COGNITIVE AND AFFECTIVE PROCESSES UNDERLYING RISK PERCEPTIONS AND INTENTIONS OF FLOOD-PRONE HOUSEHOLDS

(A dual-process approach)

BY

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I hereby certify that the work embodied in the thesis is my own work, conducted under normal supervision.

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ABSTRACT

From a socio-psychological perspective, this thesis has sought to unearth the core factors influencing householders' response to flood risk in a bid to identify how a shift towards greater protection levels can be harnessed. In doing so, a framework was developed for understanding household decision making in flood-prone areas of South East Queensland, Australia. This framework illustrates the pathways by which household decision making is influenced by dual processes (affective and cognitive) operating at different levels of influence: 1. conjointly (and directly) shaping flood preparedness intentions; 2. mediating the (indirect) influence of other core factors (personal experience, subjective knowledge, self-efficacy and trust) on flood preparedness intentions; and, 3. being moderated by the influence of benefit perception (operationalized as "residential satisfaction") on flood preparedness intentions. Additionally, the framework stresses the relevance of understating the role and the predictors of householders' non-protective response (i.e. risk denial). In this vein, a shift from non-protective to protective behavioural intentions can be best realized.

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OCTOBER 2018 **Lara Altarawneh**

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CHAPTER 1

INTRODUCTION

This introductory chapter aims to provide a brief contextual orientation and understanding of the process that was followed in order to reach a conclusion regarding the problem statement of flood risk management at the household level. It introduces the phenomenon to be studied and alludes to the dynamic (psychological) constructs under investigation. The key conceptual constructs underlying the study are provided. The chapter then outlines the overarching methodological approach that is adopted in order to reach the envisaged objectives of the thesis. A detailed overview of the study area is given, including a description of the physical settings and flood history. This introductory chapter concludes with an outline of the structure of this thesis.

1.1 BACKGROUND AND PROBLEM DEFINITION

"Clarifying the mechanisms by which feelings and cognitions are related and integrated in human judgement and decision making is a critical next step in understanding perceived risk"

(Finucane 2012, p. 61)

The paradigm shift to more integrated flood risk management strategies involves devolved responsibilities to individuals in society, and the need to understand the broader, more intractable, multi-faceted societal risk management. Here, the notion of "risk perception" among individuals at risk is central to understanding their adaptive (i.e. preparedness and mitigation) behaviour. Understanding the way in which individuals perceive flood risk on one hand, and the extent to which individuals then subsequently behave based on their perceptions, feelings, experiences, coping capacities and attitudes on the other, is the main thrust of this thesis. More generally, the theoretical perspective of this thesis will draw on the psychological analysis of risk perception and behavioural decision making in the context of natural hazards.

1.1.1 Cognitive and Affective Mechanisms Underlying Risk Perception

Given the complex and subjective nature of risk perception (Slovic, 2010a), psychology can help advance our understanding of the cognitive and affective (or experiential) processes that underlie risk perception and how these processes lead different individuals to judge the same factual risk in different ways. Such understanding is important in that it explains why some individuals consider the adoption of protective behavioural intentions while others do not. However, it has been noted that risk psychology literature has traditionally paid more attention to the importance of rationality and cognition. Cognitive perceptions usually refer to the combined judgement of how susceptible individuals are to being flooded (namely, perceived probability) and how severe the consequences of being flooded are (namely, perceived severity) (Miceli et al., 2008; Bubeck et al., 2012b). Indeed, behaviour theories in the context of flood risk largely treat risk perceptions as the cognitively-derived judgments of probability and severity, and research synthesized thus far fits this conceptualization (see, for example, the Protective Action Decision Model (Lindell and Hwang, 2008; Horney et al., 2010); the Expectancy-valence Model (Becker et al., 2014); the Social Cognitive Preparation (Paton, 2003; Paton et al., 2005; McIvor et al., 2009); the Motivation Intention Volition Model (Martens et al., 2009); the Contingent Valuation Method (Zhai and Ikeda, 2006); the Rational Action Paradigm (Zhai and Ikeda, 2008); the Fuzzy Contingent Valuation (Hung, 2009) and the Mental Model (Lave and Lave, 1991)).

However, there is evidence that relying on purely cognitive definitions provides only a limited account of how people actually perceive the risk and act sufficiently (Miceli et al., 2008). In accordance with recent theoretical models proposed in cognitive and emotional psychology, risk perception may be properly conceptualized as a complex process which encompasses both cognitive and affective aspects (Loewenstein et al., 2001; Finucane and Holup, 2006; Taylor-Gooby and Zinn, 2006; Slovic et al., 2004; Slovic et al., 2005; Slovic, 2010b; Kahneman, 2003; Weber, 2017). Affect is defined as a faint whisper of emotion, defined specifically as a positive (good) or negative (bad) evaluative feeling toward a stimulus that can occur both consciously and unconsciously (Slovic et al., 2004). As such, affective risk perceptions pertain to how bad or good the individuals feel about their exposure to the risk (Slovic et al., 2004). In fact, it is often postulated that affective responses (operating in a rapid, associative and automatic manner) are inevitable in any perceptual operation (including risk perception) in the human brain (Zajonc, 1980). In flood-risk-related research, affective responses are gaining increasingly more attention (Keller et al., 2006; Miceli et al., 2008; Siegrist and Gutscher, 2008; Zaalberg et al., 2009; Pagneux et al., 2011; Terpstra, 2011; Boer et al., 2015; Poussin et al., 2014; Babcicky and Seebauer, 2016; Kerstholt et al., 2017a).

Most research on affective risk perceptions indicates the complexity of the processes involved, but many issues are as yet unresolved (Taylor-Gooby, 2004). More specifically, literature lacks a coherent conceptualization of the affect-cognition relationship; this is reflected in both variety of models and mechanisms proposed to describe how affect and cognition are related, as well as in terms of how affect corresponds in different ways to risk behaviour. While some theorists see the relationship as unidirectional or linear (i.e. affect is either generated by or preceding cognitive risk perceptions) (Zajonc, 1980; Lazarus, 1984; Lerner and Keltner, 2000; Finucane, et al, 2000; Schwartz and Clore, 1983), others see it as more interactive or bidirectional (i.e. affect and cognitive risk perceptions reciprocally influence each other, Loewenstein et al., 2001; Slovic et al., 2005; Forgas, 2008; Pessoa, 2008; van Gelder et al., 2009). The lack of a coherent conceptualization of cognition-affect relationships limits the development of a robust theoretical model that can contribute to the study of the complex psychological mechanisms that underlie risk perceptions and behavioural intentions.

In fact, in the context of flood risk, most prior empirical studies have proposed a unidirectional relationship between both cognitive and affective processes that underlie flood risk perception (Keller et al., 2006; Miceli et al., 2008; Siegrist and Gutscher, 2008; Zaalberg et al., 2009; Pagneux et al., 2011; Terpstra, 2011; Boer et al., 2015; Poussin et al., 2014; Babcicky and Seebauer, 2016; Kerstholt et al., 2017). For example, Miceli and others (2008), who adopted the risk-as-feeling approach (Loewenstein et al., 2001), proposed that affective risk perceptions, unlike cognitive ones, have a direct relationship with the adoption of flood adaptive measures. The indirect effect of cognitive risk perceptions was hypothesized to be mediated via affective risk perceptions (Miceli et al., 2008). In contrast, a study by Zaalberg and others (2009) who adopted the protection motivation theory (Rogers, 1975), proposes a more indirect role of affective perceptions on adaptive behaviour through its influence on perceived severity. Moreover, other researchers (such as Terpstra, 2011; Siegrist and Gutscher, 2008; Keller et al., 2006; and Kerstholt et al., 2017) who have adopted the affect heuristics approach (Slovic et al., 2004), propose that affective risk perceptions may both directly and indirectly guide the adoption of flood adaptive behaviours. Regarding the indirect link, it has been proposed that feelings related to the risk may serve as a cue for estimating its severity or probability and, in turn, the adoption of adaptive behaviours.

The case for the dual-process approach (where both cognitive and affective risk perceptions are assumed to interact in shaping risk judgments and have distinct influences on behaviour) has not yet been adequately conceptualized and tested empirically. In fact, the interplay between cognition and affect has recently gained more attention, and research on risk perception is now steadily moving toward a dual-process perspective (see, for example, studies on the perception of climate change (Linden, 2014) and hurricane risk (Trumbo et al., 2016)). Such interest has been motivated in part by recent neurobiological evidence demonstrating the dynamic interaction between the brain's subcortical and neocortical circuits where cognitive and affective operations occur, respectively (Damasio, 1994; Pessoa, 2008, 2010; Pessoa and Adolphs, 2010; Brosch et al., 2013; LeDoux, 1989, 2012; Phelps, 2006; Armony and LeDoux, 1997).

There is evidence that embracing a functional definition of risk perception—one that highlights the cognition-affect interaction—is likely to be a more effective approach when investigating risk judgements (Linden, 2014). It may lead to a better understanding of how individuals think, feel, and subsequently behave against the risks to which they are exposed. This could give valuable insight to academics and decision makers interested in developing and implementing more effective risk communication strategies in order to promote public involvement interventions in risk management. In this regard, researchers (such as Finucane and Holup, 2006; Siegrist and Gutscher 2006; Marx et al., 2007; Visschers, 2007; Miceli et al., 2008; Zaalberg et al., 2009; Linden, 2014; Rakow et al., 2015; Oh et al., 2015; Bosschaart et al., 2016; and Kerstholt et al., 2017) have acknowledged the significance of affective processes in communicating natural hazard risks, including floods. To this extent, this suggest that cognitive risk perceptions and more affective responses should be examined together in order to manage better adaptive behavioural intentions.

1.1.2 Factors Influencing Risk Perception and Intentions

Beyond theoretical insufficiency in the functional definition of flood risk perception itself, there is also much variations in the mechanisms in which factors driving risk perception influence private precautionary behaviour of flood-prone households. In the present study, key socio-psychological factors driving risk perceptions include: 1) Previous (or direct) experience of flooding events; 2) Self-reported knowledge (or critical hazard awareness); and; 3) Trust in authorities and engineered flood defences (or perceived institutional control). The impact of these factors on adaptive behavioural intentions has been extensively studied. The results, however, are not necessarily consistent in their implications. Some studies have reported significant positive effects on adaptive behavioural intentions from experience (Miceli et al. 2008; Osberghaus 2015; Onuma et al., 2017); knowledge (Oloke et al., 2013; Bosschaart et al., 2013; Knocke and Kolivras, 2007), and trust (Solberg et al. 2010), respectively. On the other hand, other studies have found limited or insignificant effects on adaptive behavioural intentions from experience (Takao et al., 2004; Thieken et al., 2007; Kreibich et al., 2011a); knowledge (Siegrist and Gutscher 2008; Lindell and Hwang, 2008); and trust (Terpstra 2011; Kousky and Kunreuther, 2010; Bronfman et al., 2016), respectively. A possible explanation for these conflicting empirical results may be that the impact of these factors on intentions is (partially or completely) mediated through perceived risk. From a dual-process perspective, it is possible to assume that cognitive and affective risk perceptions may have discrepant mediating influences. However, such a proposition requires conceptual and empirical evidence to be confirmed, and is therefore worthwhile to explore in this thesis.

In fact, it seems critical for flood risk management to understand the psychological factors and mechanisms underlying risk perception to better manage the private precautionary behaviour of flood-prone households (Bubeck et al., 2012a; Babcicky and Seebauer, 2016). However, taking a more holistic view, the impact of risk perception (i.e. threat appraisals) may only tell part of the story in terms of the adoption of private precautionary behaviour. Recent research has emphasized the role of coping capacity, showing that both variables of risk perception and coping capacity have to enter the equation in order for us to understand and explain private precautionary behaviour (Grothmann and Reusswig 2006; Bubeck et al. 2012b; Poussin, et al. 2014; Dittrich et al., 2016; Babcicky and Seebauer, 2016). Coping capacity originates from the Protection Motivation Theory (PMT) (Rogers, 1975), and captures the perceived ability of a household to cope with flood risks (Babcicky and Seebauer, 2016). Grothmann and Reusswig (2006) show that households are more likely to carry out protective action measures when they rank high on both risk perception and coping ability. In contrast, households with high levels of risk perception and low levels of perceived coping ability are more likely to adopt non-protective responses or attitudes such as denial. However, the empirical literature on the importance of coping appraisals (including self-efficacy) is generally scarce in the context of flood risk. Exploring both risk and coping appraisals through the lens of dual-process theory is underdeveloped. In particular, it is unclear how coping appraisals—when functioning along with cognitive and affective risk appraisals—predict the protective behavioural intentions of flood-prone households.

Moreover, dealing with the trade-offs between "to respond" or "not to respond" may lie at the heart of understanding the deeper psychological analyses of benefit and risk perception. In this regard, benefit perception (i.e. perception of location-embedded benefits) reflects the resident's satisfaction with the physical and socio-economic qualities of their urban environments (i.e. residential satisfaction). Residential satisfaction can be explained through the variables that help to fulfil the resident's aspirations, needs or desires in a house, how content that resident is with the location-related attributes/benefits and whether there is a feeling of connectedness with his or her residential environment (Tabernero, Briones, et al. 2010). However, whether and how perceived residential satisfaction contributes to risk perception and risk behavioural intentions has rarely been investigated in behavioural research in natural hazards. A study by He, X (2009) is one of the few studies that look at flood-prone residents' perceptions and behavioural intentions to perceived (dis)satisfactions with their residential environments. An important relationship uncovered by He, X (2009) is that, compared to residents who were satisfied with qualities of their urban environments, those who were dissatisfied were less likely to accept a higher chance of flood risk in exchange for perceived location-embedded benefits, and thus more likely to adopt flood hazard adjustments.

An exploration of the role of residential satisfaction in natural hazard scenarios is another valuable contribution to the present thesis. Specifically, since the conceptualization of residential satisfaction has an implicit relationship with other place-specific biases, such as the spatial optimistic bias (Gifford et al., 2009) applied to environmental risk perception, it may function as a barrier to enacting preventive behaviours in order to cope with an environmental risk. In other words, this thesis predicts that residential satisfaction is a significant moderator of the risk perception-behaviour relationship. The moderating effect is examined for both cognitive and affective risk perceptions, because the effect may be different across these two levels of processing.

To sum up, the current study seeks to fill gaps in prior studies that have often not taken into account the complex nature of risk perception, not included an affective component, and generally not evaluated risk perceptions from a dual-risk perspective—where both cognition and affect (reciprocally) influence each other, function with other key psychological factors, and (jointly) predict flood protective behaviour. Such gaps underscore the need for more insight into the psychological factors and mechanisms underlying risk perception to effectively deliver and deploy interventions that motivate people's protective behavioural responses to natural hazards including floods.

1.2 RESEARCH AIM AND OBJECTIVES

In order to address the issues raised in Section 1.1, the main aim of the present thesis is to advance a more integrated, systematic and profound understanding of the psychological mechanisms that underlie the risk perceptions and protective behavioural intentions of flood-prone households. Building on this aim, the central question of this thesis is:

How do psychological factors and mechanisms underlying risk perception of flood-prone households function to shape their protective behavioural intentions?

The above aims will be accomplished by fulfilling the following research objectives:

1 **To examine how affective and cognitive mechanisms interact to shape risk perceptions and behavioural intentions of flood-prone households.**

2 **To examine to what extent a different set of psychological factors influence risk perception processed through both cognitive and affective systems.**

These factors include previous experience of flooding events, knowledge, self-efficacy (or perceived personal control) and trust in authorities and engineered flood defences (or perceived situational control).

3 **To examine the extent to which the impact of these psychological factors on the protective behavioural intentions of flood-prone households can be mediated through both cognitive and affective risk perceptions.**

4 **To examine the extent to which the impact of both cognitive and affective risk perceptions on protective behavioural intentions can be moderated by residential satisfaction (i.e. perceived location-embedded benefits).**

1.3 GENERAL METHODOLOGICAL APPROACH

1.3.1. Sample and Participants

For the purpose of this thesis, a cross-sectional survey has been conducted via mail, using an unmarked, reply-paid envelope. This method provides confidentiality for the participants, avoids any harm to them, and gives them the chance to choose a suitable time to complete the questionnaire. In addition, a URL link to an electronic version of the questionnaire has been provided to the research participants, along with their individual ID numbers and password for its access. Based on a random sampling technique, the total population size for this study has been estimated to be 3150 households located within two major floodplains in South East Queensland in Australia, namely the Bremer River catchment and the Nerang River catchment (see Section 1.4 for more information on the physical settings of the study area). Specifically, research participants were selected using cadastral maps of the geographical/physical distribution of low density residential uses or houses within the adopted flood regulation line (i.e. The 100-year Average Recurrence Interval flood level). Regarding the level of analysis, this research has more specifically invited the household decision-makers who are aged above 18 (husbands or wives in married-couple households and adult male or female residents in single-headed households) to complete the survey, because they seemed best placed to comment on reasons for living in flood-liable residential zones.

Because of the limited resources (regarding time and effort) of the researcher and to come up with an accurate and fair representation of the population characteristics, the researcher depended on a systematic research sample which was selected randomly from the sampling frame. During the entire survey period (from 1st of April to 30th of October 2016), 680 respondents (response rate of 22.5%) were surveyed on all psychological constructs, including risk perceptions, experiences, attitudes, feelings, coping capacities and preparedness intentions. Demographic variables were also surveyed, including gender, age, education, and income.

1.3.2. Statistical Analysis

Once the data was obtained, it was then formatted and entered into SPSS (statistical package for the Social Science V 24.0) to analyze the distributional characteristics of the survey items. For instance, frequency statistics, measures of central tendency (including the mean, median and mode), and dispersion statistics (including the range and quartiles of the data-set, and measures of variance and standard deviation) for the data were calculated and summarized using descriptive statistics techniques. Missing responses, univariate outliers, kurtosis and skewness were also screened. Subsequently, the data from the two surveys (S1 Ipswich, S2 Gold Coast) were merged and converted to text and raw data files for use with IBM SPSS Amos Version 24.0 (Byrne, 2016). Estimations of the hypothesized relationships between these research constructs in terms of association, causality, bi-directionally and mediation, were conducted using structural equation modelling (SEM) techniques with Maximum likelihood (ML) as an estimation method. For model evaluation purposes, the Chi square to degree of freedom ratio ($\chi 2/df < 3.0$), the Root mean square error of approximation (RMSEA < 0.07), the Comparative Fit Index (CFI > 0.95) and the Tucker Lewis Index (TLI > .095) were examined. The Bollen-Stine bootstrapping procedure is employed in this study due to the multi-variate non-normality of the data.

1.4 STUDY AREA

1.4.1 South East Queensland

This research focuses on the Australian region of South East Queensland, defined here as the boxed region (29°S to 23°S, 148°E to 153°E) (Fig. 1.1:A). This is Australia's fastest growing region (Q.G., 2009) with a population estimated in 2011 to be 3.2 million and expected to grow to 4.2–5.1 million people by 2031 (Roiko et al., 2012). It is large, diverse, and institutionally complex, being governed by eleven local government areas, covering 22,890 km2 with a peak elevation of 1,360 m (Bunn et al., 2007). While the population is predominantly urban—which drives the regional economy—agriculture and natural ecosystems are also economically and culturally important (Hefferan, 2014). This region has 240 km of coastline and several major drainage networks, include the Brisbane River catchment which incorporates the Lockyer, Bremer, Stanley and the Upper, Mid and Lower Brisbane River sub-catchments and their tributaries (Figure 1.1: B).

Figure 1.1.A South East Queensland location in Australia

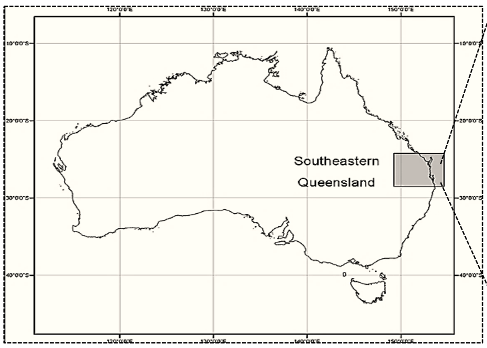

Figure 1.1.B Contextual map of the South East Queensland region

The sub-tropical climate of South East Queensland consists of wet and dry seasons as well as being influenced by non-annual variability (Smith et al., 2013). This hydrological variability is strongly influenced by atmospheric circulations associated with the El Niño–Southern Oscillation phenomenon (Smith et al., 2013), but also modulated by the Pacific Decadal Oscillation or the Inter-decadal Pacific Oscillation (Croke et al., 2016). What results is a climate regime characterised by unusually high levels of uncertainty and frequent and contrasting extremes of flooding, drought, cyclones, storms and bushfires (McDonald et al., 2010). Indeed, it may be argued that South East Queensland's climate has been an important determinant of its colonial history and subsequent socio-economic and political development (Tangney, 2015).

1.4.2 Flood History

Historically, some of the most extreme flood events occurred in the 19th century and early-to-mid 20th century. The 1893 flood (occasionally referred to as the "Great Flood" or the "Black

February flood") occurred when the Brisbane River burst its banks due to a decaying tropical cyclone. The damage across South East Queensland was considerable, especially in the Brisbane River Catchment which alone suffered approximately £4,000,000 worth of damages, although no official figures exist (van den Honert and McAneney, 2011). Seven workers were killed at a colliery in north Ipswich, which was flooded on Saturday 4 February by the Bremer River, a tributary of the Brisbane River. The 1974 flood was another defining event for the people of the Brisbane River catchment, with 8,500 homes flooded in Brisbane and Ipswich; 6,000 of these could not be recovered. The flood peaked at 5.45 m with insured losses of about $2.3 billion and 14 fatalities (van den Honert and McAneney 2011). The 1974 flood prompted changes in the Brisbane River catchment, significantly the construction of the Wivenhoe Dam in 1984 (Bohensky and Leitch, 2014).

Although smaller in magnitude than the 1893 floods, the impact of the 1974 flood was greater because Brisbane's population alone had grown from around 175,000 in 1893 to around 1 million, with greater exposure afforded by new buildings and infrastructure. A recurrence of the 1974 flood today would have more catastrophic impacts due to the massive increase in urban development driven by the rapid population growth in the study region since that time (Croke et al., 2014).

The second half of 2010 and early 2011 was characterized by one of the four strongest La Niña events since 1900. Strong La Niña events are often associated with extreme rainfall and widespread flooding in eastern Australia. The year 2010–2011 was the wettest year since 1974 for South East Queensland (Bureau of Meteorology (BoM), 2017). Continuing heavy rain through early January 2011 led the near-saturated catchments to over top their banks, resulting in almost three-quarters of Queensland (with an area the size of France and Germany combined) being declared a disaster zone (Hayes and Goontilleke, 2012; Croke et al., 2016). Major flooding occurred throughout most of the Brisbane River catchment, most severely in the catchments of the Lockyer Creek and Bremer River (major tributaries of the Brisbane River) where numerous record flood heights were experienced. The flooding caused the loss of 23 lives in the Lockyer Valley and one in Brisbane, and an estimated 18,000 properties were inundated in metropolitan Brisbane, Ipswich, Gold Coast and elsewhere in the Brisbane River Valley (QFCI 2011; Bruns et al., 2012; Croke et al., 2014; Bohensky and Leitch, 2014).

Known as the "2011 Brisbane flood", the event was Australia's most expensive natural disaster (van den Honert and McAneney 2011; QFCI 2012). Approximately 2.5 million people were affected and 29,000 homes and businesses in Queensland experienced some form of flooding. The economic cost of the flooding was estimated to be in excess of $5 billion (QFCI 2012), with damage to 28% of the Queensland rail network and damage to 19,000 km of roads and 3 ports (van den Honert and McAneney 2012). Around 300,000 homes and businesses lost power in Brisbane and Ipswich at some stage during the floods (QFCI 2012). The 2011 flood event was even more devastating in its psychological impact, as it is estimated to have affected about 1.7 million Queensland adults in some way, with 24,000 adults reporting persisting distress five months later (Clemens et al., 2013). The estimated recurrence interval for this event was up to 1 in 2,000 years in the upper catchment (Rogencamp and Barton 2012; Croke et al., 2014) with peak discharges more than 10 times the magnitude of the mean annual flood defining it as catastrophic (Croke et al., 2014). Only two years after the devastation of the 2011 floods, a follow-up storm in January 2013, when ex-tropical Cyclone Oswald delivered widespread rain, produced another major flood event (BoM, 2017). The 2013 flood waters impacted over 600 properties in the region, with this flood affecting more properties near creeks due to backflow flooding, significant bank erosion, damage to road and crossing infrastructure and damage to many agricultural areas.

More recently, hundreds of South East Queenslanders were urged to flee their homes on 30 March, 2017, as rivers and creeks rose following the aftermath of Cyclone Debbie (AAP, 2017a). On 1 April, early estimates by the Australian Financial Review (AFR, 2017) anticipated that the economic costs of Tropical Cyclone Debbie would exceed $1 billion in Queensland, where damage estimated at $250 million was wreaked on the sugar cane industry alone, as not one farm was left unscathed (AFR, 2017). As of 4 April, the Australian Associated Press (AAP) reported that some parts of South East Queensland were still waiting for flood waters to recede before the clean-up could begin (AAP, 2017a). By the same day, the Courier Mail reported that 76 residences were deemed uninhabitable in the southeast (The Courier Mail, 2017), although the indications (according to ComSEC, 2017) were that it was likely to go up by 250-300. In total, storms knocked out power to nearly 250,000 properties across Queensland (AAP, 2017b). As of 8 April, at least six deaths had been reported in Queensland, and two people were still listed as missing (AAP, 2017b).

1.4.3 Vulnerability of South East Queensland Residents to Flooding

Recent events in Queensland have highlighted the vulnerability of housing to flooding and have caused billions of dollars in losses (Maqsood et al., 2015). In 2002, Middelmann used Geographical Information Systems (GISs) to model building flood damage in South East Queensland. His study estimated that if a flood with a 1% Annual Exceedance Probability (AEP) occurred simultaneously in all rivers in the region, 47,000 properties would be inundated, with about half of the properties likely to experience over-floor flooding. Ninety percent of affected properties will be located in the Brisbane-Bremer River system and the Gold Coast catchment. Eighty nine percent of properties affected by flooding will be residential. Nearly 60% of the residential flood damage will be located in the Brisbane-Bremer River system, with damage estimated to be highest in those areas which historically have suffered high flood losses. Whereas, the equivalent average damage per residential building will be the highest in the Gold Coast catchment. Middelmann's (2010) study also estimated that if the cost of the actual damages were to be spread among all residential buildings in South East Queensland, then the equivalent flood damage would be 1.09% damage from a flood with a 1% AEP (Middelmann, 2010).

In 2010, Wang and his colleagues estimated future scenarios of coastal inundation in South East Queensland based on the population and buildings affected by a 1-in-100-year or 2.5 m inundation event. The authors estimated that about 42 km2 of built-up residential land in South East Queensland will be exposed to a 1-in-100-year event. Such an event is likely to inundate the residences of 227,000 people. It will also inundate 35,200 residential addresses (2.5% of the South East Queensland total). Most importantly, these researchers estimated that by 2030, 1-in-100-year events will reach 2.7 m which will inundate about 48 km2 of built-up residential land. In addition, as populations are expected to increase by 2030, it was also estimated that about 399,400 people and 61,500 residential building addresses will be impacted (76.3% and 74.9% increases over the 2010's 1-in-100-year 2.5 m events) if development continues in its 2010 pattern. Even without population growth, Wang and his colleagues (2010) estimated that such an event would affect about 245,000 people, and 40,300 residential building addresses. When the same population and building growth rate is assumed after 2030, these researchers estimated that the affected population could increase to 772,000 as the 1-in-100 year events begin to reach 3 m. This is a 241% increase from the 1-in-100-year 2.5 m events of 2010 (Wang et al., 2010).

In a recent FloodAUS project by Risk Frontiers it was estimated that for the Brisbane River catchment and Bremer River catchment combined, about 17,500 residential addresses would be inundated at an ARI 100 year flood level (Frontiers, 2011). The analysis also estimated that for Gold Coast (Nerang River catchment and Coomera River catchment) about 14,116 residential addresses would be inundated at an ARI 100-year flood level. In total, the analysis identified that 47,085 residential addresses across Gold Coast, Brisbane, Ipswich, and other surrounding sites. This accounts for about 79.2% of all flood-prone residential addresses in Queensland (Frontiers, 2011).

1.4.4 Physical Setting of the Selected Regions in South East Queensland

The current study specifically surveyed two regions in South East Queensland: 1) Ipswich City (Lower Brisbane catchment and Bremer River catchment) and Gold Coast city (Nerang River catchment). The following subsections provide brief descriptions of the physical settings of each study area.

1.4.4.1 Ipswich City (Lower Brisbane catchment and Bremer River catchment)

Ipswich is a city with a complex flood story due to its location on both the floodplains of the Bremer and Brisbane Rivers (ICC, Online). Flooding has always been a natural occurrence in the region and this was recorded as early as 1824 by the explorer John Oxley (Coster, 2008). While riverine floods usually dominate, flooding also occurs along the many local creeks, as well as numerous overland flow paths which exist (QRMC-KBR, 2004; ICA, 2011).

The majority of the Ipswich Local Government Area (LGA) lies within the lower Bremer River floodplain. The upper catchment areas lie within the Scenic Rim floodplain whilst the north-eastern and north-western parts are located directly on the Brisbane River floodplain. The Brisbane River also forms the city’s north eastern boundary. The Bremer River catchment has a total size of approximately 2,030km2 with a 100km river length from its source in the Scenic Rim to the Brisbane River. A number of major creeks flow into the Bremer River within Ipswich, namely the Western (Franklin Vale), Warrill (Purga), Ironpot, Mi Hi, Deebing and Bundamba Creeks. The Six Mile, Goodna, Woogaroo and Sandy Creeks flow directly into the Brisbane River along the city’s north-east boundary. Black Snake Creek, which flows through the township of Marburg, also feeds into the Brisbane River at Fernvale.

Urban development in Ipswich has historically been concentrated along the Bremer River and the eastern creeks, primarily along the Deebing, Bundamba, Six Mile, Goodna and Woogaroo Creeks. The City is currently experiencing a high level of urban development in the Ripley Valley area (Bundamba Creek), Springfield area (Woogaroo Creek) and Redbank Plains, as well as Collingwood Park areas (Six Mile Creek). This level of growth has been acknowledged in the recently adopted Advance Ipswich (the plan), with the state forecasting a population growth to

435,000 people by the year 2031 from the current population of approximately 190,000, with 14% aged 65 years or older (ABS, 2011).

1.4.4.2 Gold Coast City (Nerang River catchment)

The Gold Coast city has extensive floodplains and a large population that is exposed to the threat of flooding. The major exposure is in the Nerang River catchment, which contains almost 60,000 dwellings; 40% are flood-prone (Newton, 2008). This river system represents the single greatest flood threat to the local community because of its central role in servicing a myriad of manmade and natural waterways that epitomise the Gold Coast lifestyle and environment (Middelmann et al., 2002). The Nerang River catchment has a total size of approximately 493.3 km2 with a 928 km river length, extending from the west in the McPherson Ranges and Springbrook Plateau through to the east near Southport (GCCC, 2011). The Nerang River continues its course from the Hinze Dam wall, flowing approximately 36 kilometres through rural residential and agricultural land use areas, reaching its tidal limit just upstream from Weedons Crossing. The tidal estuary region of the system traverses through medium and high density urban residential areas and receives runoff from the Carrara/Merrimac floodplain area before joining the Broadwater system and flowing into the Pacific Ocean via the Gold Coast Seaway (GCCC, 2002).

Multi-branched canal developments and a number of artificial tidal and freshwater lake systems have influenced and altered large areas of the floodplain. These canal developments provide a range of recreational opportunities for many residents, including boating and fishing. The canals and lakes provide habitat to a range of aquatic, terrestrial and marine flora and fauna. A large number of tributaries discharge into the Nerang River system downstream from the Hinze Dam. These include Crane Creek, Bonogin Creek, Mudgeeraba Creek (via Clear Island Waters), Witt Avenue and Carrara drain, Benowa flood channel and Mooyumbin Creek (GCCC, 2011). Each of these sub-catchments face pressures associated with varying land use activities and catchment characteristics, which has the potential to impact on water quality through stormwater run-off (GCCC, 2002). Since records began in 1920, there have been six floods which have caused moderate to major flooding. Four of these—1931, 1947, 1954 and 1974—were the result of cyclonic activity. The 1967 event resulted from a moist tropical low pressure system, and the first event in 1974 was the result of thunderstorm activity associated with a trough extending through the area (BoM, 2016).

1.5 THESIS OUTLINE AND STRUCTURE

The remainder of this thesis is organised around seven chapters that jointly aim to advance a more integrated, systematic and profound understanding of the psychological mechanisms that underlie risk perceptions, attitudes and protective behavioural intentions of flood-prone households (1.2).

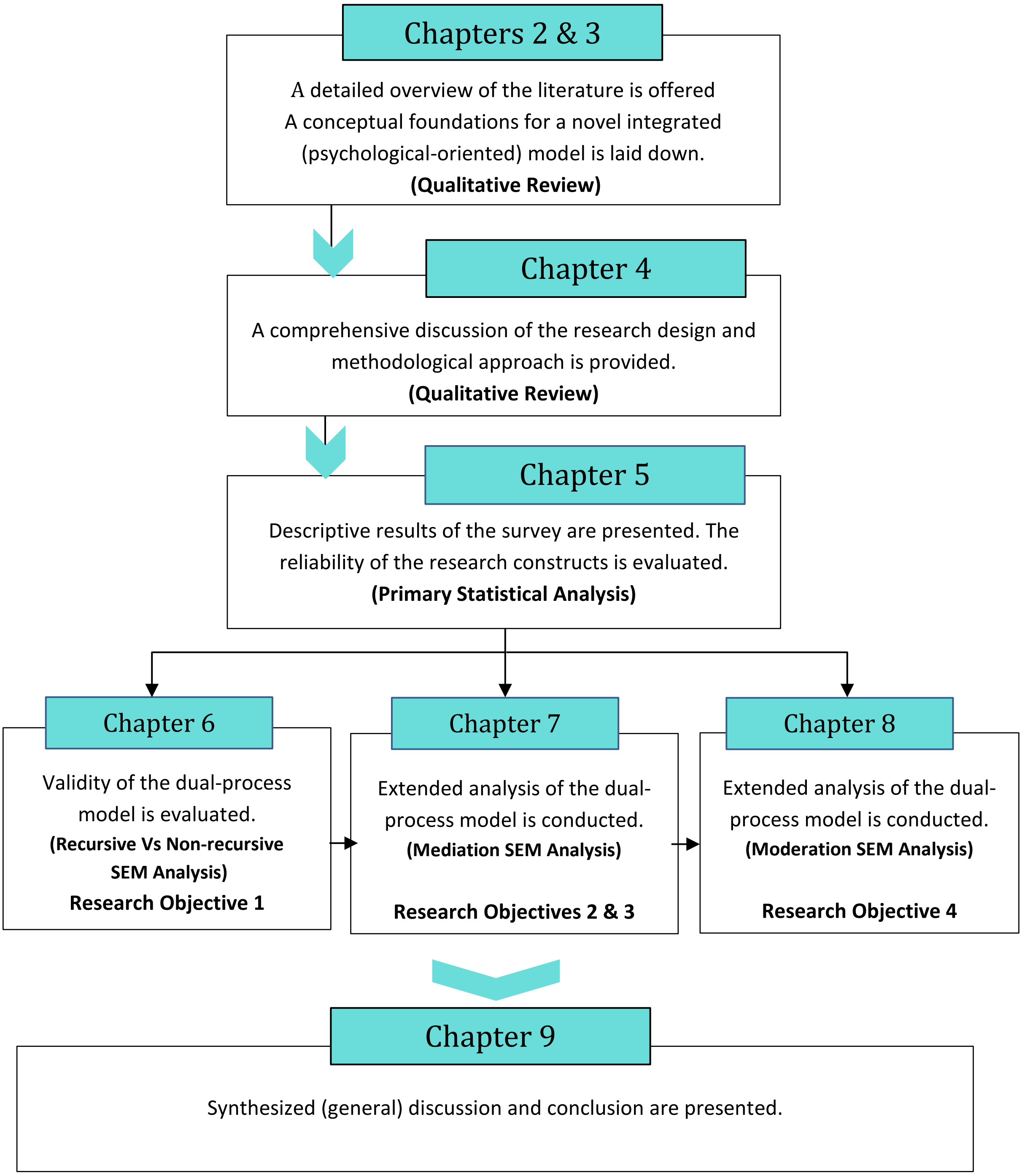

Figure 1.2 Structure of the thesis

In the theoretical part of this thesis **(Chapter 2)**, a detailed overview of the literature is offered, with a particular emphasis on exploring the mechanisms by which affective and cognitive processes are related and integrated in human risk judgement and decision making. It also provides a comprehensive discussion on different psychological variables involved in shaping attitudes and protective behavioural intentions of flood-prone households. These variables include experience, knowledge, self-efficacy and trust. **Chapter 3** lays the conceptual foundations for a novel, integrated (psychologically-oriented) model of risk perceptions and protective behavioural intentions. **Chapter 4** provides a comprehensive discussion of the research design and methodological approach. First it explains the philosophical stance of the research and its scope. It then discusses and explains the reasons for selecting research methods, with a focus on issues such as how data is collected and analysed. Finally, ethical considerations are provided.

