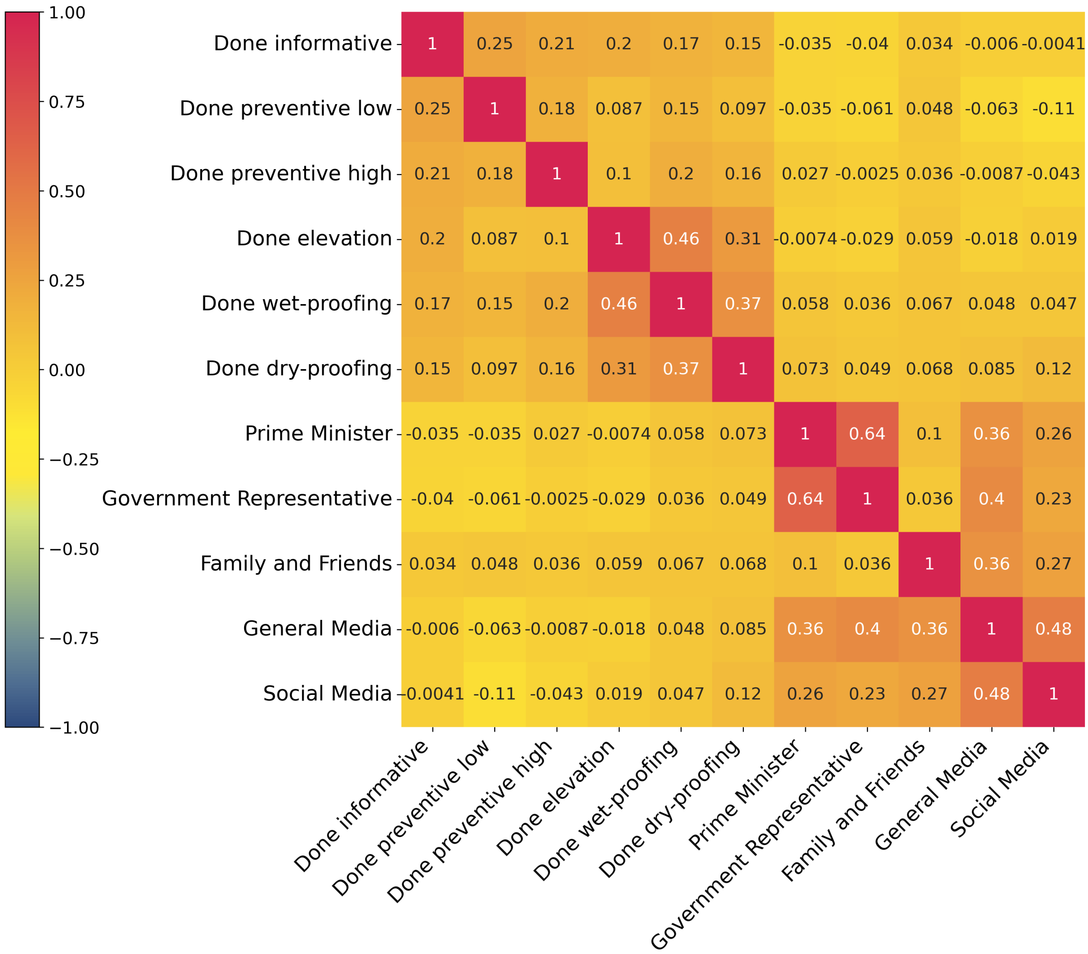


Figure E.1: Correlation with Done grouped measures

Figure E.1 shows the Spearman coefficients for the measures that have already been taken by the respondents.