The empirical part of this thesis (Chapters 5, 6 and 7) is based on data from a cross-sectional survey of flood-prone residents (N=681) in South East Queensland. Before plumbing the complex relationships between the research constructs (presented in Chapters 6 and 7), the conceptualisation and validation of these constructs are argued for based on the analyses of internal consistency and reliability (presented in Chapter 5). Specifically, **Chapter 5**, presents descriptive results (including the demographic characteristics of the participants) and reports how missing data, outliers, violations of normality and other statistical assumptions are examined and addressed. Finally, Chapter 5 details and evaluates the reliability of the research constructs using Cronbach's alpha.

Chapter 6 presents the results from the Structural Equation Modelling used to address ***Research Objective 1.*** Specifically, it tests and validates a dual-process model that integrates cognitive (analytical) and affective (emotional) processes underlying the risk perception of flood-prone households. Using IBM SPSS and Amos 24.0 software, the exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) and non-recursive (i.e. bidirectional) Structural Equation Modelling (SEM) analysis are adopted for testing how cognitive and affective processes reciprocally influence each other to shape perceptions and, subsequently, protective behavioural intentions. To validate the plausibility of the non-recursive model, this chapter then compares it with the traditional recursive (i.e. unidirectional) models in terms of the predictive power for protective behavioural intentions. The results confirm the validity of the proposed dual-process model. At the end, Chapter 6 concludes with the potential implications of the dual-process model for research and practice.

Chapter 7 extends the analysis of the dual-process model by specifically exploring how a different set of psychological variables influences perception processed through both cognitive and affective systems. In this regard, mediation and moderation analyses using SEM are conducted for cognitive and affective routes separately in order to address ***Research Objectives 2 and 3.*** **Chapter 8** further extends the analysis of the dual-process model by specifically exploring how residential satisfaction (i.e. perceived location-embedded benefits) is influencing flood preparedness intentions by altering the impact from both cognitive and affective systems. In this regard, moderation analyses using SEM are conducted in order to address ***Research Objective 4.***

Chapter 9 comprises the general conclusions drawn from the findings of this thesis. Also, the contributions of the study are discussed along with suggestions to guide future research.

1.6 CHAPTER SUMMARY

This chapter aimed to provide the reader with an orientation and understanding of the process which was followed in order to reach a conclusion regarding the problem statement. The phenomenon to be studied was introduced and the dynamic (psychological) factors under investigation were alluded to. This chapter provided the reader with some key conceptual constructs underlying the study. It also attempted to explain the methodological approach that is followed in order to reach the envisaged objectives of the thesis. The following chapter aims to provide the reader with an in-depth investigation into the development of a more integrated theoretical framework for the psychological mechanisms that underlie risk perceptions, attitudes and protective behavioural intentions of flood-prone households. It further addresses the psychological factors which contribute to flood risk reduction from a theoretical point of view.

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CHAPTER 2

LITERATURE REVIEW

The previous chapter provided an overview of the gap in the literature leading to the research problem, and framed the research question that the current thesis will address in the context of the identified gaps in the current understanding of the determinants driving flood-prone households' protective behavioural intentions. Knowledge of the determinants of risk response is indispensable for developing well-founded, effective risk communication and other interventions that are aimed at facilitating preparedness and mitigation decisions for flood-prone households.

In particular, this chapter provides a review of the theoretical and empirical literature on the underlying cognitive and affective processes of risk perceptions and protective behavioural intentions of flood-prone households. First, an introduction to the concept of risk and risk perception is presented in Section 2.1, followed by an overview of the cognitive and affective processes in risk perception. Several hypotheses about the interplay between cognition and affects, and their order and influence on risk perception and decision making, will be discussed in Section 2.3. Finally, this chapter will classify and give an overview of different determinants of risk perception—including experience, knowledge (or critical hazard awareness), self-efficacy (or perceived personal control) and trust in authorities and engineered flood defences (or perceived situational control).

2.1 THE CONCEPT OF RISK AND RISK PERCEPTION

Beginning with a brief introduction to the different conceptualizations of risk (2.1.1), the concept of risk perception and how it has evolved during the last few decades is then presented in Section 2.1.2

2.1.1 The Concept of Risk

"Risk surrounds us, it envelops us"

(Breakwell 2014: p.xi)

'Risk' is conceptualized in many different ways across scientific disciplines. Some concepts are based on probabilities or expected values (Lowrance 1976), some on undesirable consequences (Rowe 1975), danger (Campbell 2005), harm, or loss of something that humans value (including humans themselves) (Rosa 2003), and others on uncertainties (Kaplan and Garrick 1981; Aven 2010). Some consider risk as subjective and epistemic, dependent on the human knowledge or conscious awareness of the risk (via perception, thought, etc.) (Fischhoff et al., 1984; Slovic, 1992), whereas others grant risk an ontological status independent of the assessors (Aven, et al. 2011). However, most of these different approaches to the risk concept share a common denominator: the distinction between 'reality' and 'possibility' (Renn, 1992; Zinn, 2008). Thus, the term risk commonly signifies the possibility that an undesirable state of reality (adverse effects) may occur as a result of natural events or human activities (Rayner and Cantor, 1987). This conceptualisation implies that humans can and may make casual connections between events (or actions) and their effects, and that undesirable effects can be avoided or modified (Renn 1992). In other words, the concept of risk is strongly tied to the possibility that the future can be altered—or at least perceived as such—by human activities (Zinn 2009: p.4)

Looking at the reality–possibility distinction from a constructivist/relativist perspective, Solberg and Njå, (2012) argue that risk does not exist in any ontological sense. What actually exists are possible (future) states of affairs and these may or may not be interpreted to hold risk (Solberg and Njå 2012). An implication of this is that all risks are claimed to be subjective. One of the most explicit statements on this claim comes from Slovic and Weber (2002), who argue that "risk does not exist out there, independent of our minds and cultures, waiting to be measured. Instead, risk must be seen as a subjective concept that human beings have invented to help them understand and cope with the dangers and uncertainties of life" (p.4). To this extent, subjectivity enters the scene when risk is, for example, linked to uncertainty or a potential (i.e. when measuring a risk, when we do not know what will be the consequences, different events/outcomes are thinkable, they could occur) (Aven 2011; 2012).

However, it is worth noting that the subjectivity of risk does not infer that there are no risks in reality. Rather, the objective existence of risks as real dangers is socially mediated/constructed (Douglas and Wildavsky, 1982) or subjectively perceived by individuals (Fischhoff et al., 1978). This may imply that risk is a relative concept (Mitchell, 1999), that varies depending on people's state of mind, influenced by experiences, feelings, desires, social norms, values and uncertainties (Boholm, 1998; Slovic, 1987; Kasperson et al., 1988; Sjöberg et al. 2004). Thus, risk as a social construct reflects evaluations of the world: what it looks like, what it should or should not be (Boholm, 1998). In fact, understanding how different stakeholders perceive risks and choose actions based on their perceptions is vital to any strategy for disaster risk reduction (Eiser et al., 2012). Furthermore, such understanding can also support stakeholders' long-term engagement in risk management (Reed 2008) and can potentially contribute to the improvement of risk communication (Fischhoff et al., 1993; Fischhoff, 2009; Wachinger et al., 2013). The concept of risk perception and how it has evolved during the last few decades is presented in the following section.

2.1.2 Risk Perception, from a Cognitive Perspective

"Perceptions of risk are an inherent part of the decision-making process"

(Williams and Noyes 2007, p.1)

Research into risk perception draws on the discussion around the judgment and evaluation of hazardous activities or events that are automatically linked to decision-making processes (Slovic, 1987; Luhmann, 1993). Thus, judgmental processes involved in risk perception and decision-making have traditionally been conceptualized as cognitive in nature, being based upon rational and deliberate evaluations of the situation at hand (Böhm 2008). Cognitive psychologists have often described 'perception' as the process of selecting, identifying, organizing, interpreting and selectively extracting sensory input (Anderson, 1985; Westen et al., 2006). This is seen as an end-product of an active and constructive network of mental representations of the external world that draws on an individual's prior knowledge, internal hypotheses or expectations of the world (Bruner 1957). The mechanism by which perceptions are allocating and assigning meanings to the sensory world is fundamental to the decision- making process, and therefore essential to providing a better understating of risk assessment process (Morgan 2002). Indeed, several theories have been proposed to understand nature of the relationship between risk perception and decision making.

2.1.2.1 Rationality and bounded rationality

Early decision theorists defended the conventional view that the laws of rational human reasoning are the laws of probability and cost-benefit analysis (Gigerenzer and Goldstein 1996; Gonzalez and Wu 1999). These laws were incorporated into psychological theory in the midst of the 20th century, when von Neumann and Morgenstern (1944) and Savage (1954) presented axiomatic theories of expected utility. These theories stipulate that if people's preferences follow certain logical patterns (the so-called axioms of choice: transitivity, substitutability, monotonicity etc..), then they are behaving as if they are maximizing utility (Stanovich 2013; Buchak and Buchak 2013). Reflecting rationalistic origins, such maximization asserts that humans are rational optimisers, seeking maximum utility through deliberative calculation of benefits and costs (Dawes 1998; Gauthier 1975; Fishburn 1981; Hastie and Dawes 2010).

Following this time-honoured tradition, early flood risk perception research assumes rationalist statistical assessments to be the normative and descriptive tools of inference and decision making (White, G.F 1945). The premise behind this was that habitation choices (i.e. why people choose to live on floodplains, despite a constant threat of flooding) are rationally based on the trade-off that exist between benefits and hazards associated with living in a particular location (Burton et al., 1968; Fordham, 1992; Kates, 1962, 1971).

However, this generation of decision theorists soon realised that conventional and rationalist cost–benefit assessments were insufficiently nuanced to capture the way lay-people make decisions in real-life situations (Conlisk, 1996; Gigerenzer and Selten, 2001; Gigerenzer and

Goldstein, 1996; Kahneman, 2003). This shift has been picking up pace by the turn to the theory of bounded rationality and satisficing, developed by Herbert Simon (1956). The theory of bounded rationality assumes that people reason and choose rationally, but only within the constraints imposed by their limited search, information, resources and computational cognitive capacities (Simon, 1972, 1982). When applied to the context of choices in the face of natural hazards such as floods, individual decision-makers are seen as having to choose from a range of alternative responses. However, their choices are limited by their perception of those alternatives (White, 1972; Kates, 1971; Slovic et al., 1974). Influenced by characteristics of the physical and biological systems on the one hand, and by the social system on the other hand, decision-makers within natural hazard-prone areas are assumed to express their perceptions and ratings of risk through their descriptions of that risk, their articulated appraisal of the outcomes, and their actual behaviour (White, 1972). Accordingly, their decisions over risky outcomes may deviate from that predicted by expected utility theory or normatively algorithmic judgments (Birkholz et al., 2014).

Building on the concept of bounded rationality, alternative models have been proposed to explain individuals' decisions over risky outcomes. For example, Tversky and Kahneman (1975) proposed the 'heuristics and biases' approach, which assumes that in situations where time is limited and thinking is difficult, decision makers construct simplified judgmental operations (e.g. availability, representativeness, and self-adjustment and anchoring) (Tversky and Kahneman, 1975; Tversky et al., 1990; Kahneman and Tversky 2013). These operations reduce the complex tasks of assessing probabilities and predicting values, but also give rise to systematic errors and lead to suboptimal outcomes (Kahneman, 2011). The deviation between optimal and actual outcome is defined as bias (Tversky and Kahneman, 1974). For instance, the *availability heuristic* states that events are judged to be more probable if imagining or recalling similar instances from memory is easier. Consequently, people may give disproportionate weight to a few memorable events (for instance if they receive vivid press coverage) without recognising that their memory is selective (Tversky and Kahneman, 1974).

2.1.2.2 Psychometric paradigm

The psychometric paradigm is the most influential approach in cognitive risk research that investigates factors determining risk perception (Slovic 2016). Early work on the psychometric paradigm by the decision research group at the University of Oregon showed that people's ideas of what is meant by risk and, consequently, what could be described as 'acceptable risk', were complex and multi-faceted (Fischhoff et al., 1978). The simple expedient of measuring risk magnitude in terms of its probability of occurrence was shown to be inadequate (Slovic, 1987, 1992) as it failed to capture the way people—both experts and the lay public—actually understood and interpreted the risk. The psychometric paradigm perspective focuses specifically on the psychological view of human reasoning: the way we draw conclusions and how we act accordingly (Wachinger et al. 2010). It utilizes the "expressed preference" method, the approach that employs direct questioning of people regarding their attitudes towards risks and benefits associated with various hazards. In other words, this perspective tries to study several qualitative risk characteristics or risk dimensions to explain laypeople's risk perception and decision making (Slovic and Peters 2006).

Empirical studies employing the psychometric paradigm have typically used psychophysical scaling and multivariate analysis techniques (including multiple regressions, factor analysis, correlations and intercorrelations) to produce quantitative representations, or 'cognitive maps', of risk attitudes and perceptions (Slovic et al., 1979; Slovic, 2000; Slovic et al., 2004; Slovic et al., 2007; Slovic and Peters 2006). Thus, within the psychometric paradigm, people make quantitative judgments about the current and desired riskiness of diverse hazards and the desired level of regulation of each risky activity or hazard (Slovic 2010). These judgments are then related to judgments of other properties, such as the qualitative risk characteristics that make up a hazard's profile (e.g., voluntariness, knowledge, experience, dread, catastrophic potential, controllability (Siegrist et al., 2005.)

An expanded version of the psychometric paradigm appeared in the early 1990s, suggesting that 'social trust' was another influential factor in risk perception (Slovic et al., 1991). Specifically, Sjöberg, (2006) indicated that trust influences risk acceptance in two different ways: positively and negatively. Distinguishing between negative and positive impacts mainly relied on the emotional dimension 'dread' mediating the negative impact. Nevertheless, Sjöberg (2006) argued that there is a problematic issue concerning the validation of the prevailing interpretation of 'dread' as an affective dimension. Instead, he argued that the 'dread' dimension is a heterogeneous blend of different cognitive risk appraisals, rather than a quantitative measure of affective risk appraisals. This is in line with Pidgeon et al's (2006) argument that many of the 'dread' characteristics tap into concerns unrelated to affect. More recently, this view has been supported by Schusterschitz et al. (2010) who specifically found that "the explanatory power of 'dread' dimension is strongly influenced by the cognitive appraisal of severity of consequences" (p. 394).

The role of affect in risk perception is rather important and complex, as is evident from research into 'affect heuristic', 'risk-as-feeling' and, more generally, 'dual-processing' theory (Finucane et al., 2000; Rottenstreich and Hsee, 2001; Slovic et al., 2002, 2007; Loewenstein et al., 2001).

2.2 COGNITIVE AND AFFECTIVE PROCESSES IN RISK PERCEPTION

Evidence supporting the role of affect along with cognitions in risk perception fits well with the dual processing theory of thinking and decision making (Finucane and Holup, 2006; Finucane, 2012; Loewenstein et al., 2001; Slovic et al., 2004, 2007). In social and cognitive psychology, dual-process theory alleges that human beings possess affect-based and reason-based subsystems that compete in thinking processes (Chaiken and Trope 1999; Evans and Frankish 2009). Slovic and collaborators (2004) termed these two subsystems 'risk-as-analysis' and 'risk-as-feelings', respectively (Slovic et al., 2004). 'Risk as analysis' brings logic, reason and scientific deliberation to bear on hazard management (Slovic et al., 2006). 'Risk as feelings' refers to our fast, instinctive and intuitive reactions to danger (Loewenstein et al. 2001). The dual-process approaches to risky choice thus share the idea that both cognitive and affective modes of processing interact to guide and shape risk perceptions and choices. Although these two processes are thought to be continually active, interacting in what Finucane, Peters, and Slovic, (2003) characterized as "the dance of affect and reason," they are also assumed to respond to different characteristics of a risky situation (Slovic et al., 2007). On one hand, cognitive appraisals tend to depend on more objective features of the risky situation, such as probabilities of outcomes and evaluations of outcome severity (Loewenstein et al. 2001). The affective appraisals, on the other hand, often reflect a specific quality of 'goodness' or 'badness' of the risky situation—that is (1) experienced as a feeling state (with or without consciousness) and (2) demarcating a positive or negative quality of the situation (Slovic et al., 2004). Duality of the cognitive and affective systems in decision making is first introduced in Section 2.2.1, before the importance of cognitive and affective processes in shaping perception of flood risk is outlined in Section 2.2.2.

2.2.1 Cognitions and Affect Influencing Decision Making

Dual-process theories propose two distinct reasoning processes in humans—one is more cognitive and deliberative, the other is more affective and experiential (Chaiken, 1980; Epstein, 1994; Smith and DeCoster, 2000; Slovic et al. 2004; Kahneman, 2003, 2011; Evans and Stanovich 2013). The deliberative processing is an analytical, formal, verbally mediated and often conscious, cognitive mode of thinking (Epstein, 1994). The experiential mode of processing is characterized as intuitive, automatic, natural, associative and primarily nonverbal (Kahneman, 2003). In contrast to the 'deliberative' mode of thinking that is slow, effortful and operates based on conscious logic, the 'experiential' system is assumed to operate based on the rules of similarity and context, and is thus more rapid and effortless (Sloman, 1996). The 'experiential' system further encodes reality in the form of concert images, narratives and metaphors to which affective feelings have become attached (Slovic et al. 2004). The 'deliberative' system results rather in cognitive processing, whereas the 'experiential' system results in an affective processing of information. Further details on the comparative properties of the two modes are outlined in Table 2.1

Table 2.1 Comparative properties of the 'Cognitive' and 'Affective' modes of processing*

Deliberative (Cognitive) Processing	Experiential (Affective) Processing
1-Holistic	1-Analytic
2-More rapid processing	2-Slower processing
3-Parallel	3-Serial
4-Nonconscious	4-Conscious
5-Biased responses	5-Normative responses
6-Contextualized	6-Abstract
7-Encodes reality in concrete images, metaphors, and narratives	7-Encodes reality in abstract symbols, words, and numbers
8-Automatic	8-Controlled
9-Affective: Pleasure-pain oriented	9-Logical: Reason oriented (what is sensible)
10-Associationistic/Affective connections	10-Logical, rule-based connections
11-Experienced decision making	11-Consequential decision making
12-Independent of cognitive ability	12-Correlated with cognitive ability

*Sources include: Epstein, 1994; Slovic et al., 2004; Evans and Stanovich. 2013.

2.2.2 Cognitive Processes in Flood Risk Perception:

Perception of risk probability and severity of consequences

From a cognitive perspective, an individual's perception of risk depends upon an often analytic judgment of the probability of occurrence of a risky event and severity of its consequences (Sjöberg et al., 2004). Perceived probability shows how likely a person perceives the exposure of him/herself or others to any threat. For example, perceived probability of flooding is often expressed as a flood with a given average recurrence interval (ARI), such as a 1, 10, 100, or 1000-year flood or, alternatively, it could be expressed as a flood with a given percent annual exceedance probability (AEP), such as 50%, 20%, 10%, 5%, 2%, 1% AEP. Table 2.2 provides examples of the rating scales of perceived flood probability (PFP) as examined by a number of previous empirical studies across several countries.

Table 2.2 Summary of the reviewed studies examining "perceived flood probability"

Reference	Context	Rating scales
(Babcicky and Seebauer 2016)	N=226 Austria	Occurrence of flooding event on a scale from 2.5 = in 1–5 years; 7.5 = in 6–10 years; 15.0 = in 10–20 years; 25.0 = in 20–30 years; 40.0 = in 30–50 years; 78.0 = in 50–100 years; 200 = never-.
(Botzen et al. 2015)	N=1210 US	Occurrence of flooding at home on average, as often, more, or less often than 1-in-10 years/ 1-in-100 years/ 1-in-1000 years.
(Reynaud et al. 2013)	N=448 Vietnam	Occurrence of more floods in the next 10 years (No=0, Yes=1)
(Richert et al. 2017)	N=331 France	Occurrence of flooding at least once in the next 10 years? From 1 ("impossible") to 11 ("certain")
(Botzen et al. 2009)	N=1000 Netherlands	Occurrence of flooding a qualitative scale with the options: "I do not have any flood risks," "very low," "low," "not low/not high," "high," "very high," and "don't know."
(Bubeck et al. 2012)	N=300 Vietnam	Perceived probability of potential future flooding, on a scale from 1 to 7. A rating of 1 indicated that a flood event will not happen at all, while a rating of 7 indicates that a flood event will definitely happen
(Zhai and Ikeda 2008)	N=428 Japan	Frequency of flooding below (above) floor in the future: Once in 5 years, 10 years, 20 years, 50 years, 100 years, or more than 100 years; or absolutely never.

On the other hand, perceived severity indicates, if a risky event occurs, how serious or harmful people think it will be (Weinstein, 1999). Severity is mainly perceived through beliefs about adverse consequences. Consequence beliefs often refer to abstract-conceptual knowledge and concrete-perceptual images regarding psychological, physical, social or economic harm, and other negative outcomes of a risky event (Cameron, 2003; Güvenç, 2008). Nearly all of the risk-perception models contain severity. However, the terminology differs among studies. For example, in the psychometric model, immediate-delayed consequences, catastrophic potential, and fatality express perceived severity (Slovic, 1987). In the risk-as-feelings hypothesis, the dimension of anticipated consequences expresses severity (Loewenstein et al., 2001). In the context of flood-risk perception, perceived risk consequences (PRC) were assessed by different multi-dimensional scales that were developed and validated by several authors across several countries (Table 2.3).

Table 2.3 Summary of the reviewed studies examining "perceived flood consequence" (PFC)

People's conscious, analytical way of thinking may cause significant differences in risk

Reference	Context	Rating scales
(Babcicky and Seebauer, 2016)	N=226 Austria	A potential flood threatens: 1. respondent's health, 2. possessions and 3. quality of life, on a scale from 1 (strongly agree) to 5 (strongly disagree).
(Botzen et al., 2015)	N=1210 US	Cost to repair the damage to home and its contents: Continuous scale (damage in $)
(Reynaud et al., 2013)	N=448 Vietnam	Intensity of damage due to flood for the next 10 years, on a scale going from 1 (no losses and no damage) to 10 (critical damage and losses). A hypothetical flood has a negative impact on 1- respondent's house 2. household's health and 3. Agriculture, on a scale (No=0, Yes =1).
(Richert et al., 2017)	N=331 France	Water reaches respondent's street: 1 ("impossible") to 11 ("certain")
(Botzen et al., 2009)	N=1000 Netherlands	The amount of flood damage respondents expect to suffer once a flood occurs: Continuous scale (damage in Euro)
(Miceli et al., 2008)	N=407 Italy	Probability of four types of consequences : 1. assets will be destroyed, 2. home will be damaged, supplies will be interrupted and 4. loved ones will be hurt. Possible response categories ranged from 0 (not at all) to 3 (very much).
(Lindell and Hwang 2008)	N=321 US	Likelihood of three types of consequences—major damage to homes, injury to members of households, and health problems—for each type of hazard within the next 10 years. Possible response categories ranged from Not at all likely (=1) and Almost a certainty (=5).
(Zhai and Ikeda 2008)	N=428 Japan	Concern about 12 types of consequences: 1. Building collapse, 2. Inundation, 3. Damages to roads and bridges and the disruption, 4. Damages to traffic and the disruption, 5. Disruption of communications like telephone, 6. Confirmation of family safety, 7. Information confusion, 8. Life at evacuation site, 9. No evacuation site in the vicinity, 10. Assurance of food and drink water, 11. Disruption of electricity, water and gas, 12. Spread of infectious diseases.

perception. Here, conscious perception patterns reflect people's numeracy levels (i.e. their ability to reason and process basic probability or numerical concepts (Peters et al., 2006), which then determine the extent to which people differentiate between risk levels (Keller et al., 2009): "Highly numerate individuals differentiated between risk levels shown on a logarithmic scale to a higher extent than less numerate persons" (Wachinger et al., 2013: p.23). However, it is required to note that many studies on the perception of probabilities in decision making identified several biases in people's ability to draw inferences from probabilistic and numerical information (Breakwell, 2014; Covello, 1983; Goldstein and Rothschild, 2014; Ross, 1977; Wachinger et al., 2010). For example, there is evidence that people may tend to ignore low probability events even when these events may have a catastrophic potential impact (Carman and Kooreman, 2014; Barberis, 2013). This is especially relevant to natural disasters and hazardous events with a long return period (De Dominicis et al., 2015; Richard et al. 2012).

In the context of flood risk perception, Nascimento et al. (2007) indicated that "dealing with flood probabilistic concepts seems to be ... difficult", even if "respondents living in flood prone areas revealed a good knowledge of typical flood parameters" (p. 10). Accordingly, some recent research has questioned how proficient individuals are in processing abstract and analytical information about flood risks (see Godber 2005; Bell and Tobin, 2007; Ludy and Kondolf, 2012). For example, it has been found that the general public often misunderstands the term "100-year flood" and assumes that if an event occurs, the floodplain will be safe from flooding for the next 99 years (Ludy and Kondolf, 2012). As a result, it has been found that people tend to underestimate flood risks, and thus the necessity of undertaking protective actions (Botzen et al., 2009; Bell and Tobin, 2007). Indeed, misperceptions of the probability of flood risk occurrence have been found to result in larger losses than necessary (Sniedovich and Davis, 1977; Ludy and Kondolf, 2012).

Furthermore, Sjöberg (2006) argued that probabilities are usually of little concern to the public, who finds them irrelevant and hard to understand, based on questionable assumptions. Instead, the author argued that consequences are what should be addressed, not probabilities. Smith and Brooks (2013) also noted that considering consequences of an event may be more significant than its probability, and should, therefore, be more heavily weighted to reflect the greater ease with which individuals can relate, understand, and picture the outcome of an event (Smith and Brooks 2013). However, Woodruff (2005) argued that a "continued overemphasis on consequences when making risk-based decisions will over time have a negative impact… leading to risk [aversion]…" (Woodruff 2005, p. 346). However, this does not imply that lay risk perceptions are flawed or incomplete , while expert assessments reflect the true nature of risks (Wynne 2002). There is in fact some uncertainty as to whether expert risk assessment may be enhanced or weakened via reference to lay risk perceptions (Wachinger et al., 2010).

In the context of flood risk research, risk perception (as a combined measurement of perceived probability and consequences) has specifically received considerable attention (e.g., Miceli, al. 2008; Lindell and Hwang 2008; Takao et al. 2004; Zhai and Ikeda 2008; Botzen et al. 2009; Grothmann and Reusswig 2006; Knocke and Kolivras 2007; Siegrist and Gutscher 2008; Terpstra 2011; Reynaud et al. 2013; Adelekan and Asiyanbi 2016). Behind this lies a general assumption that a high level of perceived risk carries with it demands for private risk mitigation at the household level (Sjöberg 2000). However, despite the theoretical justification of this assumption, there has been mixed empirical support for the proposed role of flood risk perceptions in predicting protective behavioural intentions (Wachinger et al., 2013; Bubeck et al., 2012b). While some studies (e.g., Plapp and Werner, 2006; Plattner et al., 2006; Grothmann and Reusswig, 2006; Terpstra and Lindell, 2013; Babcicky and Seebauer, 2016; and Kerstholt et al., 2017) report a positive relationship between risk perceptions and adaptive behavioural intentions, others (e.g., Lindell and Hwang, 2008; Miceli et al., 2008; Sjöberg et al. 2004; Terpstra et al., 2009; Siegrist and Gutscher, 2006; Bubeck et al., 2013; and Väisänen et al. 2016) present no or only a statistically weak association.

Such inconsistent findings underline the important role of additional qualitative factors, including affective or emotional evaluations (Wachinger et al., 2010). For example, the emotional item "fear" may amplify perceived severity and, therefore, seems to be a factor that leads to negligence of probability (Sunstein and Zeckhauser, 2011). Furthermore, there is also evidence that it is especially the emotional item "fear" that influences flood mitigation behaviour rather than perceived probability (Miceli et al., 2008) or perceived severity (Zaleskiewicz et al. 2002). In this regard, Sobkow (2016) argues that when no information about numerical risk estimates is available (e.g., probability of loss or magnitude of consequences) people may rely on positive and negative affect toward perceived risk.

2.2.3 Affective Processes

The role of affect in human decision making is increasingly attracting research interests, across disciplines ranging from philosophy (e.g., Solomon, 1993; Knuuttila, 2004), psychology (e.g., Frijda, 1988; Lazarus, 1991; Clore, Schwarz and Conway, 1994; Loewenstein et al. 2001; Slovic et al., 2004; Li et al., 2014; Lerner and Keltner, 2000; Lerner et al., 2015) to neuroscience (e.g., Zajonc, 1980; Scherer and Ekman 1984; Damasio, 1994; Ekman 2007; Phelps et al. 2014). According to several authors, affect refers to the state of feeling that human beings experience and is often also related to evaluative feelings of 'goodness' or 'badness' with regard to an external stimulus (Finucane et al., 2000; Slovic et al., 2004; Slovic and Peters, 2006). While emotions are more complex in-depth feelings that cause psycho-physiological changes (Myers 2004: p. 500), affect —as a faint whisper of emotion— is often conceptualised as a rather fast, specific and automatic evaluation of a specific object or issue (Slovic et al., 2004).

An individual's affective state often comprises three dimensions: valence, arousal, and motivational intensity (Harmon-Jones et al., 2012). Valence describes the extent to which an experienced emotional state is positive or negative (Russell 2003; Sjoberg, 2007), whereas arousal refers to its intensity, i.e., the strength of the associated emotional state, ranging from low to high (Barrett and Russell 1999). Arousal is a construct that is closely related to motivational intensity but they differ in that motivation necessarily implies action while arousal does not (Zeelenberg, et al. 2008). Motivational intensity refers to the strength of an urge to move toward or away from a stimulus (Gable and Harmon-Jones 2010).

Research into the influence of affective responses on judgment and decision making can be distinguished according to whether one is focusing on 'anticipated' or 'anticipatory' emotions (Loewenstein et al., 2001). Decision making research is interested in the effect of 'anticipated' or expected emotions. 'Anticipated' emotions are not experienced in the immediate situation, but are prognoses about the emotional consequences of decision outcomes. That is, it is assumed that during the process of decision-making, people anticipate how they would feel in different outcome situations, which constitutes an additional factor influencing decisions (Lerner et al., 2015). With 'anticipated' emotions, the process of decision-making is still viewed as a mainly cognitive one (Loewenstein et al., 2001; Zinn, 2006). Accordingly, the emotion is experienced in the moment the decisions carries out, whereas in the moment of choice only cognitions about future emotions are felt (Rick and Loewenstein, 2008). Neuroscience and social psychology have mainly focused on the role of 'anticipatory' emotions by examining how immediate emotions (immediate visceral reaction in the decision-making situation) influence human decision-making (e.g., (Panksepp 2004; Ochsner and Gross 2004)).

Lerner and Keltner (2000) further make a distinction between 'integral' and 'incidental' affect. Studies focusing on 'integral' affect analyze the impact of emotions that are related and relevant to the object of decision-making (Rick and Loewenstein, 2008). 'Incidental' affect refers to emotions that are experienced during decision-making and that sometimes have an impact on judgment and choice even though these emotions seem, from a normative perspective, unrelated to the decision task at hand (Keltner and Lerner, 2010). Incidental affect often arise from an individual's direct environment (e.g. weather) or chronic dispositional affect (e.g. mood) and can bias decisions (Lerner et al., 2015; Loewenstein and Lerner, 2003). To distinguish from affect, moods are rather low intensity and diffuse affective responses that are not directed to a specific object or issue (Schwarz and Clore 1983).

2.2.4 Affective Processes in Flood Risk Perception

Recent research on flood risk has documented that affect plays a crucial role in risk perception. As illustrated in Table 2.5, affective responses are often integral to flood risk and refer to: 1. anticipatory emotions associated with previous flood experiences (Siegrist and Gutscher 2008; Zaalberg al. 2009; Terpstra, 2011); 2. anticipatory emotions associated with the idea of living in a flood-prone area (Boer et al. 2015) or 3. anticipated emotions associated with future flooding scenarios (Miceli et al., 2008; Zaalberg et al. 2009; Poussin et al. 2014; Babcicky and Seebauer 2016). Most, if not all, of these reviewed studies assessed broad categories of positive or negative affective responses with regard to flood risk through self-reported questionnaires.

Table 2.4 Summary of the reviewed studies examining affective (emotional) appraisals in flood risk perception

Study/ Context	Study design	Description of Affective Appraisals
(Siegrist and Gutscher 2008) Switzerland	Survey-based study -Availability & Affect heuristic -Descriptive statistics, Means and Standard Deviations	Negative affects evoked by past flooding experiences: Uncertainty, insecurity, fear, shock, and helplessness
(Keller et al., 2006) Switzerland	Experimental-based study -Availability & Affect heuristic	Negative affect of fear manipulated using photographs of flooded houses.
(Zaalberg et al., 2009) Netherlands	Survey-based study -Protection motivation theory or PMT -Structural equation modelling SEM -Analysis of the mediating processes	Positive and negative affect evoked by past flooding experiences: pleasurable tenseness, intimacy, panic, sadness, sense of beauty, stress, concern.
(Babcicky and Seebauer 2016) Austria	Survey-based study -Linear Regression	Negative affect of worry and fear associated with future flooding scenarios.
(Miceli, et al. 2008) Italy	Survey-based study -Correlational and multiple regression -Risk-as-feelings (PCM)	Negative affect of worry associated with future flooding scenarios.
(Boer et al., 2015) Netherlands	Survey-based study -Multivariate analysis of variance (MANOVA)	Positive and negative affect associated with the idea of living in flood-prone areas: pleasant, happy, good, cheerful, anxious, worried, unsafe, and restless.
(Poussin et al., 2014) France	Survey-based study -Multiple regression analyses	Negative affect of worry and fear associated with flood damage perceptions.
(Terpstra 2011) Netherlands	Survey-based study -Affect heuristic. -Structural equation modelling SEM -Analysis of the mediating processes	Positive and negative affect associated with past flooding experiences. Negative affect reflects fear, powerlessness and helplessness, worries, feelings of uncertainty, and sadness. Positive affect reflects sense of relief ('being alive'), feelings of solidarity ('feeling accompanied'), and sense of beauty or force of nature.

The reviewed studies (Table 2.4) recognized that mostly negative, emotional responses to flooding play a crucial role in altering individuals' flood risk perceptions, thus their motivations to take preventative action. For example, Miceli et al. (2008), found that emotional factors (affect) were significantly related to preparedness for disaster, whilst cognitive perceptions of risk (i.e.

likelihood judgements) were not. Likewise, Siegrist and Gutscher (2008) identified emotions as one of the most influential factors affecting preparedness of flood-prone households. Their findings point to the ability of those previously affected by floods to recall the negative emotions associated with the experience, thus motivating them to take preventative actions against future floods. In particular, the ability to recall feelings of uncertainty, insecurity, fear, shock, and helplessness were most influential. Conversely, those not affected by experiences of floods rarely cited negative emotions as consequences of a flooding experience (Siegrist and Gutscher 2008).

Equally, Zaalberg et al. (2009) also found that flood victims worry more about future flooding than non-flood victims and perceive themselves to be more vulnerable to future flooding, resulting in greater willingness to undertake adaptive actions. Moreover, Poussin, Botzen and others (2014), who conducted a household survey in France, found that the degree of worry felt about potential flooding increased perceived flood damage, which in turn increased the implementation of emergency preparedness measures. Experimentally, Keller, Siegrist and Gutscher (2006) found that the evocation of negative affect—particularly fear and dread— by means of photographs showing houses in the flood region resulted in higher perceptions of risk. Similarly, Vastfjall, Peters, and Slovic (2008) manipulated negative affect associated with the 2004 East Asia Tsunami. By reminding their Swedish subjects of the tsunami, they indeed elicited negative affect, which in turn resulted in more pessimistic expectations about the future.

Overall, the studies reviewed above suggest that the primary motivational basis for risk behaviour may be attributed to the regulation of negative emotional states—whether evoked by previous experiences, perceived future flooding scenarios (i.e. damage), or experimental manipulation.

However, not all emotional responses to risk are negative, particularly when risks are undertaken as a result of the voluntarily choice to live in areas prone to flood risks (Keller et al. 2006). Applying the affect heuristic to flooding, Terpstra (2011) explored the role of positive affect such as solidarity and unity ("feeling accompanied") that related to helping one another during the flood disaster, feelings of relief ("being alive"), and being impressed by the beauty and force of nature (e.g., water flows, views). The author found that these feelings can also have a significant role in altering risk perceptions and preparedness intentions of flood-prone households. In particular, he found that householders who had experienced positive affect and had found their community acted with solidarity tended to report positive affect. Similar to the aforementioned studies, Terpstra (2011) reported that negative affect increased risk perceptions, while positive affect had the opposite effect.

Understanding the role of affect is important not only for a better understanding of why people may or may not take the initiative to become better prepared for disasters, but also to shed light on why seemingly well-thought-out preparedness campaigns fail to take effect (Harris 2012). Moreover, the study of emotions and affect raises fundamental questions about how we, as researchers, frame the 'problem' of irrationality. In this regard, Harries's study (2008) of ineffective flood preparedness campaigns in the UK explores not only the question of why people are failing to protect themselves despite knowing they are in a flood risk area, but 'why it can seem better not to protect yourself'. Using Malsow's (1943) hierarchy of motivation—a conceptual framework that seeks to demonstrate how individuals prioritise some categories of emotions over others—Harries (2008: p. 3) seeks to demonstrate that '...the rejection of flood-risk mitigation measures—and indeed, of the whole discourse of flood-risk mitigation... can be seen as entirely rational'. In short, he argues that a better understanding of individuals' own motivational priorities can reveal that the refusal to prepare for floods is in fact rational. Accordingly, the failure, or refusal, to undertake flood risk mitigation measures reflects a rational desire to prioritise their conception that the home is a safe place, that society will protect you and that nature is benign (Harries, 2008: p. 20). This is what Giddens (1991) refers to as ontological security, which individuals are placing above their physical security: 'preferring to think of their homes as places that are innately safe, they reject the idea of defending them' (Harries, 2008: 2). This is also consistent with the notion of 'optimistic bias', originally referred to as 'unrealistic optimism' (Weinstein, 1980), which reflects the tendency of individuals to underestimate the likelihood they will experience adverse events.

However, the notion that positive affect may lead to the refusal to prepare for future floods, as found by Terpstra (2011), is in contrast with the broaden-and-build theory (Fredrickson, 2001). This theory postulates that positive emotions may contribute to the ability to cope with negative emotions and life experiences, because they stimulate thought and increase the number of perceived coping behaviours, thereby adding to one's physical, intellectual, social, and psychological resources (Tugade and Fredrickson, 2004). For example, in a very different domain, Fredrickson et al. (2003) supported the link between positive emotions (e.g., gratitude, interest) and resilience (e.g., life satisfaction, optimism) in the context of the 9/11 terrorist attacks. Moreover, increases in coping resources may be enduring, which makes people more resilient when dealing with future events (Tedeschi and Calhoun, 2004). Vazquez et al. (2005) investigated positive emotions among earthquake survivors in refugee camps in El Salvador. In addition to negative emotions, almost 75% of the interviewees recalled moments of happiness that could be attributed to either 'being alive' or 'feeling accompanied'. Community and social activities largely contributed to positive emotions and the ability to cope with the difficult circumstances (Vazquez et al., 2005). Similar findings were reported by Babcicky and Seebauer (2016) in the context of flood risk. These scholars found that social capital (i.e. features of social organization, such as trust, norms, and networks) is a marginally significant predictor for the affective components of risk perception. Regression analyses showed that high levels of social capital were associated with weaker feelings of fear and worry towards a potential flood risk. In other words, social capital was found to make individuals feeling better prepared and supported, and thus decrease their flood risk perception.

In summary, the studies reviewed above suggest that risk perception and risk behaviour could be significantly altered by both positive and negative affect. This is an important observation because it opens a possible pathway to improving risk management: if we understand affective states or responses of flood-prone households, and if we could influence these responses, then we might also be able to affect levels of preparedness at the household level. However, the consideration of affect in the formation of risk perceptions is a quite new research field. Quite a few contributions address general topics and try to clarify the functions, nature, and components of affect. Others broaden the scope to social factors that reflect upon the role of affect in risk perception.

2.3 THE INTERPLAY OF COGNITIVE AND AFFECTIVE PROCESSES

There exist several propositions on the interplay between cognitions and affect, and their order and influence on risk judgment and choice. These will be discussed in the following sections.

2.3.1 Affect Precedes or Follows Cognitions: a 'Unidirectional' Relationship

"Affective judgements may be fairly independent of and precede in time the sorts of perceptual and cognitive operations"

(Zajonc, 1980: p. 151)

"*Few would question that cognitive evaluations give rise to affective responses*"

(Loewenstein et al. 2001: p. 271)

One proposed mechanism is that affective responses may represent a more experiential information processing that fosters a reliance on heuristic and intuitive risk judgment (Slovic et al., 2007). The central principle of this mechanism is that affective responses are the first and automatic reactions to a stimulus that further serve as a cue to guide (or bias) cognitive processing of information and decision making (Zajonc, 1980). Figure 2.1 provides an abstract illustration of this mechanism. In this view, affective responses are not only assumed to be evolutionarily adaptive (Zajonc, 1980), but also indispensable for optimal judgments because they simplify the daunting task of anticipating an uncertain future and making decisions accordingly—particularly when decision-making is carried out spontaneously or with limited cognitive resources (Lowenstein and Lerner, 2003). Neurological research approves this direct link from stimulus to affective responses, as LeDoux (1996) found that there exists a direct neural projection from the sensory thalamus, which is responsible for the processing of signals to the amygdala, which in turn is important for the processing of affective reactions. Thus LeDoux (1996) proposed that emotional reactions are independent of (higher-order) cognitive processes.

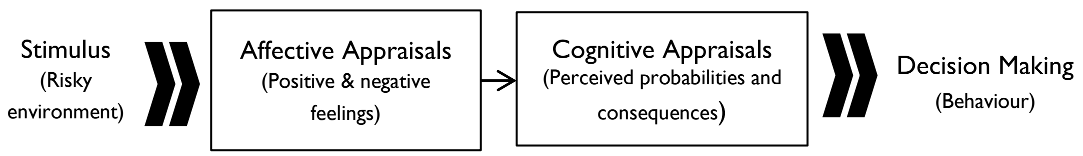

Figure 2.1 An illustration of the "Affect→Cognitions→Decisions" mechanism

Another mechanism assumes that people first cognitively evaluate a stimulus. This cognitive evaluation results in affective responses that directly influence human judgment and decision making. In other words, it is assumed that the effect of cognitions on decision making is mediated by affective reactions (Damasio, 1994; Loewenstein et al., 2001). Figure 2.2 provides an abstract illustration of this mechanism.

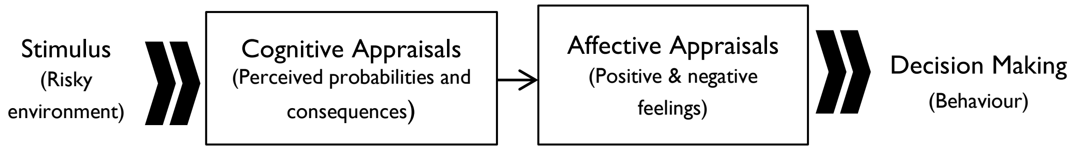

Figure 2.2 An illustration of the "Cognitions →Affect →Decisions" mechanism

Neurologically speaking, Antonio Damasio (1994) has argued that decision makers encode the consequences of alternative courses of action affectively within the ventromedial prefrontal cortex (VMPFC). Based on personal experiences, individuals over time learn to "mark" these consequences as positive or negative feelings that are further linked to 'somatic' states. Whether acting unconsciously or consciously, these 'somatic markers' were found to guide decisions in an efficient and accurate way (Damasio, 1994). Studies supporting the 'affect-as-information' hypothesis found that affect can also have a direct influence on decision-making (Schwarz, 2000, 2011; Clore et al., 2001). When feelings during a decision-making process are perceived as relevant or 'integral' to the decision-making task by the person, then these feelings can be seen as a source of information, which in turn can function as a basis for the person's judgment (Clore et al., 1994; Loewenstein et al., 2001).

Of special relevance to judgement of risk is work by Slovic and his colleagues (2004) on the affect heuristic. Similar to the 'somatic marker' hypothesis, the 'affect heuristic' approach assumes that images referring to the hazard or technology in people's minds are marked with affect and that people refer to a pool of positive and negative feelings tagged to their associations in order to make judgments (Slovic et al*.,* 2004). In particular, the 'affect heuristic' approach proposes that if people's overall feelings about an object are positive, they judge risks to be low and benefits to be high, and this overall 'summary' feeling serves as a mental shortcut in decision making (Peters and Slovic, 1996). In their study Finucane et al. (2000) tested the hypothesis for various technologies and found that giving people information stating that benefits are high results in positive affect, which further decreased perceived levels of risk. This suggests that cognitive judgements, including estimates of probability, can be strongly influenced by affective reactions. In the context of flood risk, Terpstra (2011) found that Dutch citizens who had more positive affective reactions to the risk of flooding expressed lower estimates of the likelihood of future floods and weaker responses to take protective measures. According to Slovic and his colleagues (2004), the affect heuristic is closely linked to the availability heuristic proposed by Tversky and Kahneman (1974). They propose that the stronger the emotions tagged to images, the higher is the likelihood that these images will be remembered. Furthermore, the description of an 'affect pool' has much in common with the experiential (or associative) systems in dual-process theories (see Section 2.2.1)

In contrast to affect heuristic, the appraisal theory of emotion proposes that affective risk perceptions are operating at a more deliberative level of processing, whereby cognitive appraisals give rise to affective appraisals (Lerner and Keltner, 2000, 2001; Lerner, Li et al., 2015). The central tenet of appraisal theory is that events are first appraised (i.e. evaluated, interpreted and explained) in terms of their relation to one's situation (i.e. personal experiences, goals, values, resources, abilities, and overall well-being), which in turn results in affective responses that vary from person to person (Ellsworth, 2013; Scherer et al., 2001). In other words, it is assumed that the influence of cognitive appraisals on decision making is mediated by the affective appraisals. This mechanism has received substantial empirical support from empirical research (Scherer et al., 2001; Roseman and Evdokas, 2004; So et al., 2015; Moors et al., 2013; Faustino et al., 2015). For example, Kobbeltved et al. (2005) reported in their (cross-lagged) panel study that "it is unlikely that our subjects allowed their affective impressions to guide their risk judgments" (p. 431). Instead, the authors note that over time, risk judgments gave rise to negative emotions but not vice versa. Attempts to apply appraisals models to environmental and natural risk perceptions are under way (see, for example, Keller et al. 2012; Böhm and Pfister 2000, 2005; Pfister and Böhm 2008).

2.3.2 Affect and Cognitions Influence Each Other: a 'Bidirectional' Relationship

> *"Emotion [affect] and cognition not only strongly interact in the brain... they are often integrated so that they jointly contribute to behaviour."*
>
> *(Pessoa 2008: p. 148)*

Dissecting the mechanisms that formulate risk response in the precognitive model (Figure 2.1), the influence of affective risk perceptions seems to be indirect and fully mediated via cognitive perceptions. Similarly, in the post-cognitive model (Figure 2.2), the influence of cognitive risk perceptions on risk response seems also to be indirect and fully mediated via affective perceptions. Taken together, such models do not capture the fully direct effects of both cognitive and affective perceptions of risk at the time. Loewenstein et al. (2001) propose a 'risk-as-feelings' hypothesis that models how affective and cognitive processes influence people's responses to risky situations. The hypothesis postulates that feelings, as well as people's cognitive assessments, operate in parallel and both have a direct impact on people's choices. Furthermore, cognitive evaluations affect people's feeling state, and emotional reactions have an influence on the cognitive evaluation (Loewenstein et al., 2001). Due to having different determinants, these two evaluations diverge and, therefore, a discrepant influence on risk judgment and response emerges. In this case, Loewenstein et al. (2001) further argue that affective evaluations are often more predictive of responses and behaviour than cognitive evaluations (Loewenstein et al., 2001). Whereas with low levels of emotional intensity, affect was found to give good advice when people have to judge risks, high levels of emotional intensity seem to inhibit cognitive processes.

For example, in a study by Rottenstreich and Hsee (2001), people's behaviour was hardly influenced by the probability of occurrence in the case of events linked to strong affections, whereas probability judgments had an influence on decisions with low levels of emotional intensity. Similarly, in risk judgment people reject any cognitive evaluation even when probabilities of occurrence are very small, when the possible negative consequences of a technology or hazards are perceived as catastrophic and too horrible (Loewenstein et al. 2001; Zinn, 2006; Zinn and Taylor-Gooby, 2006). For example, one may feel afraid to fly (due to the low-probability/high consequence terrorist attack) and decide to drive instead—even though base rates for death by driving are much higher than those for death by flying the equivalent mileage (Gigerenzer, 2004, 2006). Moreover, a survey study for households who had experienced flooding found that their protective decisions were influenced more by anticipated negative emotions, such as anxiety or insecurity, than by material and financial considerations (Harries, 2012). Thus, the overwhelming impact of affective reactions on people's judgements often impedes rationality (Rolls, 2000).

Moreover, aiming to expand and link the risk-as-analysis and risk-as-feelings models Finucane and Holup (2006) introduced the risk-as-value model. Their use of the term ''value'' is similar to Baron's (2000) use of ''utility'' as the measure of people's best judgments, based on their logical deliberation and experiences of processes and events, of the overall goodness of outcomes (Baron and Leshner, 2000). From a psychological perspective, Finucane and Holup's (2006) conceptualization of values (i.e. perceived risk of a hazardous activity or technology (X)) reflects the interplay of analytic evaluation (EAn) and the affective evaluation (EAff):

$$\textit{Perceived Risk } (X) = f\,(Ean\,(X)),\,(Eaff\,(X)\ \ldots\ldots\ (1)$$

Equation 1 implies that differences in perceived risk may arise in at least the following ways. They may result from differences in the analytic evaluation of X, differences in the affective evaluation of X, or differences in the way these evaluations are combined.

Importantly, Finucane and Holup (2006) do not suggest a specific rule for combining affective and analytic evaluations (such as adding, averaging, or multiplying). Instead, these authors suggest that both affective and analytic evaluations are congruent and more likely to combine additively to influence judgments. Conditions of incongruence, for example, may result in greater analytic or affective processing depending on various factors related to the task, decision maker, or context (e.g., analysis may be increased if it is viewed as more reliable, but may be attenuated under time pressure). Likewise, under conditions of ambiguous information, affect may set up an expectancy and analysis may then interpret the information in line with this expectancy (cf., Zuckerman and Chaiken, 1998; Finucane and Holup, 2006).

To this extent, it seems imperative that cognitive risk perceptions and more affective reactions should be examined together. Making matters more interesting, there may be a more dynamic interplay between cognitions and affect. In fact, some recent evidence demonstrates that cognitions and affect reciprocally influence each other and, thereby, have an interactive effect on risk judgments (Linden, 2014). This dynamic interaction has been substantially motivated by recent neurological evidence demonstrating that emotion and cognition are deeply interwoven in the fabric of the brain—so that they conjointly and equally contribute to behaviour (Armony and LeDoux, 1997; Damasio, 1994; Pessoa 2008; Brosch et al., 2013; Okon-Singer et al., 2015; LeDoux, 1989). For example, Ledoux (1989) indicated that the amygdala may be a focal structure in the affective network within the human brain. By way of neural interactions between the amygdala and brain areas involved in cognition (particularly the neocortex and hippocampus), it is proposed that affect can influence cognition and cognition can influence affect (Ledoux 1989). In illustrating the mechanism of influence, for example, Storbeck, Robinson and McCourt (2006), found that prior to affective responses, a stimulus passes through a cognitive processing, called semantic analysis, within the visual cortex. Thus, a three-step processing is proposed with an initial peripheral cognitive processing that results in emotional responses that further guide more elaborate cognitive processes (Storbeck, Robinson and McCourt, 2006). Overall, embracing a dual-process perspective, these neurologists do not support the independence of emotional and cognitive processes. Unlike the pre- or post-cognitive processing models, the dual-process model assumes a bi-directional path between cognitive and affective risk perceptions (see Figure 2.3).

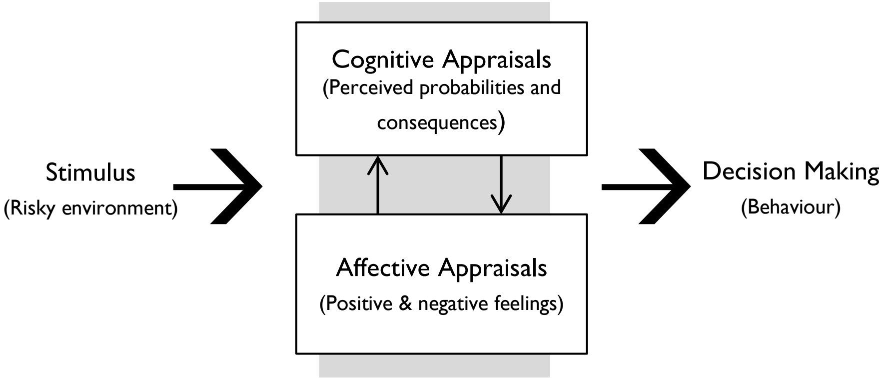

Figure 2.3 An illustration of the dual (cognitive <-> affective) processing model

To sum up, the discussion above suggests that cognitive risk perceptions alone cannot account for risk response and that there may be a more complex and interactive mechanism to link cognitive with affective risk perceptions. In one of the few studies on the topic, Linden (2014) examined whether negative affect and risk perception of climate change reciprocally influence each other in a stable feedback system. Using SEM approach on a national sample (N = 808) of British respondents, Linden (2014) contrasted three competing models, namely, (i) the "affective" model (where affect is seen as information processing heuristic), (ii) the "cognitive" model (where affect is seen as a post-cognitive process), and (iii) a "dual-process" model that integrates aspects from both theoretical perspectives. His results initially provided support for the post-cognitive specification, where personal experience predicts risk perception and, in turn, risk perception predicts affect. Yet, closer examination indicated that at the same time, a mutually reinforcing and reciprocal relationship between affect and risk perception is significantly supported. It was therefore concluded by Linden (2014) that both theoretical claims are valid and that a dual-process perspective provides a superior fit to the data than a unidirectional model. Interestingly, based on these results, the author argued that the interactive engagement of both cognitive and emotional processing mechanisms is key to fostering more public involvement with climate change (Linden 2014).

2.3.3 The Interplay of Cognitive and Affective Processes in Flood Risk Research

In the context of flood risk, most prior empirical studies (Table 2.6) have proposed a unidirectional relationship between both cognitive and affective processes that underlie flood risk perception (Keller et al., 2006; Miceli et al., 2008; Siegrist and Gutscher, 2008; Zaalberg et al., 2009; Pagneux et al., 2011; Terpstra, 2011; Boer et al., 2015; Poussin et al., 2014; Babcicky and Seebauer, 2016; Kerstholt et al., 2017). For example, Miceli and others (2008), who adopted the risk-as-feeling approach (Loewenstein et al., 2001), proposed that affective risk perceptions, unlike cognitive ones, have a direct relation with the adoption of flood adaptive measures. The indirect effect of cognitive risk perceptions was hypothesized to be mediated via affective risk perceptions (Miceli et al., 2008). In contrast, a study by Zaalberg and others (2009) who adopted the protection motivation theory (Rogers 1975), proposes a more indirect role of affective perceptions on adaptive behaviour through their influence on perceived severity. Moreover, other researchers such as (Terpstra, 2011; Siegrist and Gutscher, 2008; Keller et al., 2006; Kerstholt et al., 2017) who adopted the affect heuristics approach (Slovic et al., 2002, 2004), propose that affective risk perceptions may both directly and indirectly guide the adoption of flood adaptive behaviours. Regarding the indirect link, it has been proposed that feelings related to the risk may serve as a cue for estimating its severity/probability and, in turn, adoption of adaptive behaviours.

However, the case for the dual-process approach (where both cognitive and affective risk perceptions are assumed to interact and conjointly shape behaviour) has not yet been adequately conceptualized and tested empirically in the context of natural hazards including flooding. In fact, since flooding can pose a clearly observable physical danger, the personal experience or the presence of environmental cues (such as rapidly rising water or intense rainfall) may automatically trigger an affective, fear-based response that guides or biases cognition completely (Terpstra, 2011). Thus, it is much more likely that when someone personally experiences the likely consequences of flooding (e.g., physical damage), the individual may affectively assign to his or her psychological experience with flood risk. Yet, at the same time, when this link has been made salient, it is equally likely that cognitive risk perceptions guide and exert a strong influence over affective reactions, especially when uncertainty is reduced (due to increased awareness of the risk, its probability and potential consequences)(Raaijmakers et al. 2008). Thus, consistent with the dual-process theory, affective responses can influence cognitive risk perceptions and, simultaneously, cognitive risk perceptions can influence affective responses to flood risk. However, such a proposition requires conceptual and empirical evidence to be confirmed, and is therefore worthwhile to explore in this dissertation.

2.4 FACTORS DETERMINING RISK PERCEPTION AND PROTECTIVE BEHAVIOURAL INTENTIONS

The paradigm shift to more integrated flood risk management strategies involves devolved responsibilities to individuals in the adoption of several hazard adjustments at the household level. As part of this integrated flood-risk management approach, it is important to understand the broader, more intractable, multi-faceted societal risk management. Accordingly, insights into the social, psychological, and political factors that determine risk perceptions of flood-prone households are increasingly being required (Kellens et al., 2013). These factors often operate in a complex and interdependent way. In this regard, this section aims to provide a review on the role of specific determinants, namely, 1) personal experience with previous flooding events, 2) knowledge (i.e. critical hazard awareness), self-efficacy (i.e., perceived personal control) and trust in authorities and engineered flood defences (i.e., perceived situational control).

2.4.1 Previous or Direct Experience of (Flooding) Events

The connection between personal experience of a natural hazard event and the perception of the risk might appear, as Wachinger et al. (2013) put it, trivial: "surely you are aware and afraid of a flood when your house has been flooded before" (p. 1059). This proposition has been supported by several empirical studies (e.g., Brilly and Polic, 2005; Zaalberg et al., 2009; Heitz et al., 2009; Siegrist and Gutscher, 2006; Lindell and Hwang, 2008; Kellens et al., 2011; Kievik and Gutteling, 2011; Terpstra, 2009, 2011; Plapp and Werner, 2006; Boer et al., 2015; Babcicky and Seebauer, 2016). Terpstra (2011), for instance, argued that personal experience increases risk perception because it may make people uniquely aware of their vulnerability to an event's consequences.

Personal exposure to the natural event may also offer an illustration of the threat and demonstrates the potential for future risk (Wachinger et al., 2013). According to the availability heuristic, personal experience can create strong and instinctive negative impressions. This can result in increasing the salience of the risk, easing the recall latency of past occurrences, and heightening sensitivity to the frequency, severity and uncertainty of future risks (Tversky and Kahneman 1973). In this regard, it is suggested by the current literature that it is not the experience with flooding, as such, that drives perceptions, but that the salience and severity of the experienced negative consequences plays an important role (e.g. Ruin et al., 2007; Miceli et al., 2008; Keller et al., 2006; Kunreuther et al. 2014; Grothmann and Reusswig, 2006; Siegrist and Gutscher, 2008; Fatti and Patel, 2013). Accordingly, without a negative tag on memories, flood experience are less salient and are more difficult to recall (Trumbo et al., 2014; Maidl and Buchecker, 2015; Scolobig et al., 2012; Wachinger et al., 2013). This may be the case with low severity and seldom experienced events that can lead people to underestimate the risk, which in turn may produce a false sense of security/misjudgment of ability to cope (Green et al., 1991;; Bradford, O'Sullivan et al., 2012; Wachinger et al., 2013). Mileti and Brien (1992) describe this way of reasoning in the following way: ''If in the past the event did not hit me negatively, I will escape also negative consequences of future events'' (1992, p.53). Similarly, Renn (2017) argues that individuals perceive natural phenomena as cycles, and that if they survive a catastrophic event they possibly will not experience another one in their lifetime. Thus, he assumed that this can generate an excess of self-confidence and lack of concern in the population, which may then result in reduced disposition to take preparedness measures for natural hazards (Renn 2017).

Indications of how people interpret their previous experiences of a flooding event, in terms of the experienced feelings during and/or after the event, therefore, are important and have recently attracted much research interest (e.g., Siegrist and Gutscher, 2006; Zaalberg et al., 2009; Terpstra, 2011; Babcicky and Seebauer, 2016). McEwen et al. (2017), for instance, showed that flood victims in the UK experienced emotions ranged from typical excitement 'fight or flight' responses to calmness or depression. Siegrist and Gutscher (2006) found that negative feelings (such as uncertainty and insecurity, fear and shock, and helplessness) have predominantly been anticipated by flood victims as the worst outcomes of their flood experiences, while among non-victims, hardly any of these feelings has been anticipated as the worst outcomes of future flooding. According to Siegrist and Gutscher (2006), these negative emotions were a key factor in explaining why flood victims had taken substantially more precautionary actions against future floods than non-victims. Similarly, Becker et al. (2017) reported that disaster experience often made people think an event was "frightening", "scary" or "horrific". In this regard, the author suggested that people may then transfer this emotion to future potential disasters, thinking about the risks that may be posed by those events, how they might feel, and what they might need to do to avert any adverse feelings. For example, it was reported that one of the interviewees was "frightened by heavy rain now" after her experience of having her house flooded, and acted to prepare by ensuring her gutters were clear to avert such a disaster happening again (Becker et al., 2017: p. 187)

In fact, the empirical evidence on the correlation of flood experience with preparedness is not unambiguous, but shows a clear tendency towards the expected result (Bubeck et al., 2012): A majority of studies find a positive and significant relationship between experience and preparedness (Bubeck et al., 2012b; Grothmann and Reusswig, 2006; Harries, 2012; Kreibich et al., 2005; Lindell and Hwang, 2008; Osberghaus, 2015; Richert et al., 2017; Zaalberg et al., 2009; Siegrist and Gutscher, 2008, Osberghaus, 2017; Xian et al., 2018), while further analyses report positive and non-significant correlations, depending on the concrete mitigation measure, experience measure or regional sub-samples (Bubeck et al., 2013; Koerth et al., 2013; Poussin et al., 2014; Takao et al., 2004; Thieken et al., 2007; Cologna, Bark et al., 2017). A third group of studies does not find significant correlations between experience and self-protective behaviour (Botzen et al., 2009; Miceli et al., 2008; Terpstra 2011). Bubeck et al. (2012) suggest that these null results may be explained by a mediating role of risk perception, which is indeed always significantly but indirectly correlated with preparedness in the studies mentioned.

2.4.2 Knowledge About the Risk

Risk awareness can in simple terms be described as the knowledge about the risks associated with a hazard (Raaijmakers et al., 2008). In particular, hazard knowledge is often characterized by the depth of an individual's understanding of the hazard's genesis, its mechanisms of exposure, and types of hazard adjustments that can avoid its impacts (Lindell and Perry, 2004). However, although hazard knowledge is inextricably bound up with different theoretical models concerning risk perception and risk behaviour (such as the *Planned Risk Information Seeking Model* (Griffin, Dunwoody, and Neuwirth, 1999; Johnson, 2005); the *Mental Models* (Lave and Lave, 1991; Wagner, 2007); and the *Protective Action Decision Model* (PADM) (Lindell and Perry 2004; Lindell and Hwang, 2008; Horney et al., 2010) it has been found to be a difficult construct to quantify. In fact, the variable knowledge has been often operationalized as lay knowledge, subjective knowledge or self-reported knowledge by asking respondents: "to what extent they think or believe their knowledge reaches about risk-related topics" (Kellens et al., 2013: p. 24).

In fact, it is often considered that a degree of knowledge regarding a certain risk is likely to alter perceptions in a positive way (Visschers and Siegrist, 2008; Lopez-Marrero, 2010; Bosschaart et al., 2013). Botzen et al. (2009) studied the influence of knowledge about the causes of floods on risk perception in the Netherlands. They found that people with little knowledge about the causes of floods have lower risk-perceptions. This outcome is supported by Meng et al. (2013) who indicate that provision of flood-risk information to the public usually increases their perceptions of the risk. Moreover, there is evidence that the degree of hazard knowledge may cause a reduction in fear (or feeling of insecurity (Lopez-Marrero 2010)) because people get more acquainted with the hazard (Bosschaart et al., 2013).

Studies exploring the impact of hazard knowledge on flood mitigation behaviours of households have reported inconsistent findings. From one aspect, some studies found that people with high levels of hazard knowledge are more likely to adopt hazard adjustments measures (Oloke et al., 2013; Bosschaart et al., 2013; Knocke and Kolivras, 2007). On the contrary, Botzen et al. (2009)

found a negative influence for perceived hazard knowledge on people's willingness to invest in sandbags. From another aspect, some studies even found none or only a statistically weak relation (Miceli et al., 2008; Thieken et al., 2007; Lindell and Hwang, 2008; Zaleskiewicz et al., 2002). For example, Siegrist and Gutscher have shown that "lack of knowledge about flooding" does not relate to less flood mitigation behaviour (Siegrist and Gutscher, 2008). These results suggest that knowledge is not always a very useful predictor of flood mitigation behaviour (Bubeck et al., 2012). This is probably because the influence of knowledge on the intention to mitigate is mediated via risk perceptions, as reported by several authors (Renn and Rohrmann 2000; Lindell and Perry 2004; Earle, Siegrist, and Gutscher 2007; Visschers and Siegrist 2008; Raaijmakers et al. 2008; Meng et al. 2013).

2.4.3 Self-Efficacy: Perceived Personal Control

Self-efficacy refers to the subjective beliefs in one's capabilities to organize and execute the courses of action required to produce designated levels of performance (Bandura, 1997; Breakwell 2014; Mishra and Mazumdar, 2015). This variable has been held to be associated with risk perception, often through a common association with locus of control (internals or externals) (Trumbo et al., 2016). In this view, it has been suggested that those who believe in "internal" control see themselves as active agents; they feel that they are masters of their fates and they trust their capacity to influence the events that affect them (Rotter, 1966). On the other hand, "externals" are often assumed to see risks as less under their control and more a consequence of outside forces such as "fate, chance, luck, powerful others" (Rotter, 1966). According to Bandura's (1977) self-efficacy theory, self-efficacy beliefs could play a profound role in influencing motivations to adopt coping behaviour, effort and perseverance (Bandura 1977). The protection motivation theory (PMT) (Rogers, 1975, 1983) also illuminated the role of self-efficacy in explaining protective and non-protective responses to threats. In particular, non-protective responses, such as denial, are hypothesized to be adopted by the individual with high risk perceptions and low coping appraisals, because the latter may reduce any negative emotions produced by the high risk perception (Rippetoe and Rogers, 1987). On the other hand, protective responses are hypothesized to be enacted if high risk perceptions coincide with a strong coping appraisal. Such hypotheses have been supported by several empirical studies (e.g., Grothmann and Reusswig, 2006; Bubeck et al., 2013; Poussin et al., 2014; Dittrich et al., 2016). For example, a study on flood risk mitigation behaviour in Germany (Grothmann and Reusswig, 2006) and a similar study in three flood-prone regions in France (Poussin et al., 2014) show that self-efficacy is one of the most powerful predictors of risk mitigation behaviour among the three factors related to coping appraisal. The other factors are perceived response-efficacy and response costs, which mainly describe how a person assesses a specific response.

Furthermore, Bubeck et al. (2013) show that self-efficacy is an important variable in terms of specific precautionary behaviours (such as structural building measures, adapted building use, the deployment of flood barriers, and the purchase of flood insurance) of the flood-prone households along the river Rhine. Moreover, Dittrich et al. (2016) found that self-efficacy is significant for motivating residents to use of insurance and flood warnings. Similar results were also found in other studies that do not apply PMT (Botzen et al., 2009, Terpstra et al., 2009, Botzen and van den Bergh, 2012) confirming the profound role of self-efficacy in motivating flood-prone households to take protective actions.

2.4.4 Trust in Authorities and their Engineered Flood Defences

"Social relationships of all types, including risk management, rely heavily on trust"

(Slovic 1999: p. 8)

Individuals' risk assessment does not take place in a vacuum but in a broader social institutional context. This points to the important role of trust in the authorities and their engineered flood defences as an analytical lens to examine perceptions and protective behaviours of flood-prone households (Babcicky and Seebauer, 2016). Contemporary hazard research regards the trust variable as a way of dealing with uncertainty, especially when people are lacking knowledge, time, cognitive capacity or motivation to evaluate them deliberately (Paton, 2008; Frewer and Salter, 2007; Visschers and Siegrist, 2008; Kick, Fraser et al., 2011). Paton (2008) discussed how trust was predicted to be important only when people faced uncertainty when being asked to prepare for infrequently-occurring hazards. That is, in circumstances where they cannot find out about a hazard for themselves and thus are implicitly dependent on others, particularly civic risk management agencies, for the information they need. Paton tested this idea by comparing the model for infrequent (e.g., earthquake, volcanic hazards) and frequent hazard events (e.g., bushfires in Portugal and Australia and volcanic hazards in Kagoshima, Japan). The latter studies confirmed the premise that underpinned the original conceptualization of the theory. Trust was not supported in analyses of events about which people had knowledge and direct or indirect (e.g., highly frequent media coverage) experience (Paton, 2008, 2013). The failure to support a role for trust could be explained by people believing that they are sufficiently knowledgeable themselves. Another possibility (or a complementary one) is that the role of trust was reduced by the low perceived salience of flood hazards increasing the likelihood of people transferring responsibility for managing risk from themselves to civic agencies (Paton , 2013).