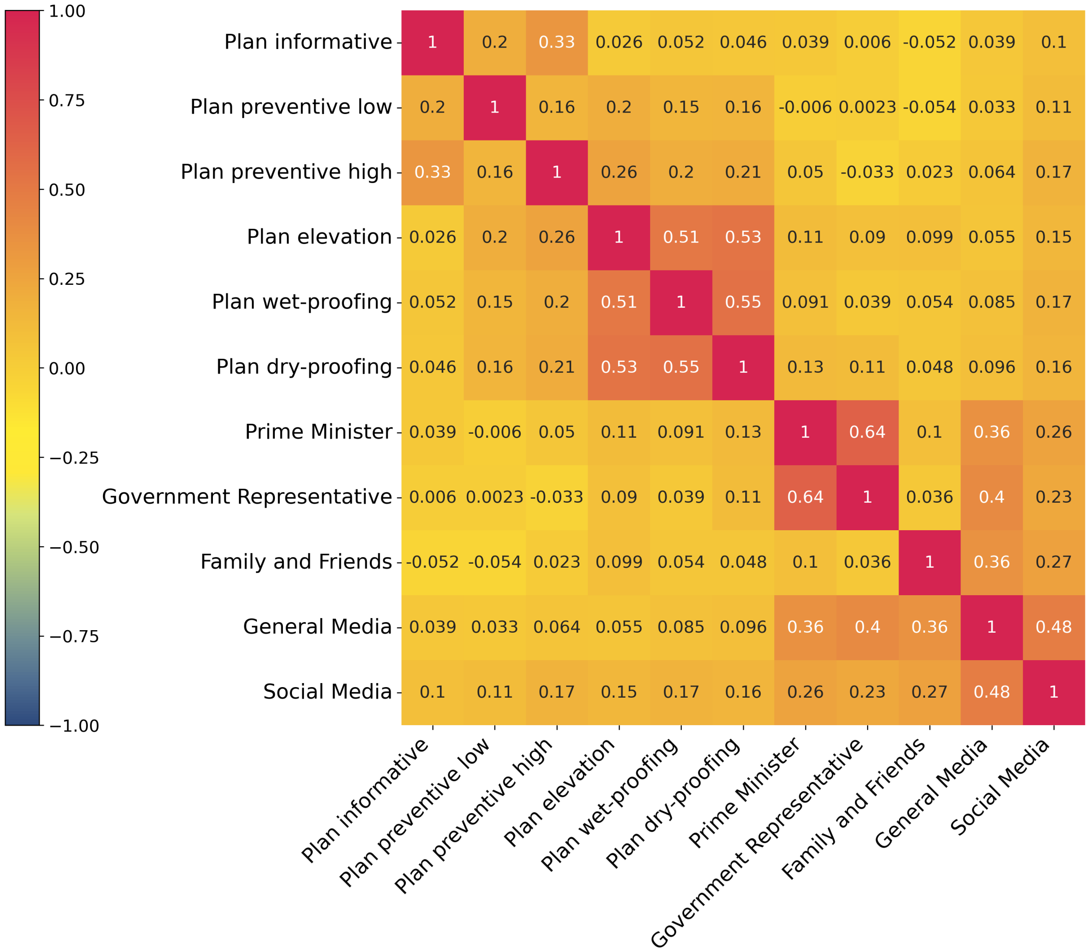


Figure E.2: Correlation with Plan grouped measures

Figure E.2 shows the Spearman coefficients for the measures that have been planned in the near future by the respondents.

E.2. Confidence Intervals

This section shows the confidence intervals of all twelve regressions in twelve different figures. The red error bars include the number one in their confidence intervals, the green error bars do not include the number one in their confidence intervals. The yellow line shows where one is located.

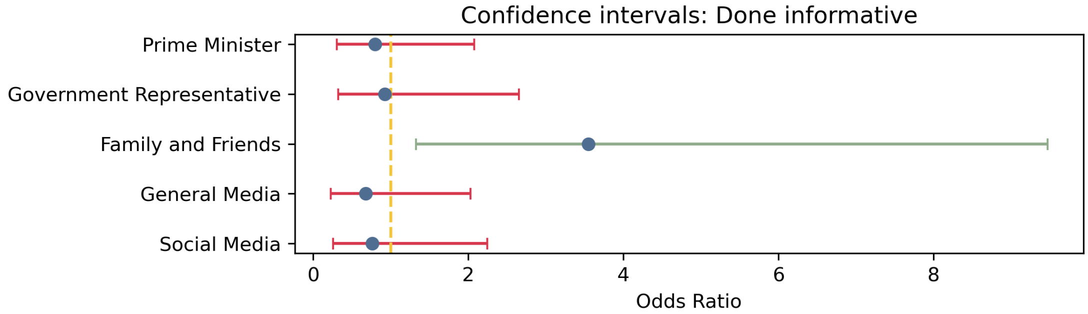


Figure E.3: Confidence Done informative

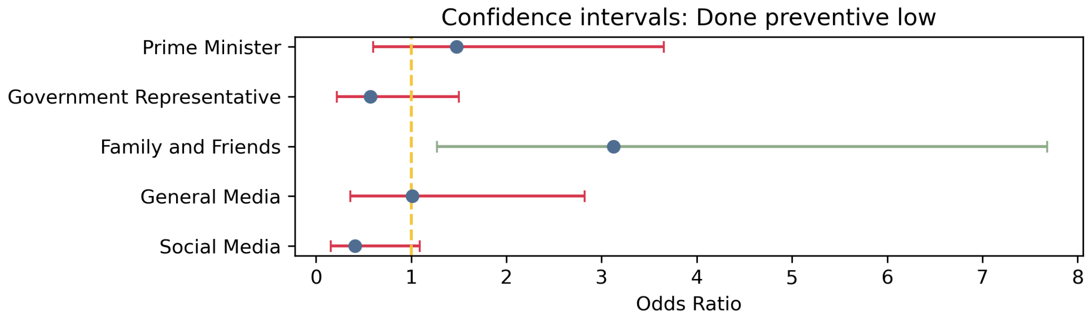


Figure E.4: Confidence Done preventive low effort

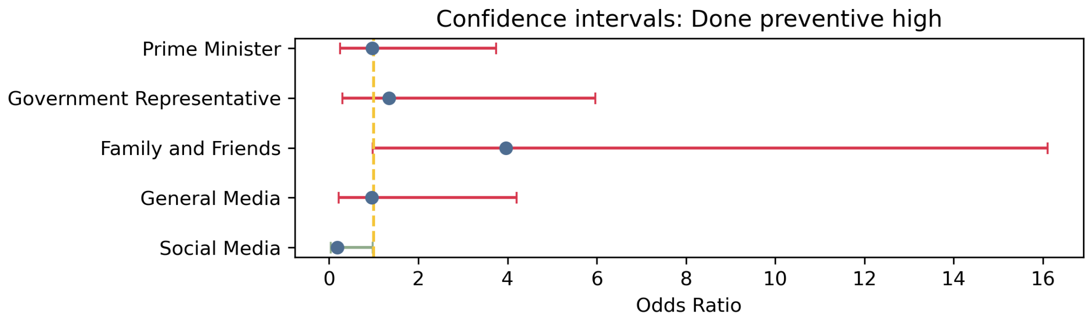


Figure E.5: Confidence Done preventive high effort

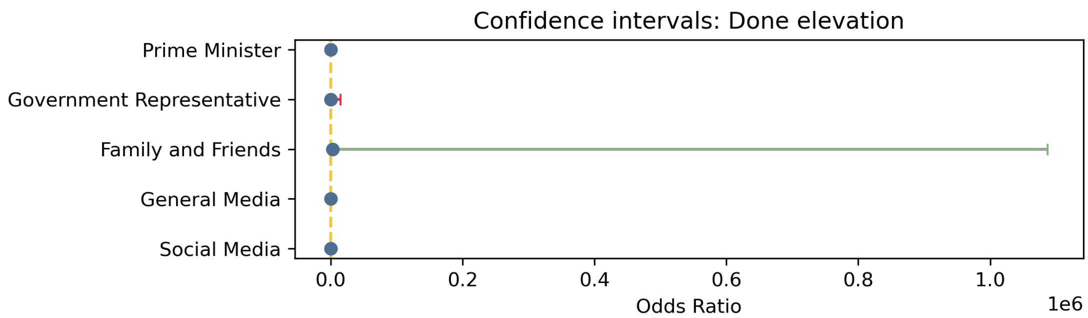


Figure E.6: Confidence Done elevation

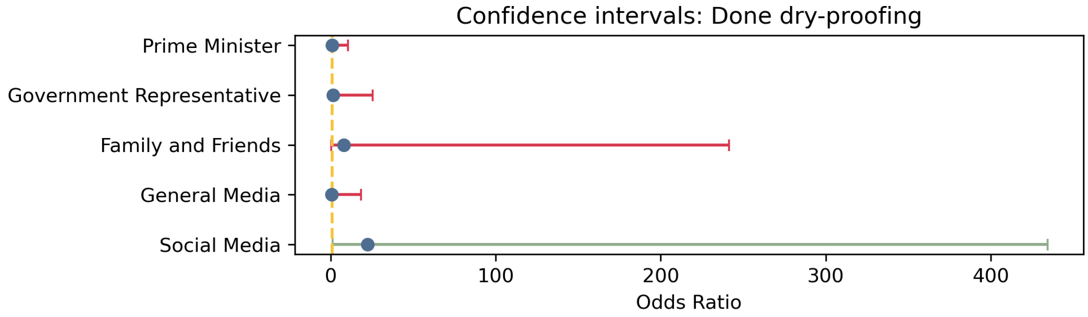


Figure E.7: Confidence Done dry-proofing

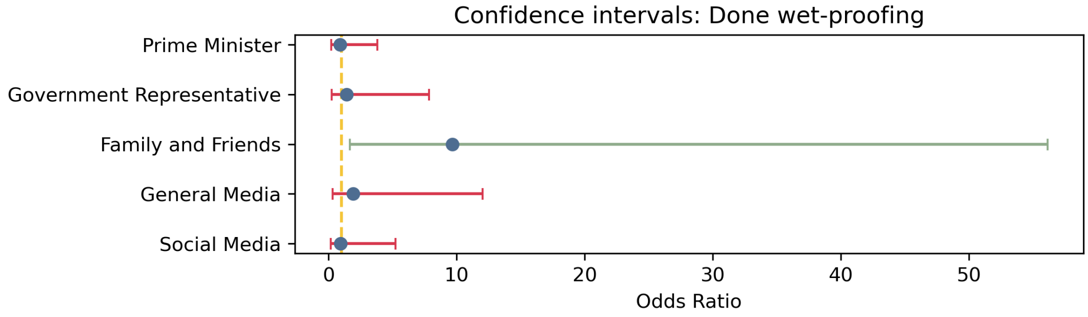


Figure E.8: Confidence Done wet-proofing

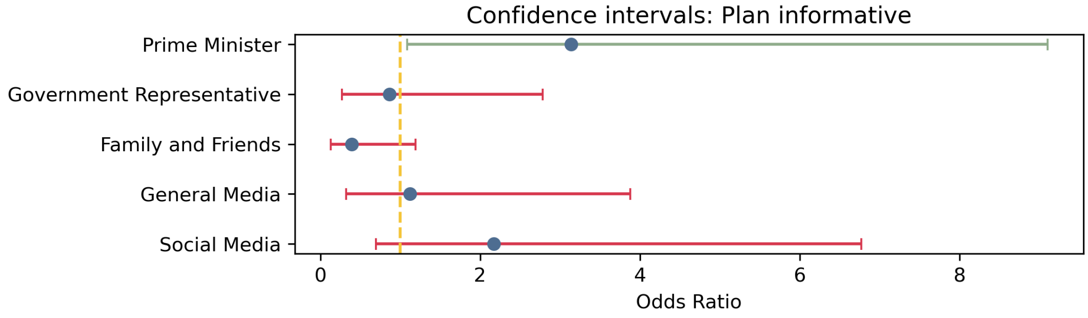


Figure E.9: Confidence Plan informative

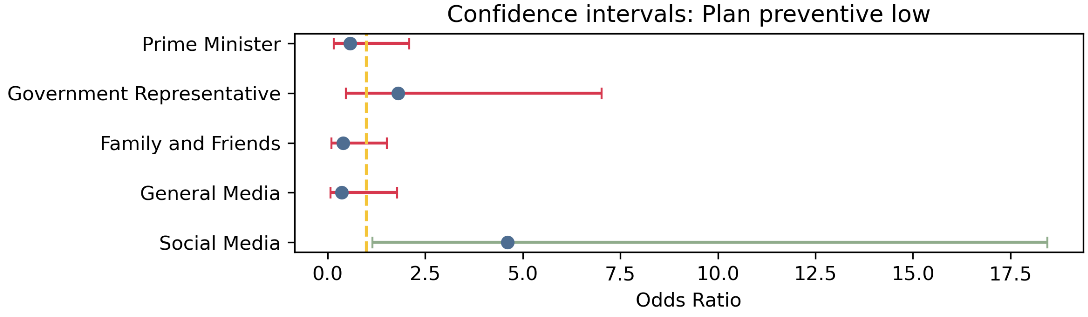


Figure E.10: Confidence Plan preventive low effort

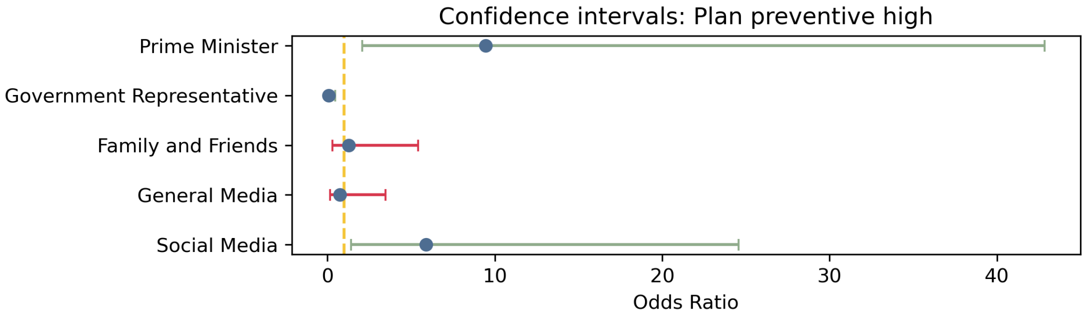


Figure E.11: Confidence Plan preventive high effort