Furthermore, Terpstra (2011) noted that trust and affect share similarities, since both constructs reduce "the complexity of risk judgments" and consequently serve as a "quick" guide for assessing risks (Terpstra 2011). Similarly, Poortinga and Pidgeon (2005) suggested that trust and affect share similarities because they reflect more general attitudes toward risk (e.g. acceptability), which in turn drive more specific risk judgments. In light of this, there is ample evidence confirming the strong relationship that trust in authorities has on the acceptability of hazards (e.g. technological hazards: Siegrist 2000; Poortinga and Pidgeon, 2005; natural hazards: Bronfman et al., 2008). However, due to the fundamental affective dimension of trust (which involves items like honesty, integrity, goodwill, or lack of particular interests) people may feel more at risk if their trust is low or if it has been damaged by the context in which they live (Espluga et al., 2009; Wachinger et al., 2013). Indeed, some studies show that a lack of trust in competent flood risk management by the authorities may decrease positive affect (Boer et al., 2015) and increase negative affect (Griffin et al., 2008; Terpstra, 2011).

As the above discussion attests, it seems, therefore, reasonable to assume that trust can be a significant predictor for the cognitive and affective components of flood risk perception. However, this assumption has been rarely investigated in prior research. Here, I consider the special case of a study by Babcicky and Seebauer (2016) that has recently attracted some attention to the significant effect of trust—measured as a dimension of cognitive social capital—

on both cognitive and affective components of risk perception. In particular, these authors found that high levels of trust are associated with weaker feelings of fear and worry towards a potential flood. However, the influence of trust on positive emotional appraisals has been overlooked in their study.

In fact, trust is a factor which impacts significantly not only individual's risk perceptions, but also their ensuing risk reduction behaviours (Wachinger et al., 2013; Kellens et al., 2013; Bronfman et al., 2016; Han et al., 2016). However, prior research was not consistent regarding the direction and strength of trust impact on behaviours. From one aspect, trust can enhance cooperation, and consequently individuals and societies, to adopt behavioural responses to natural hazards (Basolo et al., 2009) because they have a higher propensity to follow the disaster management authorities' suggestions. For example, Lin et al. (2008) found that higher levels of trust or confidence in crisis management increased behavioural mitigation responses, insurance purchase responses, and information-seeking intentions. Furthermore, findings from two studies on flood insurance (Atreya et al., 2015; Xian et al., 2018) showed that trust in local government is a positive factor driving individuals to buy flood insurance voluntarily. Such findings highlighted the importance of building trust between the government and the governed. Accordingly, these authors suggested that local policy makers need to think of ways to earn more trust from residents to motivate them to actively seek flood protection measures (Xian et al., 2018).

From another aspect, several studies come to the conclusion that excess trust in authorities can hinder individuals' motivations to actively seek flood protection measures (Armas et al., 2015; Becker et al., 2017; Siegrist et al., 2005; Terpstra, 2009, 2011; Grothmann and Reusswig, 2006; Kousky and Kunreuther, 2010; Bichard and Kazmierczak, 2012; Bronfman, et al., 2016). For instance, Becker et al. (2017) found that political and institutional entities actively sought to create a sense of security and in so doing bolstered trust and diminished risk perception in the preparedness phase, by presenting newly constructed, or reinforced, engineered flood defences as panaceas, and by referring to past floods as ''once in a lifetime" events. For these reasons, it was concluded that people may not have seen the need to take protective measures themselves (Becker et al., 2017), as was also concluded by (Paton, 2008).

Trust in engineered flood defences in terms of their strength, height and maintenance has been found to reduce risk perceptions in other studies (Terpstra, 2011; Cologna et al., 2017). Importantly, these studies pointed out that trust in engineered flood defences may lead to potentially serious adverse consequences because of underestimation of risk, which often leads to unrealistic expectations that damage from floods can be prevented. Moreover, these studies reported that the failure of such defences may leave people with a feeling of despair, disappointment and thus mistrust in political and institutional entities. In particular, Cologna et al. (2017) found that residents' ontological security was challenged as engineered flood defences seemed no longer effective to withstand nature's unpredictability. In psychological terms this may be evidence of cognitive dissonance (Festinger, 1957): "this is where individuals confronted with new information, i.e. flooding despite new investment in engineered flood defences, which conflicts with existing beliefs, i.e. reduced flood risk perception gained from new found security, leads to mental stress, which in this case we found was relieved through blaming political and institutional entities" (Cologna et al., 2017: p. 6).

In contrast with the findings of the aforementioned studies, the role for trust in motivating people to actively seek flood protection measures was not supported by Kerstholt et al. (2017). According to these authors, one explanation for the discrepancy derived from how trust has been operationalized. To illustrate, for example, Terpstra (2011) who found a positive role for trust has specifically asked for trust related to flood defences, whereas Kerstholt and his colleagues (2017) used a generalized operationalization of trust in civic agencies (also including aspects like advice and information about what people and households should do to prepare for hazard events). Further to this, another explanation for the discrepancy of the relationship may be the potential mediating influence of an individual's risk perceptions on their ensuing risk reduction behaviours (Terpstra, 2011).

2.4.5 Residential Satisfaction: Perceived Location-embedded Benefits

Previous empirical studies have attempted to answer the question of "why do people continue to develop and live in areas that are threatened by flood hazards?" (HeXueqin, 2009; James et al., 1971; Fordham, 1992; Vogt et al., 2008; Macey, 1978; Mishra et al., 2010). Findings from these studies reveal the increased significance of perceived location-embedded benefits, as compared to perceived location-related risks, in motivating people to continue their residency in flood-prone areas. What may explain this situation (i.e. why perceived benefits outweigh the perceived risks) is: the demand to meet other competing life priorities to sustain a certain quality of life, measured often by residential satisfaction—which may be rationally more eminent than risk perception.

Residential satisfaction is typically recognized as an important predictor of individuals' perception (or subjective evaluation) of the quality of thier neighbourhood environment (Mesch and Manor, 1998; HeXueqin, 2009; Permentier et al., 2011). An extensive literature in geography, planning, sociology, and psychology has been established on the conceptualization, measurement and determinants of residential satisfaction (Speare, 1974; Galster, 1987; Lu, 1999; Dekker et al., 2011; Li and Wu, 2013; Tabernero et al., 2010; Permentier et al., 2011). To analyze the relationship established by individuals with their residential environment, some researchers have begun to review the meaning of 'home' as a concept (for example, Amérigo and Aragonés, 1997) understood as an emotional state towards a house (Rybczynski, 1986) associated with security and comfort (Manzo, 2003). In this respect, the home is more than a 'physical point of reference'; home implies a sense of ownership or belonging to a place. This conceptualization has an implicit relationship with other concepts such as 'place meaning' (Hay, 1998), and 'place identity' (Twigger-Ross and Uzzell, 1996), 'sense of community' (Sarason, 1974), 'sense of place' (Hummon, 1992), 'rootedness to place' (Tuan, 1980), 'place dependence' (Stokols and Shumaker, 1981) and 'community attachment' (Kasarda Janowitz, 1974).

These concepts share the common consideration that individuals establish a 'place attachment' (Hidalgo and Hernández, 2001): an affective bond with a place that is developed as a process of dynamic interaction between the two (Mazumdar, 2005). Hence, Hidalgo and Hernández (2001) state that place attachment can be conceptualized as a positive emotional bond or affective state that individuals establish with a place and which leads them to stay close to it. Within behavioural research in natural hazards, the role of 'place attachment' is well documented see Bonaiuto et al., (2016) for a detailed review). Across different risk contexts, research in this area shows:

(a) both positive and negative relations between place attachment and natural environmental risk perception: positive: (e.g., volcanic eruption risk (Bird et al., 2011), earthquakes (Zhang et al., 2014) and flood risk (Bonaiuto et al., 2011); negative: (e.g., seismic risk exposure (Armas, 2006) and beach pollution threat (Bonaiuto et al., 1996))

(b) both positive and negative relations between place attachment and risk coping: positive: (e.g., tornado risk (Silver and Grek-Martin, 2015) and flooding risk (Mishra, Mazumdar, and Suar, 2010); negative: (e.g., bushfires (Paton, Bürgelt and Prior 2008) and climate change risk (Willox et al., 2012); and

(c) mediating and moderating effects in risk perception-coping relationship: mediation (e.g., Bonaiuto et al., 2011) and moderation (e.g., De Dominicis et al., 2015).

However, when considering residential satisfaction, the concept of 'home' expands beyond the walls of the house and encompasses various points of reference, considering the relations established by people with their neighbourhood (Tabernero et al., 2010). According to Hur and Morrow-Jones (2008), the neighbourhood is the basic environmental unit in which our social life takes place and which necessarily affects the quality of life of its residents. The sense of belonging to a neighbourhood has an implicit emotional component according to which the satisfaction experienced develops following an evaluation of the physical and social elements of the environment (Mesch and Manor, 1998; Hipp, 2010). Even in the conceptualization of 'place' this evaluative emotional component appears, given that it is usually described as a 'space endowed with meaning' (Low and Altman, 1992). Therefore, residential satisfaction can be understood as a dynamic process of interaction between residents and their neighbourhood environments (Sirgy and Cornwell, 2002; Lu, 1999; Speare, 1974; HeXueqin, 2009; Yang, 2008; Li and Wu, 2013; Tabernero et al., 2010; Dekker et al., 2011; Permentier et al., 2011; Wang and Wang, 2016). In this regard, the literature distinguishes two main groups of determinants (Table 2.5): subjective evaluations of neighbourhood (physical, social, and economic) attributes and subjective evaluation of the dwelling.

Attributes	Examples	References
1a-Social and economic Attributes of Neighbourhood	Relative closeness of neighbourhoods and social attachments within the community	(Brower 2003; Parkes et al., 2002; Basolo & Strong, 2002; Hipp, 2010; Li & Wu, 2013; Feijten & van Ham, 2009; Dekker et al. 2011; Permentier et al. 2011)
	Perception of privacy and safety at home	(Brown, Perkins and Brown, 2003, Lu, 1999; Parkes et al., 2002)
	Home values, employment opportunities, and cost of living	(Lu 1999; Galster and Hesser 1981; Balestra and Sultan, 2013).

1b-Physical Attributes of Neighbourhood	Presence of services and quality amenities, such as schools, public transportation , local shops and others, in and around the neighbourhood.	(Sirgy and Cornwell, 2002; Grillo et al., 2010; Dekker et al. 2011; Permentier et al. 2011; Basolo & Strong, 2002; Parkes et al., 2002; Dahmann 1983)
	Presence of bothersome problems such as crowdedness, pollution, noise level and traffic density	(Mohan & Twigg, 2007; Galster & Hesser, 1981, Gomez-Jacinto and Hombrados-Mendieta 2002; Bonnes, Bonaiuto and Ercolani 1991; Hur & Morrow-Jones, 2008; Permentier et al., 2011)
	Presence of green area or other natural amenities, including fresh air, serene surroundings, and recreation opportunities.	(Kaplan, 1985; Korpela et al.,2010; Hur et al., 2010)
2-Dwelling characteristics	-Size (e.g., number of bedrooms), age of dwelling, interior and proximal exterior environments and other aspects of housing (e.g., building type, quality of housing facilities, disrepair and tenure—owning or renting).	(Fang 2006; Levy-Leboyer and Ratiu 1993; Li & Song, 2009; Phillips, Siu, and Yeh 2005; Paris and Kangari 2005; Dekker et al., 2011)

Table 2.5 Examples of the attributes of residential satisfaction

Residential satisfaction can be explained through the variables that help to fulfil the individual's aspirations, needs or desires, and how content that person is with the residential location-related features and whether there is a feeling of connectedness with the residential environment (Tabernero et al., 2010). Previous studies indicate that once the incongruence between residents' aspirations and achievements passes a certain threshold, it generates a level of dissatisfaction or stress for the household (Speare, 1974; Parkes et al., 2002). Once the intensity of the dissatisfaction exceeds the threshold of tolerance, households may or individuals may adopt some behavioural adjustments to relieve their dissatisfaction (HeXueqin, 2009). The householder may improve housing or environmental circumstances so that these more closely match his/her perceived needs and aspirations through behavioural adjustments. In a situation of living in a flood-prone area, these adjustments may include mitigating the hazard on-site (i.e. adjusting the structure) or relocating out of flood-prone areas.

However, the role of residential satisfaction on behavioural adjustments is usually emphasized by household location choice studies, but is rarely found in behavioural research in natural hazards. A study by HeXueqin (2009) is one of the few studies that looks at floodplain residents' attitudes and behavioural adjustment to perceived (dis)satisfactions with their residential environments. The results revealed some possible factors that can be modified to increase the level of residential satisfaction, including: the presence of natural and social amenities, perceived low probability of flooding, low awareness of potential flood risk, cognitive adjustments (i.e. denial of exposure to risk) and lack of flood experience. Another important relationship uncovered by HeXueqin (2009) is that, compared to residents who were satisfied with qualities of their urban environments, those who were dissatisfied were less likely to accept a higher chance of flood risk in exchange for perceived location-embedded benefits, and thus more likely to adopt flood hazard adjustments. In terms of flood hazard adjustments, HeXueqin (2009) paid special attention to residential relocation. In this respect his results revealed that, compared to residents who planned to relocate their homes (to flood free zones), those who were not planning to relocate were less likely to accept higher flood risk in exchange for location-embedded benefits.

To conclude, given the fact that hazardous areas already have been developed and will continue to be developed, living with natural hazard risks—what we can accept and what we can change—can be greatly influenced by our perceptions of the social, economic and physical attributes of the 'place' where we live. However, whether and how perceived residential satisfaction contributes to risk perception and preparedness intentions has rarely been investigated in behavioural research in natural hazards. More precisely, it is unclear where this variable can exert its effect on the above mentioned relation, i.e. whether at the cognitive and/or affective level, because the effect could be different across these two levels of analysis. An exploration of the role of residential satisfaction in natural hazards scenarios is another valuable contribution to present research. Specifically, since the conceptualization of residential satisfaction has an implicit relationship with other place-specific biases, such as the spatial optimistic bias (Gifford et al., 2009) applied to environmental risk perception, it may function as a barrier for enacting preventive behaviours in order to cope with an environmental risk. In other words, this thesis predicts that residential satisfaction is a significant moderator of the risk perception-behaviour relationship.

2.5 CHAPTER SUMMARY

This chapter aimed at providing context for the identified gaps in the current understanding of the determinants driving flood-prone households' protective behavioural intentions. Knowledge of the determinants of risk response is indispensable for developing well-founded, effective risk communication and other interventions that are aimed at facilitating preparedness and mitigation decisions of flood-prone households.

In particular, this chapter provided a review of the theoretical and empirical literature on the underlying cognitive and affective processes of risk perceptions and protective behavioural intentions of flood-prone households. The concepts of risk and risk perception were first investigated. Then an overview of the cognitive and affective processes in risk perception was provided. Several hypotheses about the interplay between cognitions and affects, and their order and influence on risk perception and decision making were presented. Due to the exploratory objective of this thesis, this chapter also reviewed studies that investigated variables related to risk perception and preparedness intentions. These variables include: personal experience, subjective knowledge, self-efficacy, trust and residential satisfaction. The next chapter lays the conceptual foundations for a novel integrated (psychologically-oriented) model of risk perceptions and protective behavioural intentions.

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CHAPTER 3

THEORETICAL FRAMEWORK

This chapter concisely describes the objectives of the study by identifying research hypotheses, develops the conceptual framework and proposes a dual-process model of flood risk perception by borrowing key constructs from the theories discussed in the previous chapter. In particular, the proposed model identifies the determinant factors and mechanisms that underlie both cognitive and affective risk perceptions. The proposed model will be subsequently tested for the predictive power for protective behavioural intentions of flood-prone households, will be refined, and made more parsimonious.

3.1 BACKGROUND

After reviewing the extant literature on various theories and empirical literature on risk perception and behavioural decision making, it was felt that the current study should look into risk perception from a dual-process perspective and then focus on development of a model for the determinants that underlie protective behavioural intentions of flood-prone households. In particular, understanding the way in which individuals perceive flood risk on one hand, and the extent to which individuals then subsequently behave on their perceptions, affect, experiences, coping capacities and attitudes on the other, is the main thrust of this thesis. More generally, the theoretical perspective of this thesis will draw on the socio-psychological analysis of risk judgment and decision making.

3.2 FRAMEWORK DEVELOPMENT

In the context of flood risk, studies have not yet explicitly and sufficiently explored risk perceptions through the lens of dual process theory to confirm its plausibility in predicting better adaptive behavioural intentions. While this gap may, in part, be related to the methodological insufficiency in studying the affect-cognition relationship by (most) risk researchers in the context of natural hazards (including flood), the current thesis goes beyond traditional ways of thinking and introduces a novel dual-process model of cognitive and affective risk perceptions predicting behavioural intentions of flood-prone households (see Figure 3.1 for an illustration). In particular, this thesis follows a non-recursive (i.e. bidirectional) structural equation modelling (SEM) approach to examine the hypothesis that cognitive and affective processes reciprocally influence each other to conjointly shape perceptions and, subsequently, behavioural intentions of flood-prone households. To validate the plausibility of this model, this thesis will then compare it with the traditional (i.e. unidirectional) models in terms of the predictive power for protective behavioural intentions.

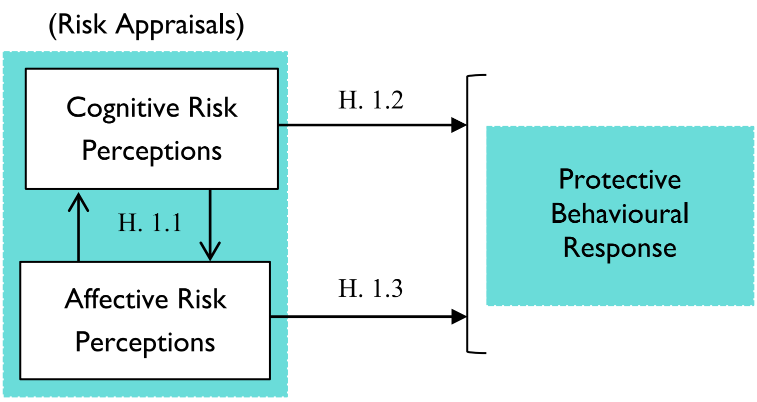

Figure 3.1 An illustration of the dual (cognitive-affective) processing model for explaining protective behavioural intentions of flood-prone households

H 1.1: In best predicting protective behavioural response of flood-prone households, the relationship between cognitive and affective risk appraisals is expected to be reciprocal. In other words, a bidirectional relationship between cognitive and affective risk appraisals can better predict protective behavioural intentions in comparison with the traditional unidirectional relationships.

H 1.2: Protective behavioural intentions of flood-prone households is positively related to perceived risk through cognitive routes (i.e. an individual's comprehension of the risk, including its probability of occurrence and the severity of consequences).

H 1.3: Negative affect (i.e. the badness that a person feels about living in a flood risk zone) promotes the protective behavioural intentions of flood-prone households, whereas positive affect (i.e. the goodness that a person feels about living in a flood risk zone) inhibits the protective behavioural intentions of flood-prone households.

Additionally, by further extending dual-process approaches to inform a deeper psychological understanding of private flood protective behavioural intentions, the present thesis will then examine to what extent a different set of psychological variables influence perception processed through both cognitive and affective systems. These variables include experiences, knowledge, self-efficacy and trust. In this regards, mediation analyses using SEM will be done for cognitive and affective routes separately. The extended model (see Figure 3.2 for an illustration) may help in comprehension of which routes the psychological processes implicated in affect-cognition interactions are followed and can be then targeted with interventions (e.g. risk communication, education, public empowerment and behavioural change campaigns).

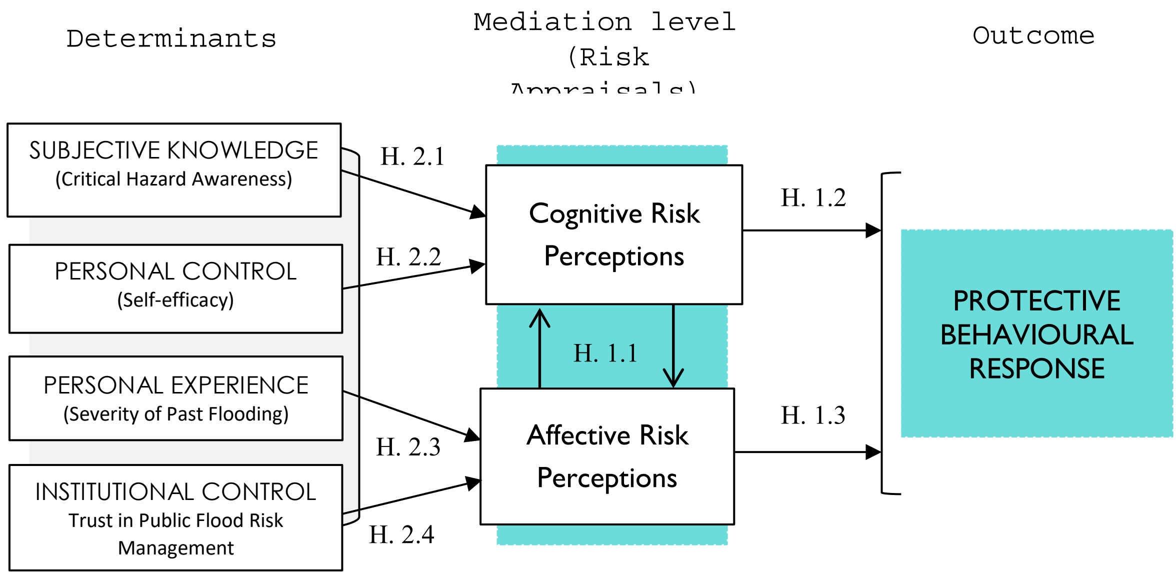

Figure 3.2 An illustration of the key factors driving (cognitive-affective) risk perceptions in explaining protective behavioural intentions

After reviewing extant literature in the previous chapter, the following plausible hypotheses were formulated in order to test the extended dual-process model (Figure 3.2):

H 2.1: The impact of subjective knowledge (i.e. critical hazard awareness) on flood protective behavioural intentions is completely mediated through cognitive routes of risk perception. Subjective knowledge increases the level of perceived risk through cognitive routes, which in turn strengthens behavioural intentions.

H 2.2: The impact of perceived self-efficacy (i.e. personal control) on flood protective behavioural intentions is completely mediated through cognitive routes of risk perception. Perceived self-efficacy increases the level of perceived risk through cognitive routes, which in turn strengthens behavioural intentions.

H 2.3: The impact of personal experience on flood protective behavioural intentions is completely mediated through affective routes of risk perception. In particular, personal experience evokes high levels of (negative) affective reactions, which in turn strengthens behavioural intentions. On the other hand, personal experience lessens the tendency to experience (positive) affective reactions, which in turn impedes behavioural intentions.

H 2.4: The impact of trust in public flood risk management (i.e. institutional control) on private flood protective behavioural intentions is completely mediated through affective routes of risk perception. In particular, trust lessens the amount of (negative) affective reactions evoked by flood risk, which in turn impedes behavioural intentions. Similarly, trust evokes high (positive) affective reactions, which also impedes behavioural intentions.

Moreover, the present thesis, with its extended perspective on the Protection Motivation Theory (PMT), examines two kinds of outcome: 1) protective behavioural intentions regarding the adoption of flood hazard adjustments in the near future, and 2) attitudes towards risk denial (see Figure 3.3 for an illustration). Dealing with the trade-offs between "to act" or "not to act" may lie at the heart of understanding the deeper psychological analyses of benefit and risk perception—where both cognition and affect are hypothesized to function in an interactive way. Benefit perception (i.e. perception of location-embedded benefits) in this study refer to resident's satisfaction on the physical and socio-economic qualities of their urban environments (i.e. residential satisfaction). Since the conceptualization of residential satisfaction has an implicit relationship with other place-specific biases, such as the spatial optimistic bias (Gifford et al., 2009) applied to environmental risk perception, it may function as a barrier for enacting preventive behaviours in order to cope with an environmental risk. In other words, this thesis predicts that residential satisfaction is a significant moderator of the risk perception-behaviour relationship.

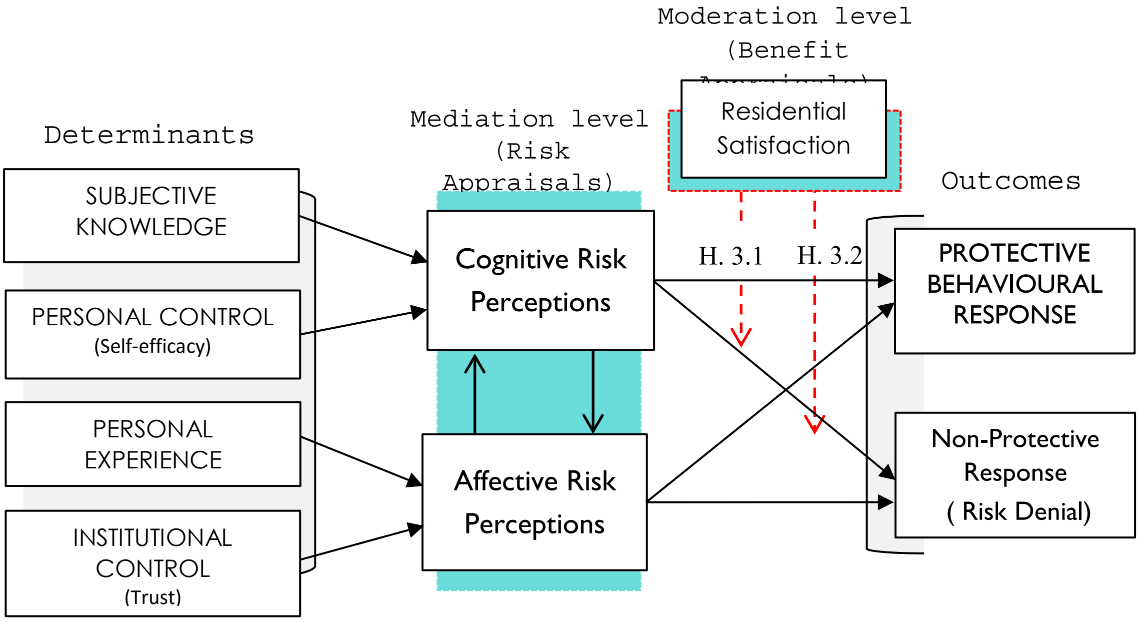

Figure 3.3 An illustration of the integrated (and moderated) model for explaining (non)protective behavioural intentions of flood-prone households

H 3.1: The impact of cognitive risk perceptions on protective behavioural intentions is significantly moderated by perceived benefits (operationalized as residential satisfaction). In particular, risk perception is more strongly positively related to protective behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to protective behavioural intentions.

H 3.2: The impact of affective risk perceptions on protective behavioural intentions is significantly moderated by residential satisfaction. In particular, (negative) affective risk perception is more strongly positively related to behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to protective behavioural intentions.

Overall, the proposed model in this study consists of four building blocks. The first block presents the determinants of risk perception and protective behavioural intention. The second presents both affective and cognitive appraisals as intervening (mediating) psychological variables. In the third block, the model was extended to include two specific responses to risk; namely, protective and non-protective responses. In the fourth block, residential satisfaction is presented as a moderated variable for the risk perception-behaviour relationship. Research constructs formulated for the proposed model are discussed below.

3.3 RESEARCH CONSTRUCTS

3.3.1 Dependent Variable: Protective Behavioural Intentions (PBI)

In this study, the 'protective behavioural intention' construct (abbreviated as PBI) refers to the willingness to adopt risk reduction measures (i.e. flood mitigation and preparedness measures) at the household level. These measures can be categorised into four groups (Bubeck et al., 2013; Kreibich et al., 2005, 2011; Duží, et al., 2017; Osberghaus, 2017; Brody et al., 2017): First, "adapted use" options are behavioural measures which are implemented in order to avoid economic damage in case the house is flooded, such as placing expensive furnishing in non-exposed storeys. Second, the implementation of "flood barriers" means the physical installation of water barriers in order to prevent water ingress into the building, such as the installation of backflow flaps and water barriers for cellar openings. Third, "structural measures" are technical measures pursued in order to reduce the economic damage in case the house is flooded and change the structure of the building, e.g. using flood-resistant paint coats or floor materials. Finally, adjustments relying purely on "information gathering and exchange" which include purchasing insurance, attending meetings, communicating with governmental agencies, and other activities that seek to procure information to raise household awareness of flood risk. These types of adjustments require the least amount of financial expenditure and commitment, but nevertheless may help to reduce effectively flood-related losses in the long term.

3.3.2 Direct Determinants (Mediator Variables): Risk Perception

3.3.2.1 Cognitive risk perception (CRP)

Cognitive risk perception describes how an individual 'assesses a threat's probability and damage potential' (Grothmann and Reusswig 2006, 104). A high level of flood risk perception (as the conjoint measure of probability and severity of a flood event) is one of the key determinants for individuals to take protective action (see Section 2.2.2 for a more detailed discussion). The perceived flood probability (PFP) construct is often expressed as the likelihood of a flood occurring with a given average recurrence interval (ARI), such as a 1, 10 ,100 ,1000-yr flood or, alternatively, it could be expressed as the likelihood of a flood occurring with a given percent annual exceedance probability (AEP), such as 50%, 20%, 10%, 5%, 2%, 1% AEP (Babcicky and Seebauer, 2016; Botzen et al., 2015; Reynaud et al., 2013; Richert et al., 2017). As a multidimensional construct, the PFP construct is targeted in this study to effectively create greater discrimination in categories of the flood inundation levels (Zhai and Ikeda, 2008): 1. over the surrounding streets within a neighbourhood (i.e. the probability of a flood occurring outside the property); 2. over the front/back yard (i.e. the probability of a flood occurring inside the property but not entering the house); 3. in the garage and non-habitable spaces of the house; 4. through habitable floors and possessions (furniture, whitegoods, clothing, curtains, floor coverings, and other).

On the other hand, the perceived severity of flood consequence often refers to abstract-conceptual knowledge and concrete-perceptual images regarding the adverse outcomes of a flood event. As a multidimensional construct, the perceived flood consequence (PFC) construct is operationalised in this study as the degree of flood damage respondents expect to suffer once a flood occurs. These adverse outcomes/damage include (Miceli, Sotgiu et al., 2008; Lindell and Hwang, 2008; Zhai and Ikeda 2008; Babcicky and Seebauer, 2016): 1. Physical damage to public facilities such as roads; 2. physical damage to house and possessions such as furniture, car, etc.; 3. disruption of supplies (food, electricity, drugs, telephone, internet, water, etc.); 4. inconvenience of recovery process after the flood (e.g. problems with rebuild, clean-up, or relocation); 5. financial loss (e.g. residential property values); 6. psychological health (e.g. trauma or anxiety after a flood event); 7 physical health (e.g. drowning, injuries, hypothermia, and animal or venomous bites); 8 confirmation of loved ones or pets' safety; and 9. disruption of daily life (e.g. job and other daily routines).

3.3.2.2 Affective risk perception (ARP)

Examining the conceptual relationship between affective risk perception (ARP) and protective behavioural intentions (PBI) is crucial in improving our understanding of the processes underlying risk judgement and decision making (Siegrist and Gutscher, 2008; Keller et al., 2006; Zaalberg et al,. 2009; Babcicky and Seebauer, 2016; Miceli et al., 2008; Boer et al., 2015; Poussin et al., 2014; Terpstra, 2011). As a two-dimensional construct, the ARP construct refers to the emotional state that a resident experiences when thinking of flooding in his/her region (see Sections 2.2.3 and 2.2.4 for a more detailed discussion). Taking a valence-based approach, this study specifically looks at the impact of negative versus positive affective risk perceptions. Negative affect (NA) reflects fear, powerlessness, worries and feelings of uncertainty. Positive affect (PA) reflects feelings of solidarity (feeling accompanied), security, excitement (pleasurable fascination) and sense of beauty or force of nature.

3.3.3 Indirect Determinants: Independent Variables

This thesis is aimed at increasing the understanding of flood-prone households' protective behavioural intentions. Knowledge of the determinants of PBI is indispensable for developing well-founded, effective risk communication and other interventions that are aimed at facilitating the preparedness and mitigation decisions of flood-prone households. The independent variables or determinants which are used in this study to measure the adoption of flood protective behavioural intentions at the household level include personal experience, knowledge, self-efficacy and trust.

3.3.3.1 Personal experience (PE)

As shown by Weinstein (1989), the most crucial factor which determines both threat perception and decisions to adopt precautionary measures seems to be previous personal experience (PPE) of a disaster. Weinstein suggests three "*major routes from experience to protective behaviour*" (1989, p. 46): Societal attention after events striking a large number of people, victim-directed influence such as tailored education about ways to prevent future damage, and intraindividual response, e.g. in the victim's perception of risk. The current thesis is specifically interested in the intraindividual response measured by (self-reported) survey data. Nevertheless, the role of experience as a predictor of protective behaviour is not straightforward (see Section 2.4.1 for a more detailed discussion). Recent studies have found that experience tends to be rather mediated by the negative emotions that may be associated with the flood experience and how far back in time the flood experience took place (Siegrist and Gutscher, 2008; Harries, 2012). Interestingly, Terpstra (2011) showed that the impact of past experience on individuals lasts longer if the consequences of a severe flood event are anchored in the public mind. A review of results on previous flood experience as an important predictor of the protective behavioural intentions of flood-prone households leads to pay more attention to the quality of experience and emotions that such experience had caused. Therefore the subject of this thesis is the degree of flood severity rather than the presence or absence of previous flood experience. This is in line with studies that explicitly state that flood experience implies the severity of physical, financial or health damage (Harries 2012; Lindell and Hwang 2008; Miceli et al., 2008; Osberghaus 2017; Peacock, 2003; Takao et al., 2004).

3.3.3.2 Subjective knowledge (SK)

Knowledge about flood risk often served as the focus of investigation, predicated on the notion that awareness is a necessary precursor to preparedness (Raaijmakers et al., 2008). According to Soley and Pandya (2003), knowledge is an intangible resource that exists within the mind of the individual. In this study, the knowledge construct is operationalized as one's subjective knowledge (SK) at the time of the survey. More specifically, as a multidimensional construct, SK measures householders' perception of how well informed they consider themselves to be about flood risk in terms of several topics. These topics include, for example (Botzen et al., 2009; Escuder-Bueno et al., 2012, O'Sullivan et al., 2012; Bradford et. al, 2012; Babcicky and Seebauer, 2016; Kellens et al., 2012; Linden, 2014): 1. knowledge of the risk situation—i.e. awareness of living in a flood risk area; 2. knowledge of the causes of flood events in the region; 3. Knowledge of the official sources of public safety information (e.g. household emergency plan, evacuation procedures, etc.); 4. Knowledge of weather or flood alerts and warning systems; 5. Knowledge of public flood risk management—e.g., the protection level provided by local flood defences such as levees, dams and floodwalls; and 6. knowledge of how to prepare and plan for floods at the household level.

3.3.3.3 Self-efficacy (SE)

The origin of self-efficacy (SE) is in Social Cognitive Theory (Bandura, 1986). Self-efficacy is the belief that the self is capable of acting effectively. In this vein Bandura (1977) wrote: "It is hypothesized that expectations of self-efficacy determines whether coping behaviour will be initiated; how much effort will be expended, and how long it will be sustained in the face of obstacles and aversive experiences" (Bandura, 1977; p. 191). Self-efficacy belief is extended in risk perception and behaviour research; it is defined as one's perception of his or her general ability to protect him or herself against a certain threat (Becker, Aerts, and Huitema 2014). Many studies already examined the importance of self-efficacy for the adoption of flood protective behavioural intentions (e.g., Griffin et al., 2008; Grothmann and Reusswig, 2006; Koerth et al., 2013; Bubeck et al. 2013; Poussin et al., 2014; Dittrich et al., 2016). As a multidimensional construct, the SE construct is operationalised in this study as a measure of three items: 1. perceived confidence that a respondent can efficiently prepare and secure his/her property ahead of time for a potential flood; 2. perceived powerfulness—i.e., that protecting a respondent's household against future flood threats is not beyond his/her ability; and 3. perceived personal skills— i.e., that it is easy for a respondent to protect himself or herself against future flood threats because he/she can rely on his/her own resourcefulness.

3.3.3.4 Trust (T)

Trust is a multidisciplinary construct which can be defined as the willingness to make oneself vulnerable to actions taken by the trusted party based on the feeling of confidence or assurance (Gefen, 2000). The term 'trust' is somewhat broad, but within the field of flood risk management it is generally used to refer to (Kellens et al., 2013): 1. Institutional trust (i.e. the government's ability to cope with flood) (Lin et al. 2006); or 2. Trust in specific mitigation measures (i.e. flood defences)(Hung, 2009; Terpstra, 2011). Based on the discussion in Section 2.4.4, the general hypothesis is that high levels of trust in public flood risk management decreases perceptions of flood-risk, which in turn keeps residents from preparing for potential flood disasters. Evidence supporting this overall relationship can be found in studies carried out by Dzialek et al. (2013), Grothmann and Ruesswig (2006), Hung (2009), Scolobig et al. (2012), Terpstra (2009, 2011), and Viglione et al., (2014). As a multidimensional construct, the SE construct is operationalised in this study as a measure of four items: 1. the confidence that the strength and height of the flood defences is based on a thorough and sound risk analysis; 2. the confidence that local authorities can control land use and development of floodplains in an effective way to reduce the risk; 3. the confidence that the technological skills of flood risk managers can efficiently prevent/mitigate all flood risks; and 4. the confidence that local authorities can provide credible information sources on flood risk.

3.3.4 Moderator Variables: Residential Satisfaction (Benefit Perception)

As discussed earlier in Section 2.4.5, residential satisfaction (RS) can be explained through the variables that help to fulfil the resident's aspirations, needs or desires in a house, how content that resident is with the location-related attributes/benefits and whether there is a feeling of connectedness with his or her residential environment (Tabernero et al., 2010). As a three dimensional construct, RS is operationalised in this study as a measure of three main variables:

a) Physical attributes of the neighbourhood (abbreviated as RS-P). This variable specifically refers to the degree of a respondent's satisfaction with 1. the physical appearance of the neighbourhood (i.e. is it aesthetically pleasant?); 2. the accessibility to the neighbourhood (i.e. is it well-connected with important parts of the city?); 3. street design and circulation system (i.e. streetscape, lighting of streets, street furniture, street width, pedestrian accesses... etc.); 4. density (i.e. level of crowdedness in the neighbourhood); 5. cleanness of the neighbourhood; and 6. provision of parks and other amenities within the neighbourhood.

b) Socioeconomic attributes of the neighbourhood (abbreviated as RS-SE). This variable specifically refers to the degree of a respondent's satisfaction with the 1. quietness of the neighbourhood; 2. safety of the neighbourhood; 3. social interactions with other residents; 4. social mix of the neighbourhood population; 5. travel distance to friends/family; 6. cost of living; and 7. travel distance to workplaces.

c) Housing/dwelling attributes (abbreviated as RS-D). This variable specifically refers to the degree of a respondent's satisfaction with the 1. value of the house/rent paid for the house; 2. privacy at home; 3. architecture of the dwelling (i.e. physical characteristics of building interiors and exteriors); and 4. size of the dwelling. Table 3.1 provides a summary of all research constructs. The codes and the descriptions of each item within each construct are particularly provided.

Table 3.1 Summary of research constructs

Research Constructs	Code	Item Descriptions	Source
Protective Behavioural Intentions (PBI)	PBI. 1	-Elevating the ground floor (at least 1 m) or having garages or simple basements/cellars as the ground floor;	This construct was developed partly on the basis of similar scales used by (Miceli et al., 2008; Zhai and Ikeda 2008; Terpstra,2011; Griffin et al. 2008)
	PBI. 2	-Implementing hydro-isolation of the walls to avoid water contact in inundated ground;	
	PBI. 3	-Installing more complex water drainage systems around the house and terrain adjustments such as earthworks, or retention basins;	
	PBI. 4	-Moving electricity outlets/meter boxes and air conditioning unit higher.	
	PBI. 5	-Assembling an emergency kit (including water, food, a battery powered radio, a first aid kit, etc.);	
	PBI. 6	- Making a to-do list that is helpful in case of an evacuation or flood (household plan);	
	PBI. 7	-Acquisition of sandbags or other barriers against water;	
	PBI. 8	-Purchasing (or modifying) property insurance policy for environmental hazards.	
	PBI. 9	-Attending a public meeting about the matter;	
	PBI. 10	-Collecting information about flood consequences, evacuation routes, and safe/high locations;	
Perceived Risk Probability (PRP)	PRP. 1	-Over the surrounding streets within neighbourhood (i.e. outside the property);	This construct was developed partly on the basis of similar scales used by (Zhai and Ikeda 2008; Babcicky and Seebauer 2016)
	PRP. 2	-Over the front/back yard (i.e. inside the property but not entering the house);	
	PRP. 3	-In the garage and non-habitable spaces of the house (i.e. below the front steps of your house);	
	PRP. 4	-Habitable floors and their possessions (such as furniture, whitegoods, clothing, curtains, floor coverings, and other).	
Perceived Risk Consequence (PRC)	PRC. 1	-Disruption of supplies (food, electricity, drugs, telephone, internet, water, etc.).	This construct was developed partly on the basis of similar scales used by (Miceli et al., 2008; Ho et al. 2008; Adelekan and Asiyanbi 2016; Morss et al. 2016)
	PRC. 2	-Disruption or damage to public facilities (roads, parks, etc.).	
	PRC. 3	-Damage to house or possessions (furniture, car, etc.)	
	PRC. 4	-Inconvenience of recovery process after the flood (e.g. problems with rebuild, clean-up, or relocation).	
	PRC. 5	-Financial loss (e.g. residential property values).	
	PRC. 6	-Psychological health	
	PRC. 7	-Physical health (e.g. drowning, injuries, hypothermia, and animal or venomous bites).	
	PRC. 8	-Confirmation of loved ones or pets' safety.	
	PRC. 9	-Disruption of daily life (job and other daily routines)	

Affective Risk Perception (ARP)	NA	Negative Affect (NA) (NA. 1) Feeling of fear; (NA. 2) Feeling of uncertainty; (NA. 3) Feeling of worry; (NA. 4) Feeling of powerlessness	This construct, was developed on the basis of similar scales used by (Boer et al. 2015; Terpstra,2011; Siegrist and Gutscher, 2008)
	PA	Positive Affect (PA) (PA. 1) Feeling of beauty and sense of nature; (PA. 2) Feeling of safety (PA. 3) Feeling of unity/solidarity; (PA.) Feeling of pleasurable fascination and excitement	
Personal Experience (PE)	PE	Severity of past experienced flooding upon the personal safety of householders	Adapted from (Adelekan and Asiyanbi 2016)
Subjective Knowledge (SK)	SK. 1 SK. 2 SK. 3 SK. 4 SK. 5 SK. 6	-Knowledge of the risk situation—i.e. awareness of living in a flood risk area; -Knowledge of the causes of flood events in the region; -Knowledge of the official sources of public safety information (e.g. household emergency plan, evacuation procedures, etc.); -Knowledge of weather or flood alerts and warning systems; -Knowledge of public flood risk management—e.g., the protection level provided by local flood defences such as levees or dams -knowledge of how to prepare and plan for floods	This construct, was developed partly on the basis of similar scales used by(Botzen, Aerts et al. 2009 ; Bradford et. al 2012; Linden 2014)
Trust (T)	T. 1 T. 2 T. 3 T. 4	-The strength and height of the flood defences is based on a thorough and sound risk analysis; -The flood defences are maintained properly; -The technological skills of flood risk managers can efficiently prevent/mitigate all flood risks; -The authorities have sufficient knowledge about flood protection.	Adapted from (Terpstra,2011)
Self-efficacy (personal control) (SE)	SE. 1 SE. 2 SE . 3	-"I am confident that I can efficiently prepare and secure my property ahead of time for a potential flood"; -"I feel powerless. Protecting myself against future flood threats is beyond my ability" -"It is easy for me to protect myself against future flood threats because I can rely on my resourcefulness".	New measure, developed partly on the basis of similar scales used by (Adelekan and Asiyanbi 2016)
Residential Satisfaction (RS)	RS-P. 1 RS-P. 2 RS-P . 3 RS-P . 4 RS-P . 5 RS-P . 6	- Physical appearance of the neighbourhood (i.e. Is it aesthetically pleasant?); -Accessibility to the neighbourhood (i.e. is it well-connected with important parts of the city?); -Street design and circulation system (i.e. streetscape; lighting of streets, street furniture, street width, pedestrian accesses... etc.); -density (i.e. level of crowdedness in the neighbourhood); -cleanness of the neighbourhood; and -provision of parks and other amenities within the neighbourhood.	This construct, was developed partly on the basis of similar scales used by (He 2009; Bonaiuto et al. 2003)
	RS-SE. 1 RS-SE. 2 RS-SE. 3 R-SE. 4 R-SE. 5 R-SE . 6 R-SE. 7	-Quietness of the neighbourhood; -Safety of the neighbourhood; -Social interactions with other residents in neighbourhood; -Social mix of the neighbourhood population; -Travel distance to friends, family or other social relationships; -Cost of living -Travel distance to workplaces	
	RS-D. 1 RS3. 2 RS3. 3 RS3. 4	-Price or rent you paid for your house. -Privacy at home. -Architecture of the dwelling (Physical characteristics of building interiors and exteriors) -Size of the dwelling.	
Non-protective responses: Risk Denial (RD)	R-D . 1 R-D . 2 R-D . 3	-"I believe that future flooding will turn out better than expected"; -"I expect that future flooding will occur somewhere else, but that it will not bother me"; -"I believe that the occurrence of flooding is grossly exaggerated".	Adapted from (Zaalberg et al. 2009)

3.4 CHAPTER SUMMARY

This chapter provided the conceptual framework, research constructs and proposed hypotheses. The final proposed model is built upon the dual-process theory (cognition-affect) but also uses other socio-psychological constructs to build a comprehensive model to investigate relationships between the constructs. Overall, this model advances a more integrated, systematic and profound understanding of the determinants and mechanisms that underlie risk perceptions in order to explain protective behavioural intentions, which aims to help enhance the saliency of socio-psychological approaches in natural risk management research. The next chapter will discuss the research approach and methodology for the study.

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CHAPTER 4

METHODOLOGY

This chapter aims at discussing the selection and implementation of an appropriate methodology for achieving the objective of the research. First it addresses the philosophical stance of the research, the research approach and the context of the research. It then discusses the implementation of the quantitative research methodology with a focus on issues such as how the selection of a research sample is conducted, what data is collected, how the collection of data is carried out and what are statistical data analysis methods used for analysing the data in the research. Finally, ethical considerations will be provided.

4.1 GENERAL PHILOSOPHICAL STANCE

The term research philosophy relates to the set of beliefs concerning the nature of the reality being investigated (Becker, Bryman, and Ferguson, 2012). Understanding the research philosophy being used can help justify the assumptions inherent in the research process and how this fits the methodology being used (Flick, 2015). There are terms used in addressing the philosophical dimensions of ontology and epistemology (Wahyuni, 2012) and the common one is paradigm (Creswell, 2013). Research paradigm is "the argument for the logical steps which will be taken to link the research question(s) and issues to data collection, analysis and interpretation in a coherent way" (Hartley, 2004: p. 326).

As illustrated in Figure 4.1 below, the identification of the research philosophical paradigm is positioned at the outermost layer of the 'research onion' (Saunders, Lewis, and Thornhill, 2007), accordingly it is the first topic to be clarified.

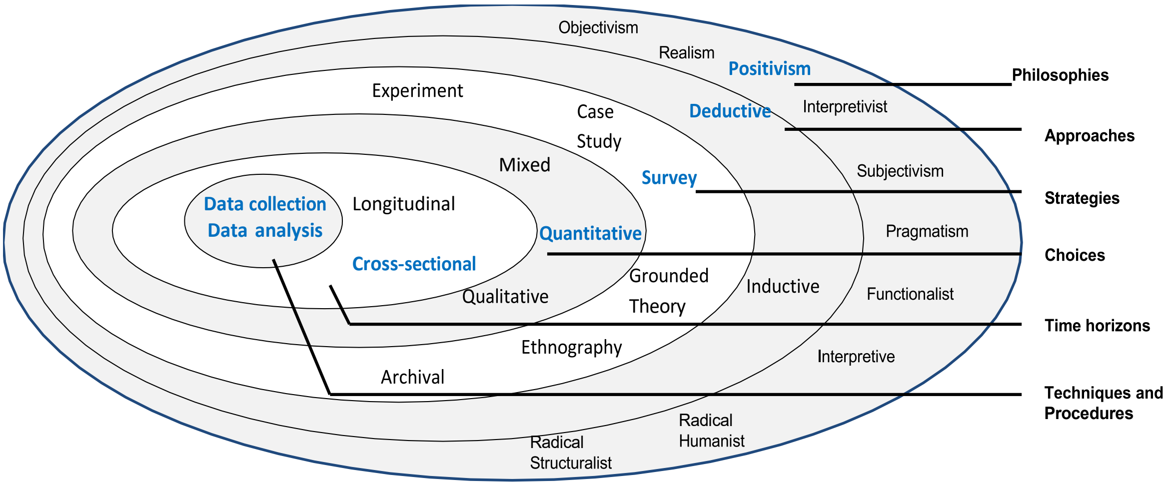


Figure 4.1: 'The research onion' model. Source: Saunders et al. (2007)

While risk psychologists with an experimental orientation aim at an "epistemic" subject and put the emphasis on the common shared environment, this thesis draws on a more personalized orientation that aims to analyze the origins of how individuals differ with respect to the psychological constructs of interest. In other words, the overarching epistemological approach adopted in thesis is strongly aligned with the "differential psychology of risk" (Breakwell, 2014) which concerns more the "individual" rather than the "situation" (which generally is maintained constant) and puts emphasis on the structures and internal dynamics of the individual. In fact, the driving motivation behind this thesis primarily draws on the argument that promoting behaviour change lies with understanding the psychology of the individual (Burge, 1986; Spikin, 2013).

From an "individualistic" point of view, the central focus of this thesis is on testing hypothesized or theory-driven relationships between psychological constructs under investigation (namely, perceived risk, perceived benefit, affect, knowledge, experience, self-efficacy, attitude and intention), in order to advance and validate a meaningful (and generalizable) explanation for the observed level of variation in risk responses. To this extent, the general scientific approach adopted in this thesis is "positivist" and based on a quantitative methodology that draws considerably on the psychometric paradigm, which is rooted in psychology and decision theory (Slovic et al., 1986; Sjöberg et al., 2004). Psychometrics is a series of psychophysical measurement procedures and multivariate statistical techniques (Fischhoff et al. 1978, Rohrmann 2003). Paul Slovic, one of the originators of psychometrics, states that the psychometric paradigm encompasses a theoretical framework that assumes risk to be subjectively defined by individuals who may be influenced by a wide array of psychological and other constructs (Slovic, 2010). Given the research objectives of this thesis, the psychometric orientation is more effective in achieving an amount of variance in data than the experimental orientation, regardless of how situations are unstable. Moreover, complex relationships (e.g. indirect or interactive) between the psychological constructs that are used in this dissertation can be best understood using multivariate statistical and psychometric estimations such as structural equation modelling (SEM).

4.1.1 Positivist Paradigm

As a philosophy, positivism sees social science as an organized method for combining deductive logic with precise empirical observations of individual behaviour in order to discover and confirm a set of probabilistic causal laws that can be used to predict general patterns of human activity (Neuman, 2002). In its broadest sense, positivism as a way of investigating human and social behaviour is a rejection of metaphysical speculations (Moutinho and Hutcheson, 2011). It entails an ontology that reality is objective and has inherent qualities that exist independently of the researcher (Crotty, 1998; Denzin and Lincoln, 2011; Perry, Riege, and Brown, 1999; Collins, 2010), where the emphasis is on the formulation of hypotheses, models, or causal relationships among constructs which are empirically tested within a controlled environment (Guba and Lincoln, 1994; DeMatteo, Festinger, and Marczyk, 2005; Sarantakos, 2012).

The positivist research paradigm underpins quantitative methodology (Antwi and Hamza, 2015). Ontologically, positivists believe that deductive reasoning, scientific inquiry and replicable (or generalizable) observable findings will converge upon objective truths (Neuman, 2002; Sarantakos, 2012), whereas in its epistemology, knowledge is derived from direct observation or manipulation of natural phenomena through empirical means (e.g. surveys, experiments and quasi experiments), where techniques for probability sampling, multivariate analysis and statistical prediction are applied (Plack, 2005; Denzin and Lincoln, 2005; Denzin and Lincoln, 2011; Sarantakos, 2012; Antwi and Hamza, 2015).

In short, positivists use validity, reliability, objectivity, precision, and generalizability to judge the rigour of quantitative studies as they intend to describe, predict, and verify empirical relationships in relatively controlled settings (Ulin, Robinson, and Tolley, 2012). Figure 4.2 below presents the characteristics that are common in a positivistic paradigm and that are applied in this thesis.

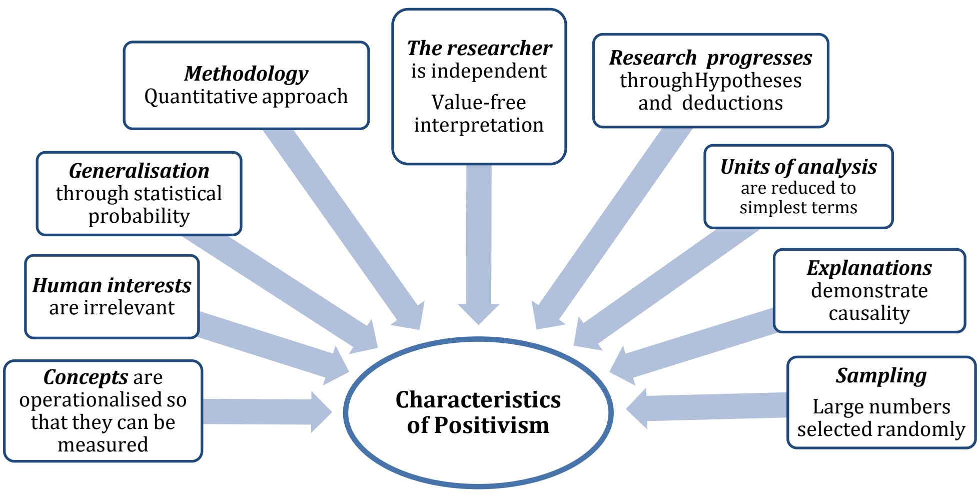


Figure 4.2. Characteristics of the positivistic paradigm applied in this thesis

Positivism, as the main philosophical approach in this dissertation, aims to, 1) provide a systematic strategy for combining deductive logic with precise empirical examinations (i.e. operationalisation of theoretical constructs) of "individual" behaviour in order to 2) explain and compare a set of competing models and hypothesized "causal" laws that can be used to 3) predict general patterns of human behaviour (Neuman, 2002; Wilson, 2010;). Here, it is noteworthy that although the deductive logic is typically quantitative in nature, the model proposed in this thesis has to be grounded on a robust theoretical foundation and to be originally based on a theory-driven approach, before being empirically tested and validated. Thus, the general philosophy adopted in this thesis is that, rather than figuring out "what works empirically" in a haphazard or a hit and miss fashion, and in order to appropriately understand behavioural intentions and relevant psychological mechanisms, a profound theoretical foundation must be laid down first (van der Linden, 2014).

4.1.2 Quantitative Methodology

Building on the quantitative methodological approach of this thesis, a survey instrument that draws on the psychometric paradigm is adopted as a research method in this thesis. In fact, survey instruments are popular and fundamental methods for acquiring information on public knowledge, perception of, and response to, natural hazards (e.g. Zhai and Ikeda, 2006, 2008; Keller et al., 2006; Knocke and Kolivras, 2007; Raaijmakers et al., 2008; Lindell and Hwang, 2008; Heitz et al., 2009; Zaalberg et al., 2009; Martens et al., 2009; Botzen et al., 2009; Takao et al., 2004; Zhang et al., 2010; Terpstra, 2011; Kellens et al., 2011; Salvati et al., 2014; O'Neill et al., 2015). In this context, survey instruments allow for the measurement of a large number of self-reported behaviours at the same time—enabling a more reliable investigation of theoretical relationships between psychological constructs that are generalizable to a representative sample of population of interest or even to other populations or other risk contexts. According to Bird (2009), key features (including questionnaire design, delivery mode, sampling techniques and data analysis) should be disclosed in the literature to ensure that reliable, replicable and valid results are produced from questionnaire-based hazard knowledge and risk perception research. These features are briefly presented in the next subsections.

4.2 SURVEY SAMPLING DESIGN

"Whom should you survey and how many respondents do you need? These are the two basic questions of survey sampling"

(Vogt, Gardner, and Haeffele, 2012: p. 121)

A sample design is a definite plan for constructing a subset of the research population which is adequate and sufficient to represent the population under investigation (Kothari, 2004). According to Krathwohl (1993), sampling procedures are the ways of selecting a small number of units from a population to enable researchers to make reliable inferences about the nature of that population. LoBiondo-Wood and Haber (1998) describe a sample as a portion or a subset of the research population selected to participate in a study, representing the research population According to Marshall (1996), the aim of all quantitative sampling approaches is to draw a representative sample from the population, so that the results of studying the sample can then be generalized back to the population with a reasonable level of confidence. Another important issue is to ensure that the procedure is viable in the context of funds available for the study, causes a relatively small sampling error and helps to control the systematic bias in a better way (Kothari, 2004). The sample design within this research will include the following steps (Figure 4.3):

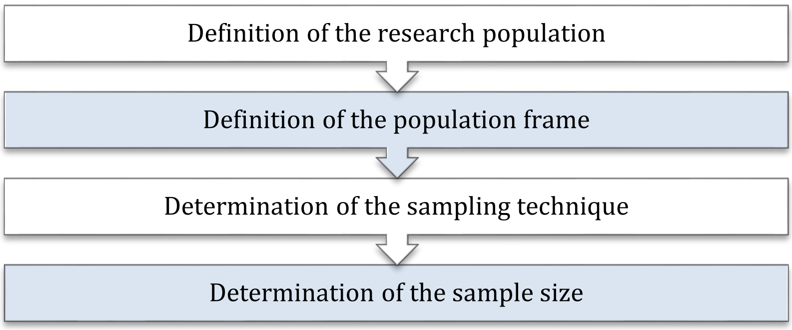


Figure 4.3 Sampling design steps

4.2.1 Research Population and Population Frame

Polit and Hungler (1999) refer to the research population as an aggregate or totality of all the objects, subjects or members that conform to a set of specifications comprising the entire group of persons that is of interest to the researcher and to whom the research results can be generalised with respect to some research problems (Polit and Hungler, 1999: 37). The listing of all the elements in the population from which the sample is drawn is called a sampling (Sekaran, 2000; Vogt et al., 2012) .

Before selecting the targeted population, a decision has to be taken concerning the unit of the analysis, which refers to the entities on which measurements are made during a survey (De Vaus, 2013). This unit may be a geographical one, such as country, state, local, district, village, etc., or an organization/group of organizations such as a particular type of firm, or a construction unit such as house, flat, etc., or it may be a social unit such as the family or it may be an individual unit (Kothari, 2004) within a particular group of people defined by some predetermined characteristics/criteria. As the main aim of this research is to examines risk perception and protective behaviour of residents living in two major floodplains in South East Queensland, namely the Brisbane-Bremer river catchment in Ipswich and the Nerang river catchment in the Gold Coast (see Section 1.4 for more detailed information on the study area), the unit of analysis is conducted at the household level. The inclusion criteria for the participants in the survey include:

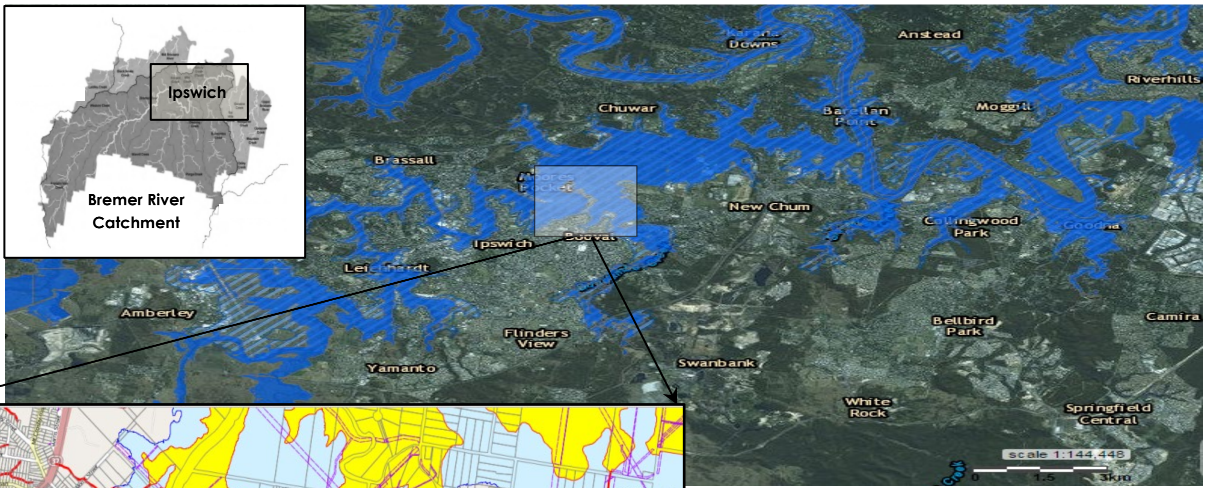
1. Potential participants should be occupying a property that is located within the Adopted Flood Regulation Line (AFRL: The 100-year Average Recurrence Interval flood level).

2. Potential participants must be the household decision-makers who are aged above 18 (husbands or wives in married-couple households and adult male or female residents in single-headed households) because they seemed best placed to comment on reasons for living in flood liable residential zones. Thus, given the nature of the questions, the respondent must be either

the householder or a sufficiently senior family member who is fully aware of the family situation with regards to socio-economic and flood-related conditions.

3. Due to the nature of this study, which emphasizes the ‘permissible' individual use of flood-prone land, free-standing houses, in low residential density areas, were selected as a criterion for floodplain residents since this urban form could be largely affected by flood impacts more than other forms (e.g. high rise apartment buildings).
Exclusion criteria include the individual who owns property but does not live in the property.

Using cadastral maps, the geographical/physical distribution of Low Density Residential (LDR) uses or houses within the Adopted Flood Regulation Line (AFRL) has been first defined for the selected floodplains in Ipswich (Figure 4.4 and Table 4.1) and Gold Coast (Figure 4.5 and Table 4.2).



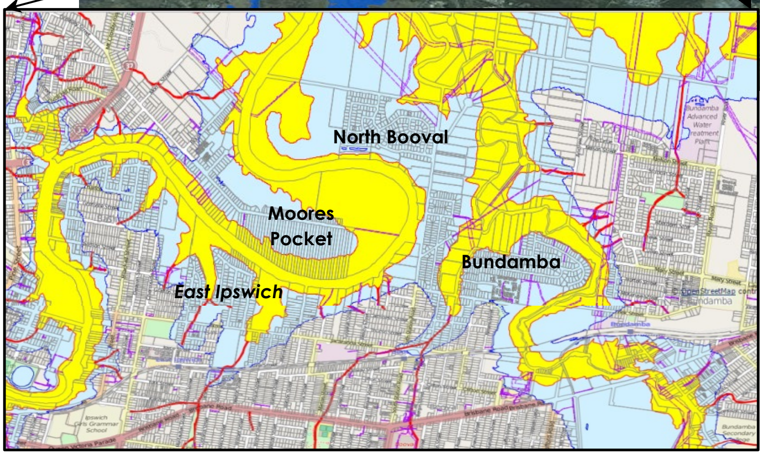


Figure 4.4 A: Spatial distribution of affected households in Ipswich with the 2011 flood extent. Source: State of Queensland (Department of Natural Resources and Mines) 2012, http://dds.information.qld.gov.au/dds/ Date of access 23-Aug-2016

2011 FLOOD LEVEL

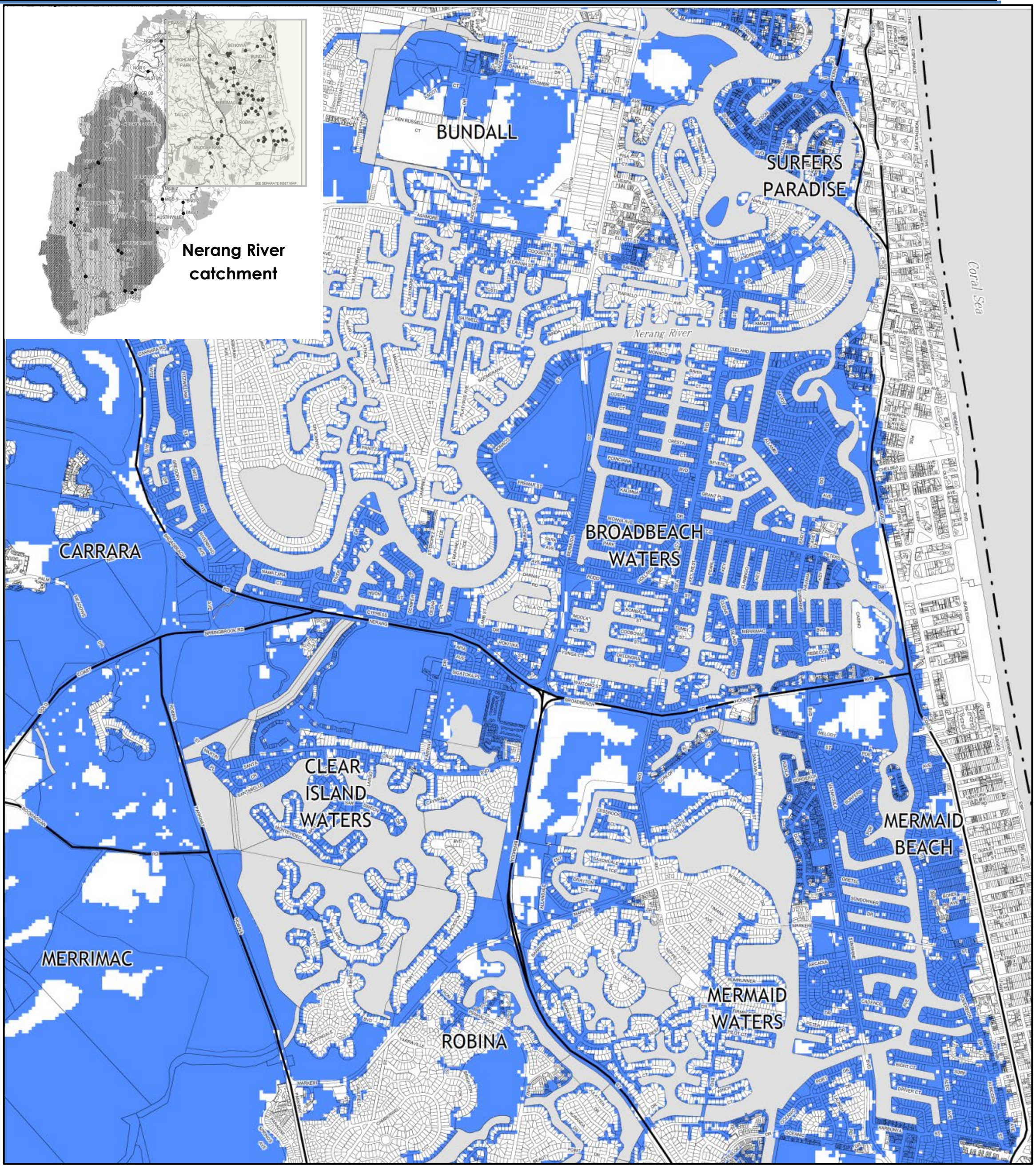
4.4 B: A cadastral map shows the spatial distribution of affected households in four of the targeted suburbs within the Bremer River catchment/Ipswich, with the 100-year ARI Extent. Source : Ipswich City Council, Food overlay (interactive online map) http://maps.ipswich.qld.gov.au/connect/analyst/?mapcfg=Boundaries

URBAN CATCHMENT FLOW PATHS
DEVELOPMENT LINE 1-20 YRS ARI
ADOPTED FLOOD REGULATION ZONE 1-100 YRS ARI

Table 4.1: Number of LDR uses within the (AFRL) of 100-yr ARI flood in the targeted suburbs in Ipswich

Flood prone Suburbs in Bremer River Catchment	Number of LRD/Houses within the AFRL of 100-yr ARI flood	Flood prone Suburbs in Bremer River Catchment	Number of LDR Houses within the AFRL of 100-yr ARI flood
Goodna	581	Karalee	96
North Booval	736	Basin Pocket	118
Bundamba	124	Tivoli	44
East Ipswich	283	North Ipswich	134
One Mile	189	Woodned	47
Brassall	88	Coalfalls	49
Leichhardt	62	Churchill	104
Riverview	47	Gailes	75

Total 2804



4.5: A cadastral map shows the spatial distribution of affected households in the targeted suburbs within the Nerang River catchment, with the 100-year ARI Extent. Source: Gold Coast City Council 2008, Natural Hazard (Flood) Management Areas - Overlay Map OM17-29, http://www.goldcoast.qld.gov.au/gcplanningscheme_1111/attachments/planning_scheme_maps/overlay_maps/OM17_POTENTIAL_FLOODING/OM17_29.pdf

DESIGNATED FLOOD AFFECTED AREA WATER BODY

Table 4.2: Number of LDR uses within the (AFRL) of 100-yr ARI flood in the targeted suburbs in Gold Coast

Flood prone Suburbs in Nerang River catchment	Number of LDR Houses within the AFRL of 100-yr ARI flood	Flood prone Suburbs in Nerang River catchment	Number of LDR Houses within the AFRL of 100-yr ARI flood
Burleigh Waters	450	**Mermaid Beach**	52
Miami	38	**Broadbeach Waters**	715
Mermaid Waters	550	**Carrara**	202
Benowa	171	**Surfers Paradise**	142
Clear Island Waters	250	**Bundall**	183
Total 2753			

4.2.2 Sampling Technique

Generally, there are two main technique of research samples: probability and nonprobability samples (Vogt et al., 2012). A probability sample is a sample in which each element within the population has a known (and non-zero) chance of inclusion in the sample, and all units in the population are independent of one another (Bryman and Bell, 2015; Kothari, 2004; Vogt et al., 2012). Bryman and Cramer (1994) argue that the main aim of using it is to reduce the sampling error and to keep it to a minimum (Bryman and Cramer, 1994). Moreover, it is generally assumed that a probability sample is a more representative sample of the population (Bryman and Cramer, 1994), because if the sample probabilities are known, techniques of inferential statistics can be used to make generalizations about populations (Vogt et al., 2012).