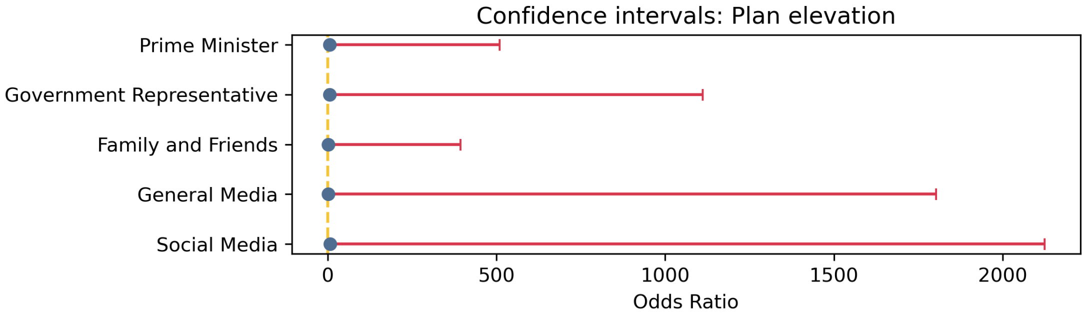


Figure E.12: Confidence Plan elevation

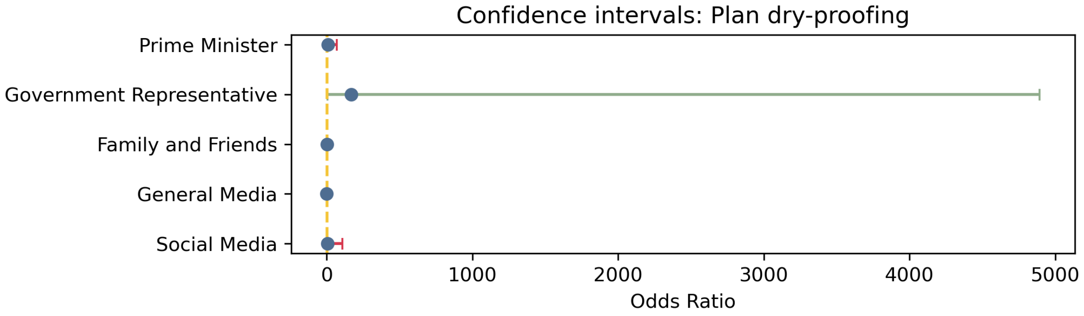


Figure E.13: Confidence Plan dry-proofing

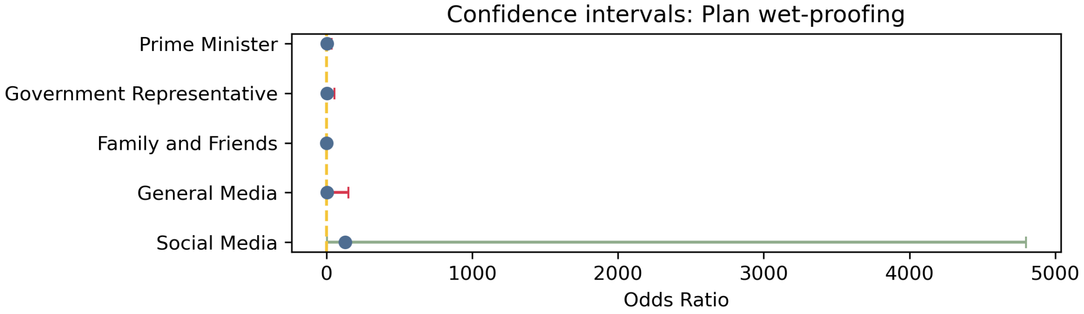


Figure E.14: Confidence Plan wet-proofing

F
Additional materials chapter 7

This appendix considers the cluster descriptives of Chapter 7. These descriptives can be found in two tables, Table F.1 and Table F.2.

Table F.1: Cluster descriptives set 1

	Cluster	0	1	2	3	4
Trust Prime Minister (1-5)	count	55	62	199	46	106
	mean	1.09	2.13	2.28	3.24	2.06
	median	1	2	2	3	2
	std	0.29	1.15	1.27	0.97	1.19
Trust Government Representative (1-5)	count	55	62	199	46	106
	mean	1.64	3	2.88	3.65	2.98
	median	1	3	3	4	3
	std	1.11	1.21	1.19	0.85	1.11
Trust Family and Friends (1-5)	count	55	62	199	46	106