Probability sampling can be (Kothari, 2004; Vogt et al., 2012) simple random sampling—in which the selection is completely arbitrary, and a given number of the total population is selected completely at random; 2) systematic random sampling—in which every nth element of the population is selected; 3) stratified random sampling—in which the population is divided into segments and a random number of each group is then selected according to particular features; and 4) cluster random sampling—in which a particular subgroup is chosen at random. The subgroup may be based on a particular geographical area.

In contrast, a non-probability sampling is that sampling procedure which does not afford any basis for estimating the probability that each item in the population has of being included in the sample (Kothari, 2004). Within the same line, a nonprobability sample is a "sample that has not been selected using random selection method…this implies that some units in the population are more likely to be selected than others" (Bryman and Bell, 2015: p. 187). Non-probability samples can be divided into three broad techniques: 1) convenience sampling, which is the least rigorous technique, involving the selection of the most accessible subjects (Marshall, 1996); 2) purposive (judgmental) sampling—in which the researcher deliberately selects the most productive sample to answer the research question (Tongco, 2007) and 3) quota sampling which is the non-probabilistic version of stratified random sampling (Kitchenham and Pfleeger, 2002).

However, for the purposes of conducting this research study, probability sampling techniques are both preferable and desirable if the theoretical orientation of the research is positivist, and the methodology used is quantitative. As discussed earlier, these techniques are more likely to produce a representative sample, reduce the sampling error and keep it minimum, and enable estimates of the sample's accuracy (Fowler Jr, 2008). Accordingly, the ideal arrangement would be a probability sample taken from the research population frame. Specifically, for the purposes of conducting this research study, systematic random sampling techniques were applied. Systematic sampling has certain plus points. It can be taken as an improvement over a simple random sample in as much as the systematic sample is spread more evenly over the entire population (Kothari, 2004; Vogt et al., 2012). Systematic sampling is easy to apply, involving simply taking every kth element after a random start (Kalton, 1983).

The systematic random sampling for the purposes of conducting this research study was conducted as follows:

1) Within each suburb in the study area, all the streets were identified and listed.

2) Within each street, one of the odd address numbers was randomly selected to initiate the sampling.
3) Then, every 2nd odd address number was automatically included in the sample.
So, the first unit is selected at random and other units are selected systematically at fixed intervals. For example, if the first randomly-selected number is 5, then the remaining odd address numbers are: 9, 13, 17, 21, 25, 29 and so on.
4) The same process was again repeated for each street, but this time for selecting the even address numbers.

Based on this sampling technique, the total population size (usually denoted N) for this research study was estimated to be 3150 households/dwellings.

4.2.3 Sample Size

Because of the limited resources (regarding time and effort) of the researcher, and to come up with an accurate and fair representation of the population characteristics, the researcher depended on a systematic research sample which has been selected randomly from the population resulting from the sampling frame. Many scholars (like Sekaran, 2000; Vogt et al., 2012; Bryman and Bell, 2015; and Zikmund et al., 2013) have illustrated that a large and adequate sample size is the main method to ensure that the data collected would provide a reliable basis for drawing inferences, making recommendations and supporting decisions. Within this respect, a large and adequate sample size would remove bias and meet the criteria required by the analytical methods used within the research.

The most demanding proposed data analysis technique for this study is Structural Equation Modelling (SEM), which is sensitive to sample size (Garson, 2009). If the sample size is not large, some statistical estimates in SEM, such as standard errors, may not be accurate, and the probability of technical problems in the analysis is greater (Kline, 2015). Plenty of studies focus on sample size and try to find an appropriate minimum sample size (Nunnally, 1967; Boomsma, 1982; Bollen, 1989; Bentler and Chou, 1987; MacCallum, Widaman, Zhang, and Hong, 1999; Iacobucci, 2010; MacCallum, Lee, and Browne, 2010; Kline, 2011; Sideridis et al., 2014).

However, there is no generally accepted criteria for determining a specific sample size or the number that can be phrased as 'large enough' for using structural equation modeling (Iacobucci, 2010). For example, various rules-of-thumb have been advanced, including (a) a minimum sample size of 100 or 200 (Boomsma, 1982; Weston and Gore Jr, 2006; Iacobucci, 2010; Kline, 2015); (b) 5 or 10 observations per estimated parameter (Bentler and Chou, 1987); (c) 10 cases per indicator variable in setting a lower bound of an adequate sample (Nunnally, 1967); (d) the ideal sample size-to-parameters ratio is 20:1 (Jackson, 2003) or 3:1, even close to 2:1 on occasion (Bagozzi and Yi, 2012). For multi-group modelling, the rule of thumb is 100 cases/observations per group (Kline, 2005).

However, according to Wolf and his colleagues (2013), such rules (i.e. rules-of-thumb) are problematic because they are not model-specific and may lead to grossly over-or underestimated sample size requirements (Wolf et al., 2013: p. 3). In this respect, other recommendations suggest that determining sample size should depend on the desired level of power (MacCallum et al., 2006) and other model characteristics such as the level of communality across the variables and degree of factor determinacy that all affect the accuracy of the parameter estimates and model fit statistics, which raises doubts about applying sample size rules-of-thumb to a specific SEM (Wolf et al., 2013).

From this, Wolf et al. (2013) used Monte Carlo data simulation techniques to evaluate sample size requirements for common applied SEMs with respect to statistical power, bias in the parameter estimates, and overall solution propriety. Statistical power is the probability of rejecting the null hypothesis when it is false. Power is dependent on (a) the chosen alpha level (by convention, typically $\alpha = .05$), (b) the magnitude of the effect of interest, and (c) the sample size. Whereas bias refers to conditions in which an estimated parameter value differs from the true population value (Kelley and Maxwell, 2003; Maxwell, Kelley, and Rausch, 2008). On the other hand, solution propriety refers to whether there are a sufficient number of cases for the model to converge without improper solutions or impossible parameter estimates. Models based on larger samples with more indicators per factor and with larger factor loadings are more likely to converge properly (Wolf et al., 2013). The results from the study by Wolf et al. (2013) revealed that a range of sample size requirements (i.e., from 30—for simple Confirmatory factor analysis CFA with loadings around .80—up to 450 cases for mediation models) ensures meaningful patterns of association between parameters and sample size.

Within the same line, a priori calculations using Soper's (2017) SEM sample size calculator have suggested the minimum sample size required for this research analysis to yield adequate power. This calculator requires input data such as the anticipated effect size, statistical power levels, the number of observed variables (all the measurement items/indicators) and latent variables (both endogenous and exogenous constructs) in the model, and the desired probability to detect the minimum sample size for SEM technique (Cohen et al., 2013; Westland, 2010). Inputting the required information such as 95% desired statistical power level, 0.05 probability level, and anticipated effect size of 0.5 and 0.25 the required number of sample size for each measurement model in this study was estimated separately according to the number of constructs and indicators (observed variables), as shown in Table 4.3.

Table 4.3 Minimum sample size for each measurement model in this study

Structural model	Latent variables	(observed variables)	Sample size	
			Minimum sample size to detect effect (0.5)	Minimum sample size to detect effect (0.25)
Dual-process Model (Chapter 6)	6	37	58	361
Mediation Model (Chapter 7)	9	47	67	403
Moderation model (Chapter 8)	5	26	68	341

4.3 QUESTIONNAIRE/SURVEY CONSTRUCTION

According to Vogt and his colleagues, surveys are “methods of collecting primary data based on communication with a representative sample, or subset, of the target population” (Vogt et al., 2012: 186). Surveys may be classified based on the method of communication, the degrees of structure and disguise in the questionnaire, and the time frame in which the data are gathered (temporal classification) (Vogt et al., 2012). For the purpose of this study, a descriptive cross-sectional survey was conducted, using a self-administered structured questionnaire through mail. A cross-sectional survey collects data to make inferences about a population of interest at one time point or over a short period. Self-administered questionnaires are surveys in which the respondent takes the responsibility for reading and answering the questions.

There are various advantages in using this method of survey research. Besides its convenience to collect data, as respondents can reply to the questions by themselves, its anonymity also can encourage frankness when sensitive areas are involved (Robson, 2002). It is inexpensive, efficient and an accurate method of gathering information that is not easy to observe (Vogt et al., 2012; Bryman and Bell, 2015). Moreover, it can be quickly distributed to collect a wide scope of information from a large population in a short period of time, so that it allows generalization from a sample to a population, and inferences can be made about the population's characteristics, present and past behaviour, standards of attitudes, beliefs and reasons for action with respect to the topic under investigation (Bulmer, 2004; Kumar, 2005; Groves et al., 2011).

Furthermore, to ensure that a good questionnaire is developed, Bird's (2009) model of questionnaire design for research on the public perception of natural hazards and risk mitigation was adopted. According to Bird (2009), the questionnaire format, sequence, wording, length and output, should be considered while designing the questionnaire. This helps to ensure the reliability, validity and sustained engagement of the participant (Bird, 2009). The questionnaire format involves a set of structured 'closed-ended' questions that provides the survey write-up with quantifiable results that are easily summarised and clearly presented in quick-look summaries. Check-box answers were provided where appropriate with the option "other, please specify", "don't know" or "not applicable" so as to minimise the effect of limiting participants to predefined answers.

Moreover, the order and flow of the questions in the questionnaire were considered to get a logical flow of questions to help in collecting the data. Double-barrelled, negative implications, unnecessarily detailed questions or dead giveaways were avoided as advised by Bird (2009). The development and validation of the questions measuring the proposed research constructs are represented in the following sections.

Overall, Figure 4.6 below shows a schematic representation of steps followed during scale development and validation.

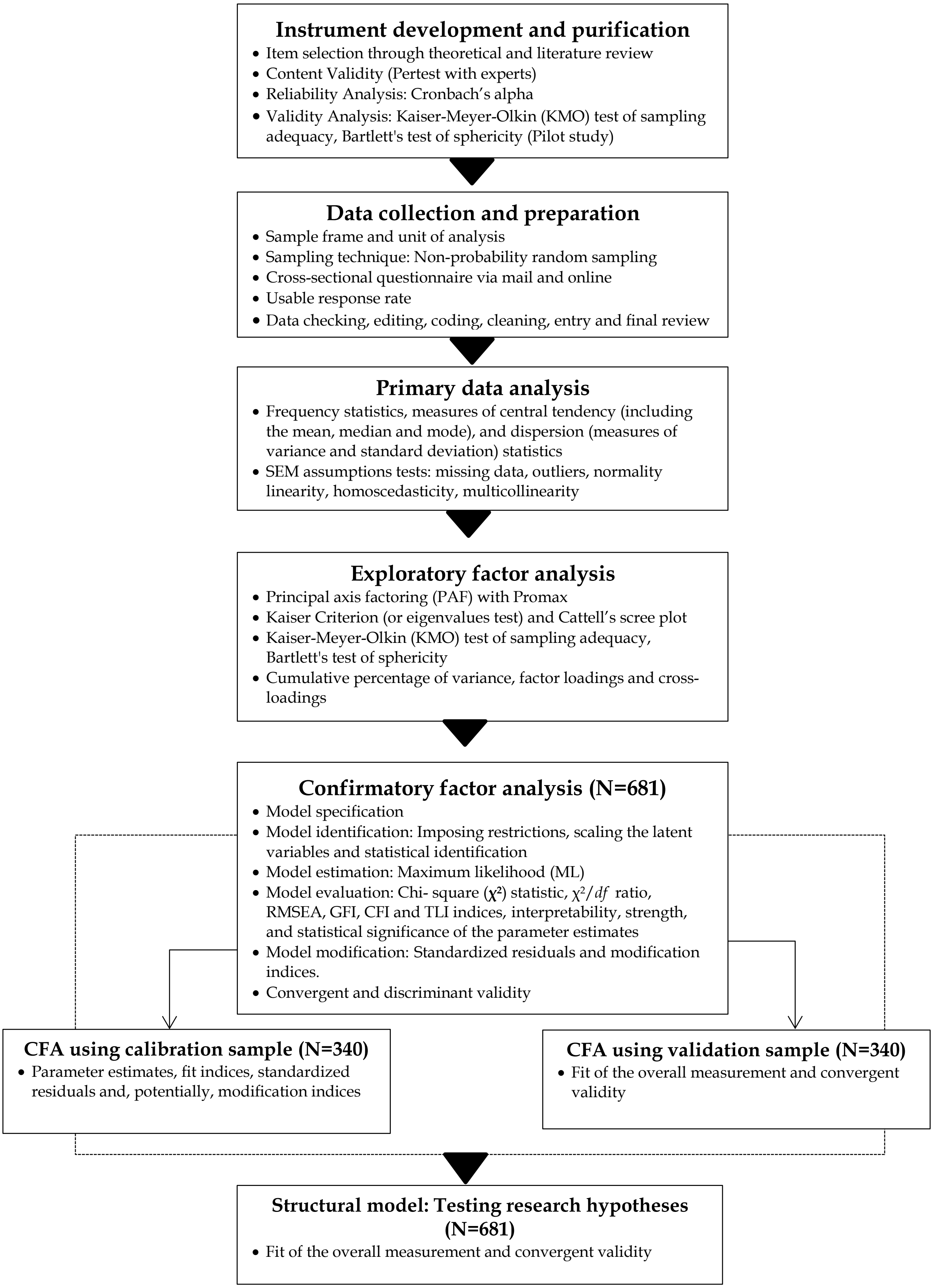


Figure 4.6 A schematic representation of steps followed during scale development and validation

4.3.1 Measurement Instruments

Churchill (1999) defines measurement as "the rules for assigning to objects to represent quantities of attributes" (Churchill, 1999: p. 447). Fundamentally, measurement focuses on the crucial relationship between the empirically grounded indicators, that is, the observable response and the underlying unobservable concepts (Carmines and Zeller, 1979). When the relationship is a strong one, analysis of empirical indicators can lead to useful inferences about the relationships among the underlying concepts (Carmines and Zeller, 1979). For the purpose of this study, multiple-item scales are used to measure all dependant and independent variables because these scales are more appropriate to measure psychological and behavioural attributes than single-item scales. This is in line with several authors (Peter, 1979; Nunnally and Bernstein, 1994; Spector, 1992; Gliem and Gliem, 2003) who proved that multiple-item measures increase the reliability and validity of the scales by allowing for calculation of coefficient alpha, coefficient beta, decrease random measurement errors, and effectively are capable of recording greater discrimination (when this is desirable) in categories of the attribute by increasing the number of categories in the answer scale or categorizing people into groups. Further to this, for the statistical approaches of SEM applied in this study, the use of a minimum of three items per construct is recommended (Kline, 2015).

The multi-items scales used in this study involve a combination of referenced, adapted and new research constructs or measures. A referenced measure is a measure that has been previously used and validated by other researchers and studies public perception of natural hazards and risk mitigation. While an adapted measure is the one that has a reference and has been slightly modified from its original form to better fit the present study. All the measures—whether referenced, adapted or new—used in designing the survey (Tables 3.1) were obtained based on the extant literature reviewed in Chapter 2. Each measure is unique in its own item pool and will be thoroughly discussed and verified for its content validity, internal consistency reliability (Cronbach's alpha α coefficients), dimensionality and construct validity.

Before proceeding further, it is worthwhile to indicate that all multi-items scales used in this study were instructed and created according to Likert's specific procedures (Likert, 1932). Specifically, a 7-point Likert scale is employed ranging from one describing 'not at all' to seven to indicate 'extremely'. The seven-point Likert scale is selected due to its advantages in generating responses that are less skewed and more consistent for parametric statistics and multivariate analysis than a five-point Likert-type scale or a three-point Likert-type scale (Finstad, 2010; Hair et al, 2010). Besides, odd-numbered Likert scales provide an option for indecision or neutrality (Croasmun and Ostrom, 2011). By giving responders a neutral response option, they are not required to decide one way or the other on an issue; this may reduce the chance of response bias, which is the tendency to favor one response over others (Fernandez and Randall, 1991). In addition, Symonds (1924) implied that the optimal reliability is with a 7-point scale. If there are more than that, the increases in reliability would be so small that is would not be worth the effort to analyze the difference or develop the instrument (Symonds, 1924, cited in Croasmun and Ostrom, 2011).

The survey was organized into five sections. **Section 1** measured residential satisfaction based on 17 location-related items (as proposed in Table 1.3) using a scale ranging from (1) ''not at all satisfied'' to (7) ''extremely satisfied". Responses to these items were assumed to reflect flood-prone residents' general opinion of their housing and neighbourhood environment. The selection of these items was based on the general principles of the residential satisfaction theory (see section 2.4.5 for more details) and partly on item wording approaches similarly employed by He (2009) to measure satisfaction of flood-prone residents in San Marcos, Texas.

Section 2 measured the cognitive and affective dimensions of risk perception. The cognitive dimensions were based on the general principles of the psychometric model and spanned the concept, including perceived probability and consequence, knowledge and experience, of risk. First, a 4-item question dealt with residents' perception of the probability of inundation in the future. Following Zhai and Ikeda (2008), who measured perceptions of flood-prone residents in the Toki-Shonai River basin in Japan, the question was worded as follows: "How often do you think your home will be flooded in the future?" Please choose the most appropriate answer from the choices below. Once a year, Once in 2 years, Once in 5 years, 10 years, 20 years, 50 years, 100 years, or more than 100 years and absolutely never."

Zhai and Ikeda (2008) divided inundation into two items below and above floor inundation. However, since the use of a minimum of three items per construct is recommended for SEM and to effectively create greater discrimination in categories of the inundation levels, the number of items in in the answer scale were increased to four: 1. over the surrounding streets within neighbourhood (i.e. outside your property); 2. over the front/back yard (i.e. inside the property but not entering the house); 3. in the garage and non-habitable spaces of your house (i.e. below the front steps of your house); 4. through habitable floors and their possessions (furniture, whitegoods, clothing, curtains, floor coverings, and other). In addition, responses to these items were assumed to better fit the present study, where most of the building floor levels of habitable rooms in the survey area are raised so as to meet the requirements of the Standard Building Regulation and Building Code of Australia.

Second, a 9-item question dealt with residents' concern about potential consequences of future flooding in their local areas (as proposed in Table 1.3) using a scale of (1) ''not at all concerned'' to (7) ''extremely concerned". This construct was based on item wording approaches previously employed by investigators in Italy (Miceli et al., 2008), Japan (Zhai and Ikeda, 2008), Taiwan (Ho et al, 2008), Nigeria (Adelekan and Asiyanbi, 2016), Colorado, USA (Morss et al., 2016) and Austria (Babcicky and Seebauer, 2016). Third, since no suitable items from past empirical research were found, the following six items were developed to measure the extent to which people think or believe their knowledge reaches about risk-related topics (Bradford et. al 2012; Babcicky and Seebauer, 2016; Kellens, Zaalberg, and De Maeyer, 2012): 1. knowledge of the risk situation—i.e., awareness of living in a flood risk area; 2. knowledge of the causes of flood events in the region; 3. knowledge of the official sources of public safety information (e.g. household emergency plan, evacuation procedures, etc.); 4. knowledge of weather or flood alerts and warning systems; 5. knowledge of public flood risk management— e.g., the protection level provided by local flood defences such as levees or dams and 5. knowledge of how to prepare and plan for floods. These items were based on the extensive review of extant literature conducted in section 3.1. The respondents used a seven-point fully-anchored rating scale (1= *Not all knowledgeable* to 7 =*extremely knowledgeable*) to evaluate each item.

Fourth, respondents' perceived flood risk relative to an average citizen was measured using a categorical scale of lower than average, equal to the average or higher than average, adopted from Botzen et al. (2009). Finally, an 8-item question dealt with residents' feelings associated with potential flooding (fear, anger, distress, powerlessness, unity/solidarity, beauty and sense of nature, safety, and pleasurable fascination and excitement). This construct was partly based on item wording approaches previously employed by investigators in the Netherlands (Boer et al., 2015; Terpstra, 2011 and Zaalberg et al., 2009).

Section 3 includes a series of questions designed to access residents' perceived situational control (i.e. trust in local flood protections), perceived self-control (i.e. self-efficacy) and intentions to adopt and implement a behavioural measure to protect against flooding. Specifically, a four-item question dealt with residents' trust and confidence in the local flood protections (as proposed in Table 3.1) using a scale of (1) ''not at all confident'' to (7) ''extremely confident". This construct was adapted from Terpstra (2011), and slightly modified from its original form to better fit the present study.

Based on the extensive review of extant literature conducted in section 2.4.3 the construct of perceived self-efficacy should reflect a belief in one's own capabilities to exert control over one's own motivation, behaviour, and social environment. In this regard, most empirical research has either employed a generalized self-efficacy scale (Dixon, Shochet, and Shakespeare-Finch, 2015) or a specialized scale that, for example, estimates respondent' ability to implement a specific flood mitigation measure (Bubeck et al., 2013). In addition, a specialized scale to flood risk context by Babcicky and Seebauer (2016) operationalised self-efficacy as a conjoint measure of two items (1) "It is too difficult for someone like me to protect against flooding; and (2) "I feel helpless over a potential flood". Similarity, a study by Koerth et al. (2013), on household adaptation to coastal flooding in Greece, operationalised self-efficacy as a measure of three items (1) "I lack an overview in this field"; (2) Individuals are able to realize adaptation measures and (3) "I consider myself as a competent person in realising adaptation options". While other researchers such as Griffin et al. (2008) operationalised self-efficacy as a measure of only one item "In my life, it would be easy for me to do something to minimize the effects of river flooding".

The present study also developed a specialized scale that operationalises perceived self-efficacy as a conjoint measure of three items (1) "I am confident that I can efficiently prepare and secure my property ahead of time for a potential flood"; (2) "I feel powerless. Protecting myself against future flood threats is beyond my ability" and (3) "It is easy for me to protect myself and my property against future flood threats because I can rely on my resourcefulness". The respondents used a seven-point fully-anchored rating scale (1= *Strongly Disagree* to 7= *Strongly Agree*) to evaluate their agreement on each item. Finally, a 10-item question dealt with how likely the respondents were to take preparation and protective measures using a scale of (1) ''not at all likely'' to (7) ''extremely likely".

Section 4 includes a series of questions designed to access residents' attitudes towards the ignorance of exposure to flood risk based on the items proposed in Table 3.1. Specifically, a 3-item question was adopted from Zaalberget al. (2009) to measure a resident's denial of exposure to flood risk: (1) "I believe that future flooding will turn out better than expected"; (2) "I expect that future flooding will occur somewhere else, but that it will not bother me and (3) "I believe that the occurrence of flooding is grossly exaggerated". The respondents used a seven-point fully-anchored rating scale (1= *Strongly Disagree* to 7= *Strongly Agree*) to evaluate their agreement on each item. Finally, **Section 5** includes a series of questions designed to access residents' socioeconomic and housing characteristics (including: age, gender, income, education, household size, home ownership, length of residence and distance of residence from source of flood hazard)

To gain meaningful results from the data analyse stage, some steps were conducted to assess the reliability and validity of the measurements used in the survey. These steps are discussed in the following sections of the chapter.

4.3.2 Survey Instruments Verification

4.3.2.1 Content Validity

The process of assessing the research measurements' reliability and validity started with ensuring the content validity of the research instrument. Content validity refers to the extent to which a measurement reflects the specific intended domain of content (Carmines and Zeller, 1991: p.20). Hence, it pertains to the degree to which the questions in the tool accurately and fully measure what is supposed to be measured (Lobiondo-Wood and Haber, 1998). Content validity is mainly evaluated through the examination of the rational sequencing, wording comprehensibility, content relevance, interpretation constancy, representativeness and the overall impression of the readability and clarity of the survey (Bolarinwa, 2015).

The evaluation of content validity in this study was conducted according to a set of systematic steps as suggested by McDaniel and Gates (2013) which include: (1) carefully defining what is to be measured; (2) conducting a careful literature review; (3) let the scales be checked by experts and (4) the scale has to be pre-tested through piloting. In this respect, the proposed research variables were developed and defined carefully through a deductive process from an in-depth literature review. Moreover, the research questionnaire and scales have been checked, reviewed and examined by the researcher as well as academic research experts from Micromex Research and Consulting (MRC) who are specialised in social research to ensure there is semantic correspondence between measurement items in the item pools and the underlying variables intended to be measured. The survey was also reviewed by an expert from the Statistical Consulting Unit at the University of Newcastle to ensure that the measurement items were appropriate for the multivariate statistical analysis and, importantly, were appropriate for the reference population from which the study sample is drawn. Several of the original items have been revised based on the constructive comments from the expert review. The improved survey instrument was then adopted for the pilot study.

4.3.2.2 Purification of measures: Psychometric analysis of the pilot data

Purification or reliability of the instruments within this study has been done depending on a pilot study of 93 participants (between 1 April 2016 and 1 May 2016) selected randomly from the sample frame. Based on their responses and using the Statistical Package for the Social Sciences (SPSS) v. 24.0, reliability tests were done to make sure that the instrument was sufficiently and significantly reflecting the underlying variables that it was attempting to measure. Cronbach alpha test of internal consistency, KMO measure of sampling adequacy and Bartlett's test of sphericity were conducted in this stage.

4.3.2.3 Internal consistency analysis

According to Hair et al. (2006), reliability is an indicator of the degree to which a set of indicators of a latent construct is internally consistent based on how highly interrelated the indicators are; that is, "it represents the extent to which they all measure the same thing" (p. 712). Moreover, reliability concerns the extent to which a measuring procedure yields the same results on repeated trials (Carmines and Zeller, 1979) while random error produces inconsistency in scale measurements, which leads to lower scale reliability (Hair, 2015). Compared to other tests of reliability, namely, test-retest (stability), and alternate-form (equivalence) (Cooper, Schindler, and Sun, 2003), the appeal of an internal consistency index of reliability is that it is estimated after only one test administration and therefore avoids the problems associated with testing over multiple time periods (Bolarinwa, 2015). Besides, evaluating internal consistency is more applicable when multidimensional constructs like Likert scales (equal intervals scales) or summated scale measurements are used as predictor components in objective models (Santos, 1999).

Basically, there are two techniques to calculate the internal consistency reliability, namely, the split-half reliability and Cronbach's alpha (Cronbach, 1951). Split-half reliability is a simple measure of internal consistency, which means the items on the scale are divided into two halves and the resulting half scores are correlated: the higher the correlation between the two halves, the higher the internal consistency (Bolarinwa, 2015). Cronbach's alpha (coefficient alpha) is the average of all possible split-half coefficients resulting from different ways of splitting the scale items (Hair et al., 2003).

In this study, reliability analysis was conducted using Cronbach's alpha coefficient for internal consistency according to the following formula by Allen and Yen (2001):

$$\alpha = \mathrm{Z} \quad \frac{n\,\bar{c}}{\bar{v} + (N-1)\bar{c}}$$

Where N represents the number of items, $\bar{c}$ represents the average inter-item covariance among the items and $\bar{v}$ is the average variance. Based on this formula the value of Cronbach's alpha will increase if the number of items increased, or if the average inter-item correlation is high.

The coefficient value can range from 0 to 1. As a rule of thumb, the higher the reliability value, the more reliable the measure and, in most cases, a value of 0.5 to 0.6 would be sufficient to consider a scale as a reliable one. However, a Cronbach's alpha value of more than 0.7 indicates that the scale is more reliable (Nunnally and Bernstein, 1994). For the data obtained from the pilot study, Cronbach's alpha were calculated for all the measuring instruments in the research questionnaire. The Cronbach's alpha (α) as shown in Table 4.4 indicates that the average of the Cronbach's alpha value is ranged between 0.901 to 0.981. This shows that the survey instrument has a high level of reliability.

4.3.2.4 Validity analysis

"Validity is an overall evaluative judgment of the degree to which empirical evidence and theoretical rationales support the adequacy and appropriateness of interpretations and actions based on test scores or other modes of assessment"

(Messick 1995: p. 5)

As the reliability has been ensured, the next step is to check the validity of the instrument through Kaiser-Meyer-Olkin (KMO) test of sampling adequacy and Bartlett's test of sphericity. KMO considers the variance proportion of the indicators that can be explained by a latent variable (Lorenzo-Seva, Timmerman, and Kiers, 2011), and provides a measure of homogeneity between variables, by comparing partial correlations coefficients with the observed (zero-order) squared correlation coefficient (Worthington and Whittaker, 2006). If the variables share common factor(s), then the partial correlations should be small and the KMO should be close to 1.0 (Dziuban and Shirkey, 1974). As a rule of thumb, it is generally recommended that the KMO value should be greater than 0.5 if the sample size is adequate (Cerny and Kaiser, 1977). The KMO value for the constructs was ranged between "0.745 to 0.938" all of which are acceptable as a good value.

Bartlett's sphericity test examines the whole correlation matrix to determine the adequacy of factor analysis based on identifying the correlation between variables (Rossoni, Engelbert, and Bellegard, 2016). It supplies the statistical significance that the correlation matrix has significant correlations between at least some of the variables (Hair et al., 2009: p. 110), and becomes more sensitive as the size of the sample increases. A statistically significant Bartlett test ($p < 0.05$) indicates that sufficient correlations exist between the variables to continue with the analysis (Rossoni et al., 2016).The Bartlett's test also showed significant results at $p < 0.001$ for all the measurements, and hence the instrument was accepted for further data analysis through inferential statistics to test the research hypothesis. Table 4.4 summarizes the entire result viz. Cronbach's alpha, KMO test values, and Bartlett's significance of the instrument. On getting middling to quite meritorious results for validity, the instrument was floated for data collection.

Table 4.4: Tests of Internal Reliability and Validity of the Questionnaire

Construct	No. of Items	Cronbach's Alpha	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	Bartlett's Test of Sphericity	
Perceived Risk Probability (PRP)	4	.977	.805	**Approx. Chi-Square**	629.02
				Df	6
				Sig.	.000
Perceived Risk Consequence (PRC)	9	.954	.920	**Approx. Chi-Square**	760.077
				Df	36
				Sig.	.000
Positive Affective Appraisals (PA)	4	.932	.853	**Approx. Chi-Square**	302.962061
				Df	6
				Sig.	.000
Negative Affective Appraisals (NA)	4	.923	.840	**Approx. Chi-Square**	284.889367
				Df	6
				Sig.	.000
Subjective Knowledge (SK)	6	.939	.898	**Approx. Chi-Square**	463.316
				Df	15
				Sig.	.000
Self-efficacy: personal control (SE)	3	.974	.786	**Approx. Chi-Square**	379.307
				Df	3
				Sig.	.000
Trust (T)	4	.937	.803	**Approx. Chi-Square**	340.101313
				Df	6
				Sig.	.000
Protective Behavioural Intention (PBI)	10	.958	.938	**Approx. Chi-Square**	854.937252
				Df	45
				Sig.	.000
Non-protective responses: Risk Denial (RD)	3	.901	.745	**Approx. Chi-Square**	176.575279
				Df	3
				Sig.	.000
				Sig.	.000
Residential Satisfaction (physical attributes of neighbourhood) **(RS_P)**	6	.961	.897	**Approx. Chi-Square**	628.451434
				Df	15
				Sig.	.000
Residential Satisfaction (Socio-economic attributes of neighbourhood) **(RS_SE)**	7	.933	.934	**Approx. Chi-Square**	456.225209
				Df	21
				Sig.	.000
Residential Satisfaction (Attributes of dwelling) **(RS_D)**	5	.929	.836	**Approx. Chi-Square**	297.196692
				Df	6
				Sig.	.000

4.4 DATA COLLECTION

After the pilot test and checking of validity and reliability, a cross-sectional questionnaire was administered via Post in an unmarked pre-paid reply envelope, which provides confidentiality for the participants, avoids any harm to them, and gives them the chance to choose a suitable time to complete the questionnaire. In addition, a URL link for an electronic version of the questionnaire was provided to the research participants along with their individual ID numbers and password for its access. The use of the unique ID codes allowed us to identify duplicates (i.e. those who have completed both the paper-based questionnaire and online survey; both were then deleted). Moreover, the online survey tool (Survey Monkey) provided a mechanism to prevent multiple online attempts at the survey by activating the response limits option (or the Formerly Maximum Response Count). This option has also enabled us to stop collecting responses after receiving one (1) response for each unique ID.

The questionnaire was bound in an A4 booklet including 4 double-sided pages. The questionnaire cover was designed incorporating the University of Newcastle logo along with the reference number of HREC (Human Research Ethics Committee) approval and a creative picture projecting the phenomena under investigation, delivering a professional and eye-contacting image. Furthermore, as advised by Vogt et al. (2012), to increase the responses rate by gaining respondents' cooperation, a short paragraph was also included explaining why the study is important, promising confidentiality, inviting participants to use an enclosed postage-paid reply envelope, describing the incentive (i.e. entering in a 250 $AUD cash prize draw), explaining that answering the questionnaire will not be difficult and will take only a short period of time, and describing how the address of the household was scientifically selected.

Households were given up to four weeks to respond. In total, the survey targeted a sample of 3150 flood-prone households FPHs. Of the 3150 FPHs, a total of 796 questionnaires were returned. This included 84 returned (not completed) with a label stating "Return to Sender" or "Not in this address any more". A further 21 questionnaires were returned without completing all the necessary questions within the questionnaires, with 8 declined participations for respondents who only returned the gift voucher but not the questionnaires. Therefore, the number of returned completed questionnaires was 681. Table 4.5 provides a summary of the responses distribution and rate. The useable response rate scored 22.5% covering 14% of total FPHs within the target suburbs located in the Bremer river catchment, Ipswich and 11% of total FPHs within the target suburbs located in Nerang river catchment, Gold Coast. The useable response rate was calculated according to the following equation (Bryman and Bell, 2015):

$$\text{Usable Response Rate} = \frac{\text{Number of usable questionnaires}}{(\text{Total sample} - \text{ unusable or uncontactable member of the sample})} \text{ X } 100$$

Table 4.5: FPHs Survey Response Summary

Response Summary	Sample size
Total number of questionnaires	3150
Number of completed and returned questionnaires	681
Unreachable FPHs	84
Uncompleted questionnaires / not FPHs	21
Number of FPHs declined participation	8
Response rate	**22.5%**

Finally, after receiving the completed questionnaires, the answers from each respondent were organised, coded and entered into SPSS. They were then analysed by using the appropriate techniques to test the proposed hypotheses.

4.5 DATA PREPARATION

Prior to actual data analysis, the data preparation carried out included data checking, editing, coding, cleaning, entry and final review as advised by Hair et al. (2016). First, the data editing stage was tailored to detect any errors and omissions in the raw data (such as illegible, incomplete, inconsistent and ambiguous responses), to correct these errors or omissions where possible, and ensure that data quality standards in terms of accuracy and precision were met and achieved. Data coding was then undertaken and all raw non-numerical data were transcribed into a format that is suitable for the statistical package that was used for analysing the data. Within this stage, each variable was given a unique label to differentiate it from other variables and each sub-item within each of the research variables was given a unique number to differentiate it from other sub-items. Negatively worded items that were distributed to balance all sub-items were turned to give all item scores the same direction.

Afterward, the coded data were manually entered into the statistical package for the Social Science (SPSS, V 24.0). The final stage of data preparation was the final review of the entered data. In this stage, the data entered were reviewed to make sure that the values of the data had been entered into the computer software correctly. The review process was conducted by the researcher and two other researchers from the Statistical Consulting Unit at the University of Newcastle and MRC (Micromex Research and Consulting) through spot-checking several random assortments for accuracy and cross-checking double-entered data for discrepancies. By finishing this stage, the data became ready for analysis.

4.6 DATA ANALYSIS METHODS

Once the data was obtained, it was then formatted and entered into SPSS to analyze the distributional characteristics of the survey items. For instance, frequency statistics, measures of central tendency (including the mean, median and mode), and dispersion (including the range and quartiles of the data-set, and measures of variance and standard deviation) statistics for the data were calculated and summarized using descriptive statistics techniques. Missing responses, univariate outliers, kurtosis and skewness were also screened. Subsequently, the data from the two surveys (S_1 Ipswich, S_2 Gold Coast) were merged and converted to text and raw data files for use with IBM SPSS Amos Version 24.0 (Byrne, 2016) to estimate the hypothesized relationships in terms of association, mediation, and moderation using structural equation modeling (SEM) techniques.