	mean	3.27	3.11	3.61	3.72	3.57
	median	3	3	4	4	4
	std	1.19	1.06	1.03	0.93	1.02
Trust General Media (1-5)	count	55	62	199	46	106
	mean	1.87	2.48	2.65	3.65	2.75
	median	1	2	3	4	3
	std	1.02	1	1	0.77	1.02
Trust Social Media (1-5)	count	55	62	199	46	106
	mean	1.58	1.81	1.71	3.46	2.27
	median	1	2	1	3.5	2
	std	1.03	0.85	0.86	0.96	1.12

Table F.2: Cluster descriptives set 2

	Cluster	0	1	2	3	4
Household Income (1-5)	count	55	62	199	46	106
	mean	3	4.21	4.05	3.61	2.16
	median	3	5	4	4	2
	std	1.41	1.15	1.13	1.45	1.22
Household Savings (1-7)	count	55	62	199	46	106
	mean	3.98	6.1	5.81	4.02	1.92
	median	4	7	7	4	1
	std	2.59	1.84	1.97	2.28	1.66
Multiple Incomes (0-1)	count	55	62	199	46	106
	mean	0.16	0.85	0.85	0.33	0.05
	median	0	1	1	0	0
	std	0.37	0.36	0.36	0.47	0.21
Any measure done non-structural (0-1)	count	55	62	199	46	106
	mean	0.22	0.84	0.79	0.22	0.83
	median	0	1	1	0	1
	std	0.42	0.37	0.41	0.42	0.38
Any measure done structural (0-1)	count	55	62	199	46	106
	mean	0.04	0.13	0.08	0.17	0.12
	median	0	0	0	0	0
	std	0.19	0.34	0.27	0.38	0.33
Any measure plan non-structural (0-1)	count	55	62	199	46	106
	mean	0.65	0.94	0.05	0.76	0.18
	median	1	1	0	1	0
	std	0.48	0.25	0.22	0.43	0.39
Any measure plan structural (0-1)	count	55	62	199	46	106
	mean	0.09	0.03	0.04	0.3	0.09
	median	0	0	0	0	0
	std	0.29	0.18	0.2	0.47	0.29
Flood Experience (0-1)	count	55	62	199	46	106
	mean	0.13	0.29	0.16	0.22	0.19
	median	0	0	0	0	0
	std	0.34	0.46	0.37	0.42	0.39
Age Group (1-5)	count	55	62	199	46	106
	mean	2.6	3.29	3.17	2.22	2.65
	median	2	4	3	2	3
	std	0.95	1.14	1.14	1.03	0.89