4.6.1 Structural Equation Modelling

Over the last decade, structural equation modelling (SEM) has attracted increasing attention among academicians and practitioners in different disciplines, including in the perception of natural hazards and disasters research ((Zhai and Ikeda, 2008; Zaalberg et al., 2009; Terpstra, 2011; Linden, 2014; Paton, 2013; Paton, Okada, and Sagala, 2013; McIvor, Paton, and Johnston, 2009; Champ and Brenkert-Smith, 2015). SEM is a powerful, yet complex, analytical technique for delineating linear relations in multivariate data (Shook et al., 2004). Such complex relationships are commonly expressed in either algebraic form or graphical format (usually referred to as a *path diagram*) (Ho, Stark, and Chernyshenko, 2012). According to Byrne (2016), SEM is “a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to the analysis of a structural theory bearing on some phenomenon” (Byrne, 2016: p. 3). That is, the point of SEM is to test a theory by specifying a model that represents predictions of that theory among plausible constructs measured with appropriate observed variables (Hayduk et al., 2007).

As emerging from the nonparametric perspective, Pearl (2012) defines the logic of SEM as a causal inference method that takes a set of qualitative causal assumptions and queries of interests along with a set of experimental or nonexperimental data to generate three outputs (Pearl, 2012: p. 71; cited also in Kline, 2015; p. 10): (1) numeric estimates of model parameters (i.e. factor loadings, error variances and covariances, factor variances and covariances (Kenny and Milan, 2012) for hypothesized effects or target queries; (2) a set of logical implications of the model that may not directly correspond to a specific parameter but that still can be tested in the data at hand, for example, that X has no effect on Y if we hold Z constant, or that Z is an instrument relative to (X, Y); and (3) the degree to which the testable implications of the model are supported by the data.

For the purpose of this research, several unique characteristics make SEM an appropriate multivariate analytical technique. First, SEM allows the estimation of a series of separate, but interdependent, multiple regression equations simultaneously by specifying a structural model that accommodates reciprocal causations and multiple indicators which all allow the researcher to model relationships among independent and dependent variables, even when a dependent variable becomes an independent variable in other relationships (Gefen, Straub, and Boudreau, 2000; Ullman and Bentler, 2003; Hair et al., 2010; Marcoulides and Schumacker, 2013). Second, SEM has the ability to incorporate constructs or latent variables and account for measurement errors in the estimation process of construct values by using observable or manifest variables (Jöreskog and Bollen, 1993; Grewal, Cote, and Baumgartner, 2004; Kaplan, 2008; Hair, Gabriel, and Patel, 2014; Kline, 2015). This is unlike alternative methods (e.g., those rooted in regression, or the general linear model) that assume that error(s) in the explanatory (i.e., independent) variables vanishes, which in turn may lead, ultimately, to serious inaccuracies—especially when the errors are sizeable (Byrne, 2016).

Furthermore, SEM permits complicated variable relationships to be expressed through hierarchical or non-hierarchical, recursive or non-recursive, structural equations, to present a more complete picture of the entire model (Marsh and Hocevar, 1985; Bullock, Harlow, and Mulaik, 1994; Gefen et al., 2000; Bentler and Raykov, 2000; Wetzels et al., 2009). Included in these advances is assessment of mediating effects, moderation, invariance/equivalence of constructs across multiple groups, and higher order modelling of constructs (Cole and Maxwell, 2003; Hoyle and Kenny, 1999; Preacher and Hayes, 2004; Muthén, 2002; Cheung and Lau, 2008; Iacobucci, Saldanha, and Deng, 2007; Little et al., 2007; Henseler and Fassott, 2010; Hayes, 2009; Gunzler et al., 2013; Hair et al., 2014).

Thinking of SEM as a hybrid of factor analysis and path analysis, and following Anderson and Gerbing's (1988) two-step approach to structural equation modelling with latent variables, basic analysis in this research includes measurement models followed by structural models (Anderson and Gerbing, 1988). The measurement models were used to assess if a specified model underlying hypothesized constructs to measures was consistent with the observed (measured) data (Arbuckle, 2016; Byrne, 2016). As a result, any items with insufficient explanation for the current sample were dropped. By doing so, the psychometric properties, measurement invariance, and validity of the constructs can be optimised (Floyd and Widaman, 1995). In contrast, full structural models were used to assess if the hypothesised directional relations (here, associations, mediations and moderations) between constructs were consistent with the observed data. The specific procedures for developing measurement models and testing hypothesised relationships regarding association, mediation and moderation are detailed in the following sections.

4.6.2 Measurement Models: Factor Analysis

SEM's goal is similar to that of factor analysis: to provide a parsimonious summary of the interrelationships among variables (Weston and Gore Jr, 2006). Factor analysis refers to a set of statistical procedures designed to determine the number of distinct constructs needed to account for the pattern of associations among a set of observed measures or items (Fabrigar and Wegener, 2011). According to Henson and Roberts (2006), it is hoped, generally, that the number of distinct constructs will explain a good portion of the variance in the original matrix of associations (e.g., correlation matrix) so that the constructs, or factors, can then be used to represent the observed variables (Henson and Roberts, 2006). In short, factor analysis partitions the variance of each indicator (derived from the sample correlation or covariance matrix) into two parts: (1) "common variance," or the variance accounted for by the latent variable(s), which is estimated on the basis of variance shared with other indicators in the analysis (Brown and Moore, 2012); and (2) "unique variance," which is a combination of reliable variance specific to the indicator (i.e., systematic latent variables that influence only one indicator) and random error variance (i.e., measurement error or unreliability in the indicator) (Harrington, 2009). Factor analysis is "intimately involved with questions of validity" (Nunnally, 1978; p. 112 cited in Thompson, 2004: p. 5).

Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) were used here in a two-stage measurement model analysis.

4.6.2.1. Exploratory Factor Analysis (EFA)

Exploratory Factor Analysis (EFA) is used to determine what theoretical constructs underlie a given data set and the extent to which these constructs represent the original variables (Henson and Roberts, 2006). As its name implies, EFA is heuristic (Gerbing and Hamilton, 1996) in the sense that the researcher has no specifications in regard to the number of common factors (initially) or the pattern of relationships between the common factors and the indicators (i.e., the factor loadings) (Williams, Onsman, and Brown, 2010). Rather, it allows the researcher to (1) explore how indicators used empirically are configured in factors that are not directly observed, representing the facets or dimensions of the phenomenon being investigated as the main dimensions to generate a theory (Johnson and Wichern, 2002; Henson and Roberts, 2006), and (2) obtain a minimum number of factors that contain the maximum possible amount of information contained in the original variables used in the model, and with the greatest possible reliability (Williams et al., 2010; Hair et al., 2014; Rossoni et al., 2016).

EFA was performed using SPSS V. 24.0. As commonly practised in the empirical studies, EFA involved a linear sequence of decisions (Thompson, 2004; Williams et al., 2010): First, the statistical assumptions of EFA in terms of sample size, measurement scale, normality and factorability were checked. Second, factors were extracted using the principal axis factoring (PAF; also known as common factor analysis) method with Promax as a rotation method. PAF is a least-squares estimation of the common factor model (De Winter and Dodou, 2012). According to Pett et al. (2003), an advantage of PAF is that "squared multiple correlations are easy to obtain from the correlation matrix. The values are unique and intuitively make sense" (Pett, Lackey, and Sullivan, 2003: p. 100). In PAF the leftover or residual correlations will be smaller in absolute value and, as a result, will produce a smaller root mean square RMS error (Nunnally and Bernstein, 1994). Another advantage of PAF is that it can be used when the assumption of normality has been violated (Fabrigar et al., 1999).

Compared to the principal component (PCA) method, PAF is more likely to produce superior solutions, because of the lower values of RMS which indicate a better fit to the data (Nunnally and Bernstein, 1994; Pett et al., 2003). PCA is a data-reduction technique that produces components whereas PAF produces factors (Yong and Pearce, 2013). Specifically, PAF analysis yields the least number of factors that account for the common variance (places communality estimates on diagonal of correlation matrix) in the original data (Harman, 1976; Cureton and d'Agostino, 1983; Tucker and MacCallum, 1997; Henson and Roberts, 2006; Stevens, 2012). That is, PAF is only analyzing common factor variability, removing the uniqueness or unexplained variability from the model. Thus, PAF is preferred because it accounts for co-variation, whereas PCA accounts for total variance.

Factor rotation was carried out with the objective of obtaining a solution that is more parsimonious and provides easier intepretations of the results by concentrating the variable loadings on a particular factor (Kieffer, 1999; Hair et al. 2009; Williams et al., 2010; Rossoni et al., 2016). There are two main classes for rotation—orthogonal and oblique. Orthogonal rotation seeks to find a solution that minimises the relationship between factors (Baglin, 2014). However, this method has been criticised, since factors that make up a latent variable are generally correlated with each other to some degree (Reise, Waller, and Comrey, 2000; Costello and Osborne, 2005; Gaskin and Happell, 2014; Beavers et al., 2013; Yong and Pearce, 2013). Therefore, for the purpose of this research, oblique rotation which allows the factors to be correlated was carried out as a rotation method in EFA analysis. Oblique rotation produces a pattern matrix that contains the factor or item loadings and factor correlation matrix that includes the correlations between the factors (Baglin, 2014).

The common oblique rotation techniques are Direct Oblimin and Promax. Direct Oblimin generates correlated factors with high but very complex eigenvalues, which makes analysis difficult (Rossoni et al., 2016). Therefore, in this study, Promax is expedient because of its speed in larger datasets. Promax involves "raising the loadings to a power of four which ultimately results in greater correlations among the factors and achieves a simple structure" (Gorsuch, 1983, cited in Yong and Pearce, 2013: p. 84).

Third, the number of factors within each instrument were decided based on examination by two approaches, namely Kaiser Criterion (or eigenvalues test) and Cattell's (1966) scree plot. Kaiser's criterion is a rule of thumb which suggests retaining all factors that are above the eigenvalue of 1.00 (Kaiser, 1960; Comrey and Lee, 1992). This would mean these factors account for more than their share of the total variance in the items (Pett et al., 2003: p. 115). It has been argued that this criteria may result in overestimation in the number of factors extracted (Costello and Osborne, 2005; Field, 2013); therefore, it is suggested to use the scree test in conjunction with the eigenvalues to determine the number of factors to retain (Yong and Pearce, 2013). According to Bentler and Yuan (1998), the objective of the scree plot is to visually locate an elbow, which can be defined as the point where the eigenvalues form a descending linear trend. To conduct a scree test, a plot was created with the number of dimensions on the *x*-axis and the corresponding eigenvalues (percentage of variance accounted for by a dimension) on the *y*-axis (Reise et al., 2000).

Another criterion for determining the number of factors is the cumulative percentage of variance extracted by successive factors. That is, the factor extraction process should be terminated when a threshold for maximum variance extracted has been achieved (Pett et al., 2003). No fixed threshold exists, although certain percentages have been suggested (Williams et al., 2010). In the social sciences, the explained variance is commonly as low as 50-60% (Pett et al., 2003).

Fourth, when interpreting the factors, the factor loadings were used to determine which variables are attributable to a factor, and giving that factor a name or label. Traditionally, at least two or three variables must load on a factor so it can be given a meaningful interpretation (Henson and Roberts, 2006). Williams et al. (2010) note “the reason for thorough and systematic factor analyses is to isolate items with high loadings in the resultant pattern matrices… In other words, it is a search to find those factors that taken together explain the majority of the responses” (Williams et al., 2010: p. 9). Tabachnick and Fidell (2001) cite 0.32 as a good rule of thumb for the minimum loading of an item. Garson (2010) recommends that factor loadings < .40 are weak and factor loadings ≥ .60 are strong (Garson, 2010). Hair et al. (1995) categorized Factor loadings using a rule of thumb as ±0.30=minimal, ±0.40=important, and ±.50=practically significant. The signs of the loadings show the direction of the correlation and do not affect the interpretation of the magnitude of the factor loading or the number of factors to retain (Kline, 2014).

In addition, there should be no or few item cross-loadings (i.e., split loadings) so that each factor defines a distinct cluster of interrelated items (Yong and Pearce, 2013). According to Costello and Osborne (2005), a cross-loading happens when there is an item with loads at .32 or higher on two or more factors (Costello and Osborne, 2005). In such a case, the complex variable can be retained with the assumption that it is the latent nature of the variable, or the complex variable can be dropped when the interpretation is difficult (Yong and Pearce, 2013). Strong factor loadings that do not cross load may indicate good convergent validity.

Finally, to produce factor scores that can be treated as individual variables, the Bartlett method (or regression approach), which produces unbiased scores that are correlated only with their own factor (Yong and Pearce, 2013), was conducted as a final step in the EFA analysis.

4.6.2.2. Confirmatory factor analysis (CFA)

After the number of factors underlying each item that best fit the data was statistically identified through EFA, measurement models for each of the study’s constructs were refined by implementing confirmatory factor analysis (CFA) to verify the number of the underlying dimensions of the instrument (*factors*) and the pattern of item-factor relationships (*factor loadings*) (Hair et al., 2009; Brown, 2014). CFA statistics aim to determine if the sample data are consistent with the imposed constraints or, in other words, whether the data satisfy a particular conceptual structure extracted from a theory (Hoyle, 1995; Thompson, 1997; Jackson et al. 2009; Hox and Bechger, 2007; Rossoni et al., 2016). That is, the prototypic use of CFA is deductive, focusing on the correspondence between the pattern of associations in observed data and the pattern implied by a model specified apart from a knowledge of those data (i.e., hypothesized model) (Hoyle, 1995). That is, the objective of CFA is to obtain estimates for each parameter of the measurement model (i.e., factor loadings, factor variances and covariances, indicator error variances and possibly error covariances) that produce a predicted variance–covariance matrix that resembles the sample variance–covariance matrix as closely as possible (Brown, 2006).

Confirmatory analysis is also characterized as being an interdependence technique, because it does not define any type of dependence relationship between the variables used and the resulting factors (Thompson, 2004). Comparing to EFA analysis, CFA allows the researcher to conduct two forms of data analysis not available in EFA: (1) CFA allows for the examination of second-order (i.e., higher-order) latent variables. (2) CFA allows for testing hypotheses related to construct validity (i.e. testing the statistical significance of the effect of a latent variable on each of the observed variables posited to measure it).

In practice, CFA is often confined to the analysis of the variance-covariance structure (Brown, 2014). In this case, the parameters (i.e. factor loadings, error variances and covariances, factor variances and covariances (Kenny and Milan, 2012) are estimated to reproduce the input variance-covariance matrix (Brown and Moore, 2012), p. 365). In order to estimate the aforementioned parameters in CFA the model must be specified and identified. Model specification in CFA (and SEM, in general) involves designating the variables (*observed or latent/ exogenous or endogenous*), relations among the variables (*directional* in the case of structural models or *nondirectional* in the case of CFA models), and the status of the parameters in a model (f*ree or fixed*) (Hoyle, 2012a). A specified model offers a parsimonious (i.e. includes relatively few unknowns to be estimated from the data), plausible (i.e. high in hypothesis validity), and substantively meaningful account of the processes that gave rise to the observed data (i.e. leaves relatively little unexplained) (Hoyle, 2012a).

A key concern in specification is identification. Each parameter in a specified model must be identified. A model is identified if, on the basis of known information (i.e., the variances and covariances in the sample input matrix), it is possible to obtain a unique set of parameter estimates for each parameter in the model whose values are unknown (e.g., factor loadings, factor correlations, etc.) (Kenny and Milan, 2012). Identification is achieved by incorporating or imposing substantively motivated restrictions into the model (Hoyle, 2012b). According to Scott Long (1983), in the confirmatory factor model these constraints determine: which pairs of common factors are correlated, which observed variables are affected by which common factors, which observed variables are affected by a unique factor, and which pairs of unique factors are correlated. A typical CFA model has the form (Luo, 2011):

$$x = \Lambda\xi + \delta$$

Where $\mathbf{x}$ *is a vector of p observables, the matrix* $\boldsymbol{\Lambda}$ *of order p × k contains the factor loadings* $\boldsymbol{\lambda ij}$, $\boldsymbol{\xi}$ *is a vector of k latent factors and* $\boldsymbol{\delta}$ *is a vector of p error terms representing "unique" variance in* $\mathbf{x}$.

To make sure the model is identified, some elements of Λ may be fixed at zero (Hoyle, 2012). So, let Φ of order k ×k and Θ of order p×p be the covariance matrices of ξ and δ, respectively. We assume that the unique factors are uncorrelated so that Θ is a diagonal matrix. The covariance matrix of x then becomes:

$$\Sigma(\Lambda, \Phi) = \Lambda\Phi\Lambda + \Theta$$

Where $\Sigma = E(x\,x')$, $\Phi = E(\xi\,\xi')$, $\Theta = E(\delta\,\delta')$, *and* $E(\delta)=0$. *We write* $\Sigma(\Lambda, \Phi)$ *to emphasize that* Σ *is a function of* Λ *and* Φ.

The path diagram of a typical CFA model with two factors and six indicators is shown in Figure 4.7. In matrix form, the model is:

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \\ x_6 \end{pmatrix} = \begin{pmatrix} \lambda_{11} & 0 \\ \lambda_{21} & 0 \\ \lambda_{31} & 0 \\ 0 & \lambda_{42} \\ 0 & \lambda_{52} \\ 0 & \lambda_{62} \end{pmatrix} \begin{pmatrix} \xi_1 \\ \xi_2 \end{pmatrix} + \begin{pmatrix} \delta_1 \\ \delta_2 \\ \delta_3 \\ \delta_4 \\ \delta_5 \\ \delta_6 \end{pmatrix}$$

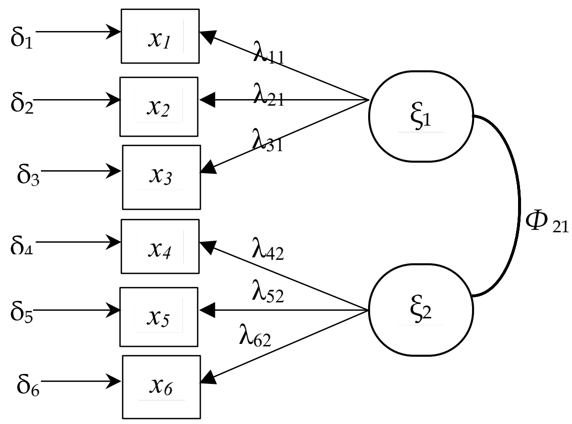


Figure 4.7: Path Diagram of a typical CFA model with two factors and six indicators

In Figure 4.7 above, latent factors ξ_i are drawn as circles or ellipses, manifest variables X_i are drawn as squares with the error δ_i associated with the manifest variables (Ho et al., 2012). Single-headed arrows indicate the causal paths between latent factors with the factor loading denoted as λ_{if}, which are coefficients that give the impact of the variable at the base of the arrow on the variable at the head. Double-headed arrows denote either correlation between the error terms of manifest variables or latent factors. Correlations between manifest variables are denoted by Θ_{if} while that between latent factors is denoted by Φif.

The two necessary aspects of CFA model identification are scaling the latent variables and statistical identification. By definition, latent variables are unobserved and thus have no inherent metrics; thus, their units of measurement must be defined by the researcher (Ho et al., 2012). In CFA, this is accomplished by fixing the loading of one indicator, called the "marker variable," to 1. Alternatively, the variance of a latent exogenous variable can be fixed to some value, usually 1 (Kenny and Milan, 2012). Since the latter method does not produce an unstandardized solution, the former method, i.e. "marker variable method", which produces both a standardized and an unstandardized solution, was applied in this research.

Besides scaling the latent variable, the parameters of a CFA model can be statistically identified. Statistical identification pertains in part to the difference between the number of freely estimated model parameters and the number of pieces of information in the input variance–covariance matrix (Brown, 2006). The difference constitutes the model's degrees of freedom (*df*) (Brown and

Moore, 2012). This approach recommends that the number of freely estimated parameters should not exceed the number of pieces of information in the input variance/covariance matrix. Overidentified solutions have positive *df*, whereas underidentified solutions have negative *df* (Brown, 2006). An underidentified model is one in which it is impossible to obtain a unique estimate of all of the model's parameters. For CFA models, there are three types of overidentifying restrictions, and all involve what are called *vanishing tetrads*, in which the product of two correlations minus the product of two other correlations equals 0 (Kenny and Milan, 2012). However, According to Kenny and Milan (2012), if the model contains correlated errors, then the identification rules need to be modified. For the model to be identified, then as a rule of thumb, each latent variable needs two indicators that do not have correlated errors, and every pair of latent variables needs at least one indicator of each that does not share correlated errors.

By ensuring that CFA measurement models are adequately identified, the estimation process was carried out using maximum likelihood (ML) (Jöreskog, 1967; 1969) as the method for the model estimations. The estimation process in CFA (and SEM, in general) entails a "fitting function," a mathematical operation to minimize the discrepancy between the sample variance–covariance matrix (S) and model-implied variance–covariance matrix (S(Θ)) (Schreiber et al., 2006; Hair et al., 2014; Kline, 2015; Lei and Wu, 2012).

The underlying principle of ML estimation is to find the parameter values that make the observed data most likely (or conversely, maximize the likelihood of the parameters given the data). The fit function for ML given by Bollen (1989) is shown in the equation:

$$F(ML) = \log|\Sigma\ (\theta)| + tr\big(\ S\Sigma - 1(\theta)\big) - \log|S| - p$$

Where log(.) is the natural logarithm function, tr(.) is the trace function, and p is the number of observed variables.

Under the assumption of multivariate normality of observed variables (that should be measured on continuous scales) and a correct model specification, the ML estimator is asymptotically consistent, unbiased, efficient, and normally distributed, and the model fit statistic (T_{ML}) is asymptotically distributed as chi-square (χ^2) with *df* = p(p + 1)/2 – t, where t is the number of model parameters estimated (Lei and Wu, 2012). Although the actual parameter estimates (e.g. factor loadings) may not be affected, non-normality in ML analysis can result in deflated standard errors (hence, faulty significance tests) and inflated chi-square (χ^2) (Bollen, 1989; Chou, Bentler, and Satorra, 1991), which are both corrected for non-normality in large samples (Brown and Moore, 2012).

Once model parameters have been estimated, the implementation proceeds to evaluation, one of the most important steps in structural equation modelling. The objective of evaluation is to determine whether the specified model offers an acceptable account of the data or should be rejected or re-specified. Three major aspects of the results from the model estimation process should be examined to evaluate the acceptability of the CFA model (Brown and Moore, 2012): (1) overall goodness of fit; (2) the presence or absence of localized areas of strain in the solution (i.e., specific points of ill fit); and (3) the interpretability, size, and statistical significance of the model's parameter estimates.

The key question for assessing the overall fit of the model is how well the estimates implied by the model match the variances, covariances, and means of the observed data (West et al, 2012). Most of the practical fit indices involve the chi-square (χ^2) test statistic (Jöreskog, 1969) for the hypothesized model. For standard ML estimation, if the observed χ^2 exceeds the critical value given the *df* and the nominal Type I error rate (typically a = .05), the null hypothesis that $\Sigma(\theta) = \Sigma$ is rejected. This means that the null hypothesis of perfect fit in the population is false, the assumptions are wrong, or both (West et al., 2012). That is, a smaller χ^2 , relative to its degrees of freedom, suggests that the model fits the data better. An insignificant χ^2 suggests the model fits the data well. However, there are salient drawbacks of the χ^2 statistic, including the fact that it is highly sensitive to sample size (i.e., solutions involving large samples would be routinely rejected on the basis of χ^2 even when differences between the sample and model-implied matrices are negligible) (Bentler and Bonett, 1980; Box, 1979; Jöreskog and Sörbom, 1981; MacCallum et al. 2001; West et al., 2012).

Because of the critical importance of the decision to accept or reject a specified model, special emphasis has historically been placed on the criterion that the value of fit indices for correctly specified or slightly misspecified models should not be affected by sample size (Marsh, Balla, and McDonald, 1988; Hu and Bentler, 1998). Fit indices are distinguished mainly as "absolute fit", "incremental fit" or "parsimony fit" by SEM scholars (McDonald and Ho, 2002; Bentler and Bonett, 1980; Hooper, Coughlan, and Mullen, 2008; West et al., 2012). Absolute fit indices are functions of the test statistic T or of the residuals (Yuan, 2005). The aforementioned $\chi 2$ statistic, the root mean square error of approximation (RMSEA) (Steiger, 1990; Steiger and Lind, 1980) are the most cited absolute fit indices. In contrast, incremental fit indices (also known as comparative or relative fit indices) capture how well a specified model fits the sample data, by comparing it with an alternative baseline model, e.g. an independent model. The comparative fit index (CFI) (Bentler, 1990), the Tucker–Lewis index (TLI) (Tucker and Lewis, 1973), the normed fit index (NFI) (Bollen, 1989; Marsh et al., 1988), the relative non-centrality index, and the incremental fit (IF) index are comparative fit indices. On the other hand, parsimony fit measure is a measure developed to provide information about which is the best model among a set of competing models, after considering its fit relative to its complexity. Some of the parsimony fit measures are the $\chi 2/\mathrm{df}$ ratio (Jöreskog, 1969), goodness-of-fit index (GFI) (Jöreskog and Sörbom, 1981), adjusted goodness-of-fit (AGFI) and parsimony normed fit index (PNFI).

In practice, it is suggested that multiple fit indices should be reported and considered because they provide different information about model fit (Brown and Moore, 2012). Considered together, these indices provide a more conservative and reliable evaluation of the fit of the model. In one of the more comprehensive and widely cited evaluations of cutoff criteria, the findings of simulation studies by Hu and Bentler (1999) suggest the following guidelines for acceptable model fit: (1) SRMR values close to .08 or below; (2) RMSEA values close to .06 or below; and (3) CFI and TLI values close to .95 or greater (Hu and Bentler, 1999). To summarise, for this study, the selected fit indices and their acceptable thresholds recommendations are demonstrated in Table 4.6 below.

Table 4.6: Summary of the fit measures used in this present study

Fit Index/Reference	Goodness-or badness-of-fit ?	Theoretical range	Cut-off criterion	Sensitive to Sample size N?	Penalty for model complexity?

$\chi^2 = (N\text{-}1)F$ *(Jöreskog, 1969)*	Badness	≥ 0	**Insignificant (p) value (p>0.05)***	Yes	No
χ^2/df **ratio** *(Jöreskog, 1969)*	Badness	≥ 0	**< 5**	Yes	Yes
$\mathbf{GFI} = 1 - \frac{e'We}{s'Ws}$ *(Jöreskog & Sörbom, 1981)*	Goodness	0-1	**> 095**	Yes	No
$\mathbf{RMSEA} = \sqrt[2]{\frac{\lambda n}{df}} = \sqrt[2]{\frac{Max(\chi 2 - df, 0)}{df(N-1)}}$ *(Steiger & lind, 1980)*	Badness	> 0	**< .06**	Yes, to small N	Yes
$\mathbf{TLI} = \frac{\chi_o^2/df_o - \chi_i^2/df_i}{\chi_o^2/df_o - 1}$ *(Tucker & lewis, 1973)*	Goodness	0-1	**> 0.95**	NO	Yes
$\mathbf{CFI} = \frac{\max(\chi_o^2 - df_o, 0) - \max(\chi_i^2 - df_i, 0)}{\max(\chi_o^2 - df_o, 0)}$ *(Bentler, 1990)*	Goodness	0-1	**> 0.95**	NO	Yes

Source: West et al. (2012: p. 212-213). Note: **e**, a vector of residuals from a covariance matrix; **s**, a vector of the p* nonredundant elements in the observed covariance matrix; **W**, a weight matrix; **Ws**, a diagonal weight matrix used to standardize the elements in a sample covariance matrix, **o**, baseline model; **i**, tested or hypothesized model. *The value of χ2 varies largely with the sample size and tends to be more inaccurate with large sample size and thereby significant p values are expected.

However, the global goodness-of-fit indicates that a satisfactory model does not always mean certain parameters corresponding to hypothesized relations are significant and/or all measurement models are good in reliability. From this, the second aspect of model evaluation is to determine whether there are specific areas of ill fit in the solution (Brown and Moore, 2012). Two statistics that are frequently used to identify specific areas of misfit in a CFA solution are standardized residuals and modification indices. Residuals are the difference between the expected **Σ** and observed **S** variable covariances (McDonald and Ho, 2002). When standardized, these residuals are analogous to standard scores in a sampling distribution and can be interpreted like *z*-scores (Brown and Moore, 2012). Stated another way, these values represent estimates of standard deviations that the observed residuals are from the zero residuals (i.e., the residuals if model fit were perfect) (West et al., 2012; Byrne, 2016).

Examination of residuals provides evidence of the degree of disconfirmability of a model, as "it becomes possible to judge whether a marginal or low index of fit is due to a correctable misspecification of the model, or to a scatter of discrepancies, which suggests that the model is possibly the best available approximation to reality" (McDonald and Ho, 2002: p. 73). In general, large standardised residuals (larger than |2.58| (Jöreskog and Sörbom, 1996) or |1.96| (Bagozzi and Yi, 1988) indicate that a particular covariance is not well reproduced by the model's parameter estimates (Holmes-Smith, Coote, and Cunningham, 2006). On the other hand, small residuals indicate that the model is good at accounting for the data, regardless of the implications of the chi-square χ 2 test or fit indices. When a problematic variable is identified, the researcher may, depending on theoretical reasoning, proceed by estimating additional parameters (e.g. error covariance) or by deleting that variable from the model (Holmes-Smith and Coote 2002).

Modification indices (MI) are another useful aid in assessing the potential source of model misspecification (Jöreskog and Sörbom, 1989). MI are calculated for each fixed parameter (i.e. that are fixed to zero, such as indicator cross-loadings and error covariances) and each constrained parameter in the model (e.g., parameter estimates that are constrained to be the same value) (Brown and Moore, 2012). Each such MI measures how much a chi-square value with 1 *df* is expected to decrease if a particular non-free parameter is set free (i.e. estimated) and the model is re-estimated (Ho, 2013). All freely estimated parameters have MI values equal to zero (Byrne, 2016). An MI greater than 3.84 (i.e., the critical value CR of $\chi 2$ at $p < .05$, df = 1) or 6.63 (i.e. CR of $\chi 2$ at $p < 0.01$, df=1) suggests model modification might need to be considered (Bagozzi and Yi, 1988) and that the overall fit of the model could be significantly improved if the fixed or constrained parameter were freely estimated (Brown and Moore, 2012). Associated with each MI is an expected parameter change which measures magnitude and direction of change of each fixed parameter, if it is set free.

However, model modification based on purely empirical grounds is ill advised and discouraged since it often results in further model misspecification and overfitting (Hair et al., 2010; Brown and Moore, 2012). Bagozzi and Yi (1988) suggest that models should not be modified unless there are some theoretical and/or methodological justifications. Accordingly, these modification indices should be used with extreme caution and should never be relied on as the sole guide to model modification (MacCallum, Roznowski, and Necowitz, 1992) because they often suggest atheoretical but statistically significant models that perform poorly in cross-validation samples (i.e. little generalizability and limited use in testing casual relationships) (Reise et al., 2000; Hair et al., 2010).

The final major aspect of CFA model evaluation pertains to the interpretability, strength, and statistical significance of the parameter estimates (Brown and Moore, 2012). The parameter estimates (e.g., factor loadings and factor correlations) should only be interpreted in the context of a good fitting solution; otherwise, the parameter estimates are likely biased (incorrect). From a substantive standpoint, all factor loadings are required to be a magnitude and direction that is in accord with conceptual or empirical reasoning (e.g., each indicator should be strongly and significantly related to its respective factor, and the size and direction of the factor correlations should be consistent with expectations and within the range of ± 1.00 if standardised (Brown and Moore, 2012; Ho, 2013). That is, they are greater than zero for a positive relationship and less than zero for a negative relationship (Hair et al., 2011). A rule of thumb suggests that factor loadings (i.e. standardised regression weights) should be at least 0.5 or higher, and ideally 0.7 or higher (Hair et al., 2010).

Furthermore, to assess the issue of uni-dimensionality in CFA, it is recommended that the squared multiple correlations (SMC) (i.e., a measure of statistical variance and equivalent to the estimated communality (R^2) in EFA) of each item (i.e. observed variable) measuring the underlying construct should be greater than 0.3 (Holmes-Smith et al., 2006). A low SMC value (i.e., less than 0.3) for an item indicated that the variable has little in common in regard to statistical variation with the construct it reflected and, thus, it should be dropped from the analysis (Holmes-Smith et al., 2006). Another important step in this stage is to assess the standard errors of the loadings, with small values indicating accurate estimation (Byrne 2016). However, Byrne (2016) further explains that poor fit can also be represented by extremely small or large loadings standard errors, as, on the one hand, a standard error that approaches zero indicates that the parameter cannot be defined, while, on the other hand, a standard error that is excessively large shows that parameters cannot be determined. There is as yet no set measure of small and large standard errors to determine the cut-off points (Jöreskog and Sörbom 1989). The final step in assessing the fit of individual parameter estimates is to examine their statistical significance. Parameters are considered statistically significant when their z-statistic, operating as the critical ratio (C.R) values, are greater than ± 1.96 at $\alpha = 0.05$ significance level (Hair et al., 2010); (Byrne, 2016). Small or statistically nonsignificant estimates may be indicative of unnecessary parameters (e.g., a non-salient error covariance or indicator cross-loading). In addition, such estimates may highlight indicators that are not good measures of the factors (i.e., a small and nonsignificant primary loading may suggest that the indicator should be removed from the measurement model). On the other hand, extremely large parameter estimates may be substantively problematic (Brown and Moore, 2012). Another examples of parameters displaying awkward estimates are negative variances, correlations greater than one (>1), and covariance or correlations matrices that are not positive definite.

The results of CFA can provide compelling evidence of the convergent and discriminant validity—that are adjusted for measurement error—of theoretical constructs. “Convergent validity” refers to the degree to which scores on a test correlate with scores on other tests that are designed to assess the same construct. Convergent validity is indicated by evidence that different indicators of theoretically similar or overlapping constructs are strongly interrelated. On the other hand, “discriminant validity” is the degree to which scores on a test do not correlate with scores from other tests that are not designed to assess the same construct (Farrell, 2010).

Convergent validity was evaluated for all of the constructs in this research using three criteria recommended by Fornell and Larcker (1981): (1) All measurement factor loadings must be significant and exceed 0.70, (2) Construct reliabilities (also termed Composite Reliability (CR): the overall reliability of a set of items loaded on a latent construct) must exceed 0.70 (or 0.60 (Bagozzi, Yi, and Phillips, 1991), and (3) Average Variance Extracted (AVE) by each construct must exceed the variance due to measurement error for that construct (Hair et al., 2010). AVE is “the average amount of variance in observed variables that a latent construct is able to explain” (Farrell, 2010: p. 325). It is commonly suggested that all latent factors should have an AVE of at least 0.5 (Hair et al., 2010); an AVE less than 0.5 is considered questionable (Fornell and Larcker, 1981). An AVE less than 0.5 indicates that, on average, less than 50% variance of observed variables can be explained by the latent factor, or more than 50% error remains in the observed variables (Hair et al., 2010). Accordingly, AVE is a strict measure of convergent validity. Malhotra and Dash (2011) note that "AVE is a more conservative measure than CR. On the basis of CR alone, the researcher may conclude that the convergent validity of the construct is adequate, even though more than 50% of the variance is due to error.” (Malhotra and Dash, 2011: p. 702).