G
Respondent counts per region

This appendix shows the respondent counts per region for the comparison of results. Three figures can be seen here. Figure G.1 shows the MSOA respondent counts for Norfolk/Suffolk coast, Figure G.2 shows the respondent counts for the Somerset area and Figure G.3 shows the respondent counts per Local Authority region in Greater London.

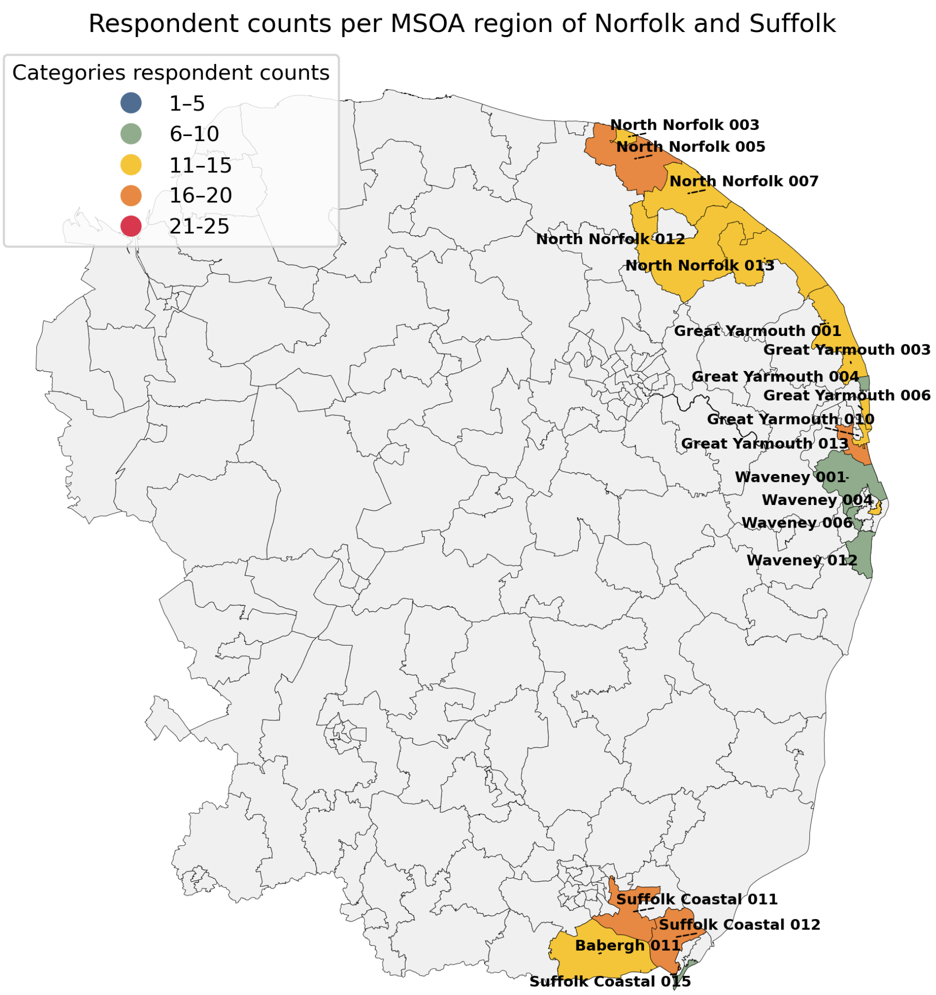


Figure G.1: MSOA counts Norfolk/Suffolk coast

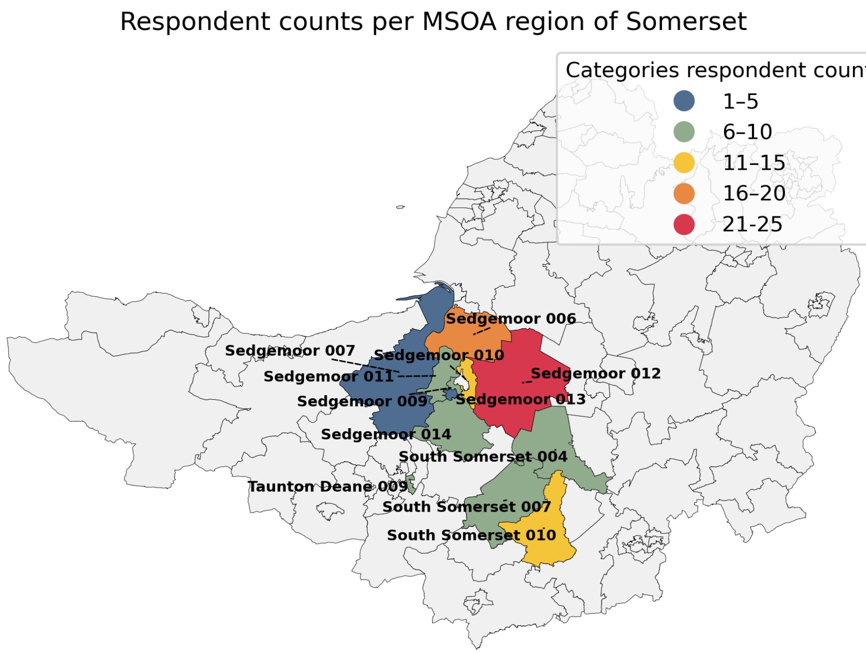


Figure G.2: MSOA counts Somerset

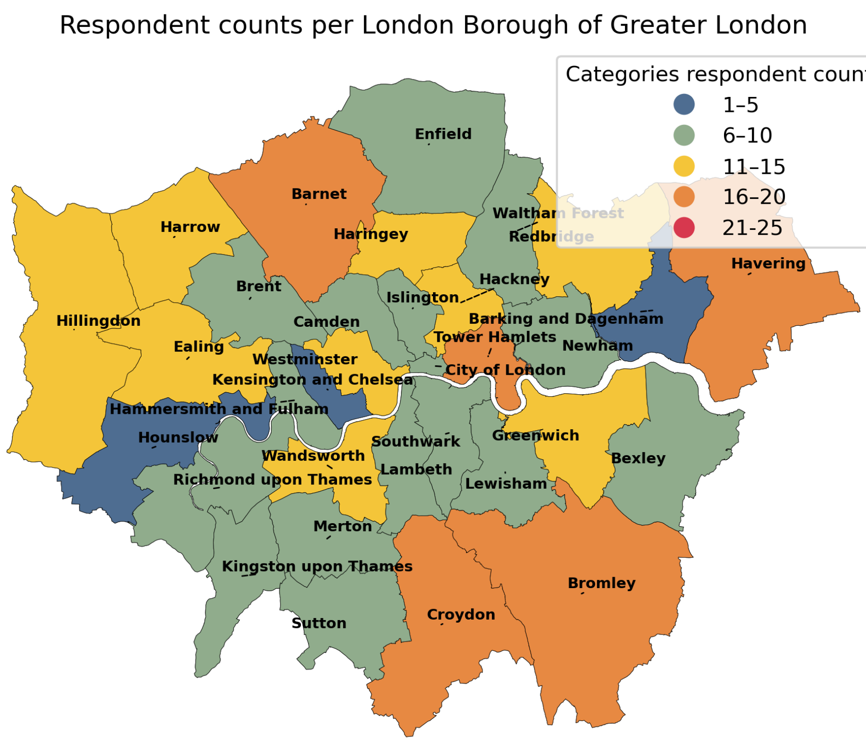


Figure G.3: MSOA counts Greater London