Discriminant validity is the extent to which a construct is truly distinct from other constructs. It means that a latent variable should explain better the variance of its own indicators than the variance of other latent variables. In other words the loading of an indicator on its assigned latent variable should be higher than all of its cross loadings on other latent variables. Discriminant validity check is done by comparing the variance-extracted estimates (AVE’s) with the squared correlation for each of the constructs (Bove et al., 2009). The AVE of a latent variable should be higher than the squared correlations between the latent variable and all other latent variables (Fornell and Larcker, 1981). Composite Reliability (CR) Average Variance Extracted (AVE) were calculated based on the final model using an excel tool given by Gaskin (2016).

Finally, this thesis took extra precautions to increase confidence in the replicability of the final measurement model by cross-validating it— i.e. fitting the model to a new sample of data (Cudeck and Browne 1983; Anderson and Gerbing, 1988; Thompson, 2013). Cross-validation, the final step in the SEM research process, is necessary to guard against the possibility that sample-based solutions have capitalised on chance relationships within the sample that are not present in another sample (Holmes-Smith et al., 2006). In cross-validation, a sufficiently large sample is randomly split into two subsamples with the purpose to repeat the intended analysis (in thiss case factor analysis) in each subsample (Brown, 2015; Byrne, 2012; Hair et al., 2010; Thompson, 2013). Replicating a factor analytic solution in a different sample can provide support for generalizability and stability of the model, thus contributing to its validity (DeVellis, 2017).

Using the split-sample validation approach, this thesis evaluates the measurement models using CFA to achieve scale purification and assessment of model fit. As performed previously in studies using split-sample validation for factor analyses (e.g., Pohlmann, 2004; Shah and Ward 2007; Kyriazos, 2018), the generally suggested method to split a sample is by randomly dividing it into two equal parts. The first part is called the calibration sample, and the second the validation sample. On the calibration sample, the hypothesized factor structure is tested, as well as any initial analyses for achieving a well-fitting model. Once a feasible solution is found, its validity is verified and confirmed by testing it on the validation sample. Anderson and Gerbing (1988) described this process as follows: "ideally, a researcher would want to split a sample, using one half to develop a model and the other half to validate the solution obtained from the first half" (Anderson and Gerbing 1988: p. 421).

4.7 STRUCTURAL MODELS: TESTING RESEARCH HYPOTHESES

"SEM is a comprehensive and flexible approach to modeling the relations among variables in a set".

(Rick H Hoyle, 2012: p. 15)

The model is a statistical statement, expressed with equations or path diagrams, about the hypothesized relationships among variables based on theory and research (Hoyle, 1995; Pearl, 2012; Kline, 2012). The coefficients generated to describe the strength of these relationships are interpreted in much the same way as regression weights (Weston and Gore Jr, 2006). Accordingly, equations in the structural portion of the model specify "the manner by which particular latent variables directly or indirectly influence (i.e., "cause") changes in the values of certain other latent variables in the model" (Byrne, 2001: p. 12). A direct effect represents the effect of an independent variable (exogenous) on a dependent variable (endogenous). An indirect effect represents the effect of an independent variable on a dependent variable through one or more mediating variables (Baron and Kenny, 1986).

In this research, all analyses were performed using models that focus primarily on unidirectional effects among latent constructs as dictated by theory (Bollen and Hoyle, 2012; Pearl, 2012). In this type of structural models there may be multiple outcomes (dependent variables) among which there are directional relations. There may also be directional relations between predictors or independent variables (Hoyle, 2012), which in turn may allow for a dependent variable in one model equation to become an independent variable in other components of the SEM system (Bollen, 1989; Gunzler et al., 2013). Besides the application of structural equation models that focus on unidirectional effects, this research uses structural equation models that focus on bi-directional effects which are more complicated in the sense that two variables are thought to simultaneously predict each other .

4.7.1 Non-recursive Structural Equation Models

The most straightforward types of SEM analyses commonly seen in the literature are models that test cross-sectional, linear, recursive (i.e., unidirectional) relationships among continuously measured variables during a single period (Martens and Haase, 2006). It is possible, however, to test more complex designs of non-recursive models. The hypothesized dual-process model of cognitive-affective risk perception (Figure 3.1) is estimated using a nonrecursive (i.e., a bi-directional) structural equation model. Nonrecursive models commonly have direct feedback loops or reciprocal relationships where two latent variables are specified as both causes and effects of each other (Kenny and Milan, 2012; Finch and French, 2015; Nagase and Kano, 2017). According to Kline (2015), each of these variables is measured only once and also simultaneously; that is, "feedback is estimated with data from a cross-sectional design ….(which) assumes equilibrium, or that changes in the system underlying reciprocal causation have already manifested their effects and that the system is in a steady state." (Kline, 2015: p, 135-136). The assumption here implies that if a causal feedback loop has not fully stabilized yet, cross-sectional data would not be able to endorse a concurrent bi-directional relationship (Kline, 2012). Violation of the "functional equilibrium assumption" can lead to substantially biased estimates of the direct effects (Kenny, 1979; Kaplan, Harik, and Hotchkiss, 2001).

In this sense, the dispute has arisen over estimating simultaneous causation in designs with synchronous measurement (i.e. with the absence of temporal precedence in which the cause did indeed happen before the effect in such designs) (Wong and Law, 1999). This entails that the bi-directional relationship that forms a direct feedback loop, such as 'Y1⇄Y2', represents an "instantaneous cycling process", but in the actual world there may be no such causal 'bi-directional relationship (Hunter and Gerbing, 1982 cited in Kline, 2015: p. 136). The use of cross-lagged panel models (CLPMs) where two or more variables are measured at two or more occasions and interest is focused on the associations (often causal theories) with each other over time (Kenny, 2005) is believed to overcome this complication. However, the use of CLPMs is undeniably not always suitable because, first, the lag for some causal reciprocal effects is so short (or even zero) that it would be impractical to measure them over time (Finkel, 1995), e.g. it has been argued that cognitive processing and emotional processing of information in the human brain are more likely to occur simultaneously but not sequentially (LeDoux, 1989; Pessoa, 2015). If so, the assumption of instantaneous cycling for feedback loops in nonrecursive models would be more defensible (Kline, 2015). Second, the actual length of causal lags is not always known (Wong and Law, 1999). If so, longitudinal data collected according to some particular temporal measurement schedule are not automatically superior to cross-sectional data (Kline, 2015).

Another complication (often neglected) of nonrecursive models is empirical identification (Nagase and Kano, 2017; Kline, 2012). One approach to remedy this complication is adding an exogenous variable (instrumental variable IV (Finch and French, 2015)) that has a direct effect on one of the endogenous variables involved in the feedback loop but at the same time must be excluded from having a direct path to the other endogenous variable in the model (Kenny, 1979; Martens and Haase, 2006). The added instrumental variable must also make sense theoretically. For example, presented in Figure 4.8 is the most basic type of nonrecursive structural model with a direct feedback loop identified (Bollen, 1989). Here, the instrumental variables X=(X1,X2) have to satisfy that there are no direct effects from X1 to Y2 and from X2 to Y1, in other words, Y12=Y21=0.

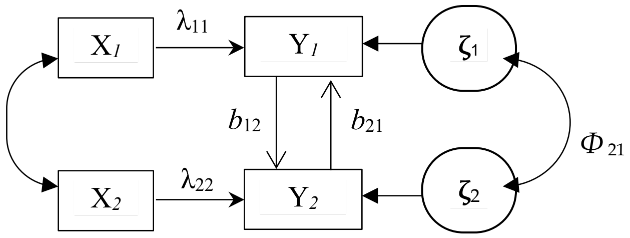


Figure 4.8: A basic type of nonrecursive structural model

The parameter matrices B, Γ and ψ for this model are cited in Nagase and Kano (2017) :

$$\boldsymbol{B} = \begin{bmatrix} 0 & b12 \\ b21 & 0 \end{bmatrix}, \Gamma = \begin{bmatrix} \lambda 11 & 0 \\ 0 & \lambda 22 \end{bmatrix}, \boldsymbol{\psi} = \begin{bmatrix} \Phi 11 & \Phi 12 \\ \Phi 12 & \Phi 22 \end{bmatrix}$$

The structural equation for this model is:

$$Y = By + \boldsymbol{\Gamma x} + \boldsymbol{\zeta} \quad \Leftrightarrow \quad Y = (1\text{-}B)^{-1}\,(\boldsymbol{\Gamma x} + \boldsymbol{\zeta})$$

Where Y and X are p×1 and q×1 random vectors of observations, respectively. There may be reciprocal relationships between several variables within the vector y. The variables in vector x are usually referred to as instrumental variables. Although there is no requirement for correlated disturbances for variables involved in feedback loops, the presence of disturbance correlations in particular patterns in nonrecursive models helps to determine their identification status (for further details see Kline (2013: p. 45-50)

In the data-analytic realm, a considerable literature discusses the mechanics of the statistical solution to non-recursive models (Kenny, 1979; Berry, 1984; Schaubroeck, 1988; Schaubroeck, 1990; Bentler and Raykov, 2000; Martens and Haase, 2006; Paxton et al. 2011; Kline, 2015; Nagase and Kano, 2017). Following Schaubroeck's (1990) recommendations (and as commonly practiced in research: e.g., Eveland et al. 2005; Martens and Haase, 2006; Linden, 2014; Kitamura et al. 2013), this thesis tests the fit of this nonrecursive model against the strictly recursive model by a chi-squared difference test, the root mean squared error of approximation (RMSEA), the ratio of the chi-square statistic to the degrees of freedom for the model ($\chi 2/df$), and the GFI, CFI and TLI indices. However, there is additional evidence in the fit of the nonrecursive model that is compelling: both the path from Y1 to Y2 and the path from Y2 to Y1 must be significantly different from 0 (Martens and Haase, 2006).

The 'stability index' is another important criteria to judge when a nonrecursive model is anlayzed (Bentler and Freeman, 1983). It is based on certain mathematical properties of the matrix coefficients for direct effects among all endogenous variables in the structural model, not just those involved in feedback loops (Kaplan et al., 2001). According to Kline, (2013) these properties concern "whether estimates of the direct effects would get infinitely larger over time. If so, the system is said to "explode" because it may never reach equilibrium" (Kline, 2013: p. 58). A standard interpretation of the stability index is that values less than 1.0 are taken as positive evidence for equilibrium (Finkel, 1995). However, this index is not always sufficient as there is a need to evaluate the equilibrium assumption on rational rather than statistical grounds (Kline, 2013).

4.7.2 Mediation Analysis: Indirect Effect

A "mediator," or "mediating variable," is defined as "a third variable that intervenes in the relation between an independent variable and a dependent variable, transmitting the effect of the independent variable on the dependent variable" (Cheong and MacKinnon, 2012: p. 418). Baron and Kenny (1986) defined mediation as "the generative mechanism through which the focal independent variable is able to influence the dependent variable of interest" (p. 1173). Statistically, a third variable is considered a significant mediator when the relation between the independent and the dependent variables is completely or partially accounted for by the third-variable intermediate in the causal chain (Preacher and Hayes, 2008; Rucker et al. 2011; Cheong and MacKinnon, 2012; Tofighi and Thoemmes, 2014). More specifically, the basic idea of mediation analysis is to test the existence of an indirect effect from an independent variable to a dependent variable through a mediating variable (Baron and Kenny, 1986). Figure 4.9 depicts a simple mediation model with observed variables. The coefficients relating the exogenous variables to the endogenous variables are indicated as γ's and the coefficient relating the endogenous (mediator) variable to the endogenous is indicated as β'.

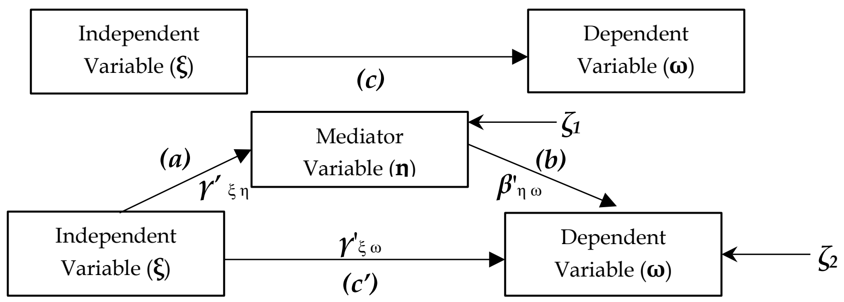


Figure 4.9: A simple mediation model.

The relations between the independent variable, the mediator, and the dependent variables are specified in the structural relations as follows (Cheong and MacKinnon, 2012):

$$\boldsymbol{\eta} = \beta\eta\omega + \Gamma\xi + \zeta$$

*where **Γ** matrix is a 2 × 1 vector representing the relations of the independent variable to the mediator and the dependent variable, and the **β** matrix is a 2 × 2 matrix representing the relation between the mediator and the dependent variable (Cheong and MacKinnon, 2012).*

The **Γ** matrix contains the direct effects of the exogenous independent variables (**ξ'**) on the mediators and the dependent variables (**ω'**), and the **B** matrix contains the direct effects of the mediators on the dependent variables. The direct effect, quantified by **c'** or $\boldsymbol{\gamma'_{\xi\,\omega}}$, is the influence of the causal variable on another variable involving "a chain of length one" in the sequence of the causal relation (Sobel, 1987; Baron and Kenny, 1986). The indirect effect, quantified by **ab** or (**γ' ξ η)(β'ηω)**, is the effect of one variable on another variable that is intervened by at least one additional variable in the "chains of length r (r ≥ 2)" causal relations (Sobel, 1987; Baron and Kenny, 1986). The total effect is the sum of indirect effect and the direct effect: c = c' + ab (Bollen, 1987). Equivalently, c' is the difference between the total effect of **ξ** on **ω** and the indirect effect of **ξ** on **ω** through **η**—that is, c'= c – ab (Cheong and MacKinnon, 2012). Complete mediation occurs when **ξ** no longer has an effect on **ω** after controlling for the mediator **η**, whereas in partial mediation, the effect of **ξ** on **ω** is diminished but remains significant after controlling for the mediator **η**.

In more complex models, as in Figure 4.10, the same rules apply. The total effect is equal to the direct effect of **ξ** on **ω** plus the sum of the indirect effect through **η1** and the indirect effect through **η2**. That is, $c = c' + a_1b_1 + a_2b_2$ (Hayes, 2009). In a model with two or more intervening variables, the indirect effect through a given intervening variable is called a specific indirect effect (e.g., the specific indirect effect of **ξ** on **ω** through **η**), and the sum of the specific indirect effects is called the total indirect effect of **ξ**.

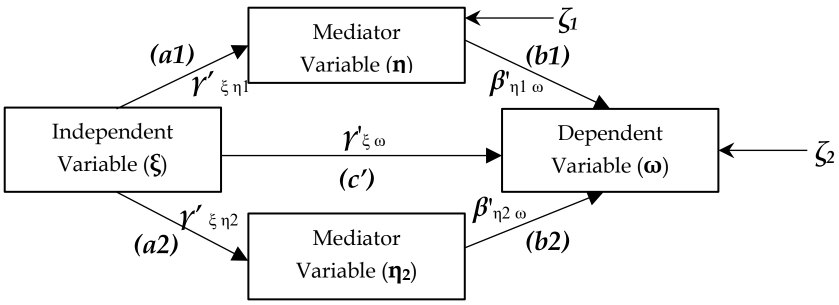


Figure 4.10: A single-step multiple mediator model with two proposed mediators

For testing hypotheses about mediation that involve assessing whether a mediated effect is large enough to be considered important (i.e. statistically significant) (MacKinnon and Fairchild, 2009), several methods have been proposed. By far the most commonly used method is the causal-step approach, popularized by Baron and Kenny (1986), which involves conducting a series of multiple regressions that can evidence a valid mediation effect. Specifically, four criteria should be met to claim the validity of mediation effect: i) there is significant effect from independent variable to the mediator, here, **a** in Figure 4.10; ii) there is significant effect from the independent variable to the dependent variable before the potential mediating variable is taken into account, here, **c** in Figure 4.10; iii) there is significant effect from the mediator to the dependent variable, controlling for the effect of the independent variable on the dependent variable, here, **b** in Figure 4.10 and iv) in comparison with **c**, the magnitude of **c'** is reduced substantially (Little et al., 2007). Although being highly recognised, the causal-step approach has been widely criticised for its low statistical power and its significance testing nature (MacKinnon and Fairchild, 2009; Rucker et al., 2011).

Most other approaches to testing mediation hypotheses focus not on the individual paths in the mediation model but instead on the product term **ab**, under the logic that this product is equal to the difference between the total and direct effect. The Sobel test (Sobel, 1982), also called the product-of-coefficients approach, involves computing the ratio of **ab** to its estimated standard error (SE). Numerous formulas have been proposed for estimating this SE (MacKinnon et al. 2002), but the differences among them usually have negligible effects on test outcomes. A ***p*** value for this ratio is computed in reference to the standard normal distribution, and significance supports the hypothesis of mediation (Preacher and Hayes, 2008). The Sobel test has a major flaw. It requires the assumption that the sampling distribution of the indirect effect is normal (Hayes, 2009). But the sampling distribution of **ab** tends to be asymmetric, with non-zero skewness and kurtosis (Bollen and Stine, 1990).

Alternatively, bootstrapping, a nonparametric resampling procedure (Efron and Tibshirani, 1993), is a method advocated for testing mediation that does not impose the assumption of normality on the sampling distribution (Shrout and Bolger, 2002; MacKinnon and Fairchild, 2009; Preacher and Hayes, 2008). Specifically, it is a computationally intensive method that "involves repeatedly sampling from the data set with replacement" (Shrout and Bolger, 2002: p. 426) and estimating the indirect effect in each resampled data set. By repeating this process for a total of k times, where k is some large number, typically at least 1000 (Hayes, 2009), an empirical approximation of the sampling distribution of **ab** is built and used to construct upper and lower confidence intervals for the indirect effect without having to assume normality (Bollen and Stine, 1990; Preacher and Hayes, 2008; Cheong and MacKinnon, 2012; Little et al., 2007). The mean and the standard deviation of this distribution are the bootstrap estimates of the indirect effect and standard error of the indirect effect, respectively (Cheong and MacKinnon, 2012).

Statistically, an inference is made about the size of the indirect effect in the population sampled by using the k estimates to generate a confidence interval (Mallinckrodt et al., 2006). This is accomplished by sorting the k values of **ab** from smallest to largest (Hayes, 2009). In this ordered set, confidence intervals of the indirect effect of the mediator can then be obtained by sorting the k values of **ab** from smallest to largest and defining the lower and upper bounds of a confidence interval (ci) as the value of **ab** in the k(.5 - ci/200)th ordinal position (lower bound) and the 1+ k(.5 + ci/200)th ordinal position (upper bound). This procedure yields a percentile based bootstrap confidence interval (Efron, 1981). The endpoints can be adjusted to yield a bias-corrected (BC) or a bias-corrected and accelerated (BCa) confidence interval (Efron, 1987). If zero is not between the lower and upper bound, then it can be inferred that the indirect effect is significantly different from zero at 100- ci%, indicating that the mediating variable accounts for some portion of the relationship between IV and DV (Hayes, 2009).

4.7.3 Moderation Analysis: Testing Latent Interaction Effects

When a third variable changes the relationship between two related variables (e.g. an exogenous and an endogenous construct), a moderating effect is present (Hair et al., 2016). In their classic presentation of moderation, Baron and Kenny (1986: p. 1174) defined a moderator variable to be a "variable that affects the direction and/or strength of the relationship between an independent or predictor variable and a dependent or criterion variable." An interaction effect occurs when the effect of at least one predictor variable on an outcome variable is moderated by one other predictor (i.e., depends upon or varies as a function of this variable) (Marsh et al., 2012).

Latent interaction modelling using SEM was used to test the hypothesized latent causal relationships in this study using the unconstrained, mean centring approach (Marsh, Wen, and Hau, 2004) for representing interaction terms. Regression analyses often understate the interaction effect and exhibit low statistical power because they fail to control for measurement error in the predictor variables. Alternatively, latent interaction modelling makes it possible to account for different kinds of random error and nonrandom measurement error, which in turn reduces bias in the estimation of the effects, and, ultimately, provides more defensible interpretations of the interaction effects (Steinmetz, Davidov, and Schmidt, 2011; Marsh et al., 2012).

In the last few years, there have been many approaches for estimating interactions between latent variables in structural equation modelling—"best practice" is still evolving (Kenny and Judd, 1984; Jaccard and Wan, 1995; Jöreskog et al. 1996; Algina and Moulder, 2001; Lin et al. 2010;

Marsh et al., 2004; Little et al., 2007; Little, Bovaird, and Widaman, 2006; Coenders, Batista-Foguet, and Saris, 2008; Bauer, 2005; Wen, Marsh, and Hau, 2010; Mooijaart and Bentler, 2010). Although the approaches of these researchers differ in details, most of them agree that a latent product variable is included in the model to represent the interaction term (Steinmetz, Davidov, and Schmidt, 2011). The indicators of the latent product variable (the so-called product indicators) are computed by multiplying the indicators of the latent variables which interact with each other (the indicators of the so-called first-order effect variables). A technical consequence of this procedure is that it requires various nonlinear constraints to be incorporated in the model to express the mathematical relationships between the product indicators and the first-order effect indicators (Jöreskog et al., 1996). Consequently, these approaches have been summarized as constrained approaches (Marsh et al., 2004).

The constrained product indicator approaches, initially proposed by Kenny and Judd (1984) and applied by many researchers (see, e.g. Algina and Moulder, 2001; Jaccard and Wan, 1995; Jöreskog and Yang, 1996), was unduly cumbersome and overly restrictive in terms of the assumptions upon which it was based (Marsh et al., 2012). In 2004, Marsh et al. criticized the fact that specifying nonlinear constraints would require normally distributed latent variables, a situation which is unlikely to be the case in reality. Even if the first-order effect variables (e.g. $\xi 1$ and $\xi 2$) are normally distributed, the product latent variable ($\xi 1 * \xi 2$) is non-normal because the product of two normally distributed variables is not normal (Jöreskog and Yang, 1996). Klein and Moosbrugger (2000) have developed a method of estimation that does not require nonlinear constraints and their procedure is described by Marsh, Wen, and Hau (2004), who proposed the unconstrained approach, as follows:

suppose that endogenous latent variable η has three indicators: y1, y2, y3; exogenous latent variables $\xi 1$ and $\xi 2$ also have three indicators, respectively: x1, x2, x3 and x4, x5, x6. In order to analyze the interaction effect of $\xi 1$ and $\xi 2$ on η, following the interaction model for the continuous manifest variables, we use the structural model with product term as below (Cohen, Cohen, West, and Aiken, 2003):

$$\boldsymbol{\eta} = \gamma_1\xi_1 + \gamma_2\xi_2 + \gamma_3\xi_1\xi_2 + \zeta$$

where γ_1 and γ_2 represent the first order effects, and γ_3 represents the interaction effect. The intercept term in the Equation above is set to zero for identification of the latent outcome variable $\boldsymbol{\eta}$ (see Jöreskog and Yang, 1996; Yang, 1998).

When treating the product term **ξ**1 **ξ**2 as the third latent variable after **ξ**1 and **ξ**2, Marsh and colleagues (2004) suggested matching three indicators of **ξ**1 and three indicators of **ξ**2 to form three pairs of product indicators (x_1x_4, x_2x_5, x_3x_6) as the indicators of **ξ**1 **ξ**2. The corresponding path diagram of such a latent interaction model is illustrated in Figure 4.11. The usual supposition is that **ξ**1, **ξ**2, ζ and all **δ** and **ε** terms are multivariate normal with mean of zero, and each is uncorrelated with the other (except that **ξ**1 and **ξ**2 are allowed to be correlated).

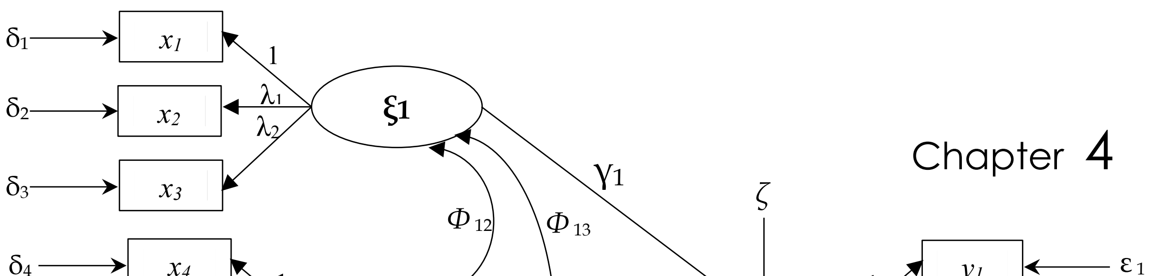


Figure 4.11 The path diagram of the latent interaction model under the unconstrained approach (Marsh, 2012)

As is well known, interaction models typically violate the normality assumption. Even when the indicators of $\xi 1$ and $\xi 2$ are normally distributed, the distributions resulting from the products of these indicators are generally non-normal (Jöreskog and Yang, 1996). Hence, in this investigation we use the maximum likelihood (ML) estimation method which is sufficiently robust in relation to the violation of the assumption of normality (e.g., Boomsma, 1983; Hau and Marsh, 2004). We also adopted a more conservative estimation method—generalized least squares (GLS)—that does not depend on a normal distribution assumption that is necessarily violated at least in the interaction term, though simulation studies of latent interaction effects suggest that ML estimation outperforms such conservative estimation procedures (e.g. GLS) under most conditions (Wall and Amemiya, 2001; for further discussion, see Marsh et al., 2004, 2012).

Another important problem that can occur when analyzing product terms is extreme collinearity (Kline, 2015). This is because in the unconstrained method, it is likely that the product terms of the interaction constructs will be correlated with the main effect constructs (Jackman, Leite, and Cochrane, 2011), so that the analysis can fail or the results are unstable. One way to address this problem is to mean-centre the original variables before calculating product terms based on them (Marsh et al., 2004, 2006). Mean centring occurs when the average of a variable is adjusted to zero (the mean is subtracted from every score: denote xC as the mean-centred variable of $\boldsymbol{x}$, that is, $\boldsymbol{x}^C = \boldsymbol{x} - \mathbf{E}(\boldsymbol{x})$), and centring tends to reduce—but not typically to eliminate—correlations between product terms and constituent variables, and thus simplify the model considerably (Marshet al., 2012). The matched product indicators in figure 4.11 will become $\boldsymbol{x_1}^C\boldsymbol{x_4}^C$, $\boldsymbol{x_2}^C\boldsymbol{x_5}^C$, $\boldsymbol{x_3}^C\boldsymbol{x_6}^C$. More importantly, after the indicators of the latent predictors have been centred, the intercept terms of the measurement equations of the original and the product indicators are no longer necessary (Marsh, 2012).

An alternative is to create a residualized product term using the technique of residual centring that is calculated controlling for the main effects, and consequently is uncorrelated with them (Little et al., 2006). The only other special parameterization in this approach is that error covariances are specified between pairs of residualized product indicators based on common nonproduct indicators (Little et al., 2006; Kline, 2015). Both the residual centring approach and the mean-centring approach have generally produced similar outcomes (Marsh et al., 2007). Accordingly, the simpler mean-centring approach was chosen for this study. Therefore, prior to creating product terms for the latent construct, main-effect indicators were mean centred.

To form the product indicators of **ξ**1 **ξ**2, this research applies the "matched pairs" strategy in which information from the same indicator is not repeated and which requires the number of indicators of each exogenous factor to be the same (Marsh, 2012). Specifically, the items with the highest reliability from one predictor were matched to the item with the highest reliability in measuring the other latent predictor, and so on (Jackman et al., 2011). According to Marsh and colleagues (2004), this will lead to more reliable indicators of the latent interaction term. Additionally, given the large, unequal numbers of indicators for the two first-order effect factors (**ξ**1 and **ξ**2) in this study, the indicator parcelling method was used in combination with the mean-centring approach (Marsh et al., 2004). The parcelling approach was chosen to reduce the unwieldy number of indicators for the interaction construct (**ξ**1 **ξ**2) down to a manageable *n*-item set.

The technique of parcelling, compiling or bundling items in structural equation modelling (SEM) has recently received considerable attention within the SEM community and become a common strategy for handling latent construct indicators (Hall, Snell, and Foust, 1999; Bandalos and Finney, 2001; Hagtvet and Nasser, 2004; Hau and Marsh, 2004). A parcel can be defined as an aggregate-level indicator comprised of the sum (or average) of two or more items from the same scale (Little et al., 2002). According to Bandalos (2008), parcelling differs from creating subscales in at least two important ways. First, whereas subscales are based on some type of theory about how and why the particular items on a subscale are related, creation of parcels is typically done in an ad hoc, atheoretical fashion. Second, subscale scores are usually interpretable in their own right as subdimensions of a broader theoretical construct, whereas parcel scores do not typically have any meaningful interpretation. Thus, item parcelling is simply a heuristic device for combining items (Bandalos, 2008)). Item parcelling has been advocated on the grounds that it exhibits more reliability and results in improved model fit and values that are more continuously and normally distributed (Hall et al., 1999; Bandalos, 2002; Little et al., 2002). Furthermore, Little et al. (2002) argued that, for situations in which one's interest is in modelling relations among the latent constructs, item parcelling can be efficacious as it results in "cleaner" constructs in which the specific variance due to method or response bias is effectively eliminated. However, the sets of items being parcelled should be strictly unidimensional, otherwise, the use of parcelling can result in substantial bias in the estimates of structural parameters, as well as high Type II error rates (Bandalos, 2008).

To sum up, the latent interaction term was created in three steps. First, parcelling items was performed to reduce the unwieldy number of indicators for the interaction construct down to a manageable *4*-item set. The items of the larger latent construct (i.e., ξ2: Residential Satisfaction RS construct) were parcelled to be equal to the number of the smaller latent construct (i.e., **ξ**1: 4-item Negative Affect NA construct). Second, all **ξ**1 and **ξ**2 items were mean-centred prior to creating product terms. However, in considering this parcelling approach it was emphasized that parcels are only used as indicators of the latent interactions and that individual items are used as indicators of first-order factors, thus avoiding many potential problems in the use of item parcels (e.g., Marsh et al., 2012). In addition, where parcels are used to form the product indicators with the unconstrained approach, it was emphasized that it is inappropriate to scale latent interaction terms by fixing the loading of a product indicator. Instead, Jackman and colleagues' (2011) recommendations that variances of latent variables should be fixed for scaling were followed. When the variances of two exogenous factors $\xi 1$ and $\xi 2$ are set to 1, the variance of their product $\xi 1$ $\xi 2$ is set to 1 + cov($\xi 1$,$\xi 2$) (Jackman et al., 2011. See also Wu et al., 2013) who examined the performance of this strategy under both normal and non-normal conditions).

Third, the averages of the mean-centred items on the $\xi 1$ scales were then multiplied by the mean-centred $\xi 2$ items. In this study, a moderating effect would be observed when there was a significant path coefficient connecting the interaction term (i.e., $\xi 1$ $\xi 2$) to either endogenous variable (Baron and Kenny, 1986). The computation of the product interaction term was performed in SPSS and previously has been described in this section. AMOS was used to test the moderated hypotheses of this study. Model fit was assessed following guidelines outlined earlier in this section.

4.8 AMOS AS A SEM PROGRAM

Computer programs are critical tools for the conduct of SEM (Kline, 2015). A steady increase in the development and revision of alternative SEM computer software has occurred since the development of the first SEM in 1974 (Byrne, 2012), including: AMOS (Analysis of Moment Structures, (Arbuckle, 1994, 2008; Arbuckle, 2010; Byrne, 2016)), CALIS (Covariance Analysis and Linear Structural equations, (SAS, 2016)), EQS (Equations, (Bentler, 1995; Byrne, 2013; Jöreskog and Sörbom, 1986; Jöreskog, 2006), Mplus (Muthén and Muthén, 1998, 2010), RAMONA (Reticular Action Model or Near Approximation (Browne and Mels, 1990)), and SEPATH (Structural Equation Modeling and Path Analysis, (Steiger, 1995)). In addition to the core analytic features, each program has its own special features. Kline (2015), made a review of Amos, CALIS/TCALIS of SAS/STAT, EQS, LISREL, Mplus, Mx, RAMONA of SYSTAT, and SEPATH of STATISTICA. Byrne (2012) made a comparative review of AMOS, EQS, LISREL, and Mplus, four of the most widely-used SEM computer programs.

The software chosen for this study was IBM SPSS AMOS (Arbuckle, 2016; Byrne, 2016) which is made up of two modules: Amos Graphics and Amos Basic. Using Amos Graphics, the researcher worked directly from a path diagram that provides an easy-to-use graphical interface, so that he or she could perform an analysis without having to write any computer code (Kline, 2015). Using Amos Basic, the researcher worked directly from equation statements (Byrne, 2012). AMOS is a Microsoft Windows program and can be used either as a stand-alone application or an optional part of SPSS (Kline, 2015). It has undergone almost yearly revisions since 2003, at which time Version 5 introduced the capability to do specification searches and automated multiple group analyses (Byrne, 2012). At the time of writing this chapter, the latest version was AMOS 24.0 (Arbuckle, 2016). With AMOS, researchers can quickly specify, view, and modify their model graphically, assess the model's fit, make modifications, and obtain a publication-quality graphic of the final model. In addition, several notable features of AMOS include (Kline, 2015; Byrne, 2012, 2016):

(1) It has a special maximum likelihood (ML) method for automatically dealing with raw data files, in which some observations are missing at random, and special estimation methods for censored data and ordered-categorical (ordinal) outcome variables;

(2) It can analyse mixture models with latent categorical factors;
(3) It has the ability to produce bootstrapped standard error estimates, bias-corrected percentile estimates and confidence intervals for parameter estimates as well as for sample means, variances, covariances, and correlations;
(4) It has extensive capabilities for Bayesian estimations of model parameters.

4.9 RESEARCH ETHICS

In order to protect the well-being and interests of participants, researchers should ensure the anonymity and confidentiality of respondents. Confidentiality implies that while certain responses can be traced back to a certain participant, assurance is given not to make it public. Anonymity, on the other hand, means that it is not possible to trace back a certain answer to a respondent (McGivern, 2008). The researcher collecting the data must be transparent about the purpose of the study, the end use of the data and whether anonymity or confidentiality is promised or not (McGivern, 2008).

With reference to this research, it incorporated University of Newcastle ethical guidelines which ensured the quality of data obtained. The research received ethical approval from the Human Research Ethics Committee (No. H-2016-0005). This involved lodging a Human Research Minimal Risk Application Form, along with the questionnaire form and the plain language Information Sheet to be sent to each potential participant prior to their participation (copies of these are to be found as Appendix A). Thus, participants' answers were anonymous and could not be traced back to a certain respondent. Further, in the introduction to the survey, participants were informed about the purpose of this research (doctoral thesis), that all information is anonymous, confidential, and the passing on of information to third parties is excluded.

Gaining consent from the participants has been done on a fully informed and freely given basis depending on an information sheet that clearly declared the voluntariness of participation. Also, it was used to give the participants full information about the research which included: the title and purpose of the research/the research team (the researcher and the supervisors)/the research sample and who is being asked to participate, the kinds of data required, assurances about participants' privacy, confidentiality and anonymity, assurances about data security and that it is only for the purpose of, and will be used only for scientific research, etc). Participants in the research were informed that information provided was to be securely stored against access by persons other than the researcher for a period of five years. At the end of that five-year period all data provided by participants will be destroyed, paper records will be shredded and electronic records deleted.

4.10 CHAPTER SUMMARY

In this chapter the methodology used to conduct the study as well as the issues related to the chosen research methodology were discussed. This discussion was built on the outcomes of Chapters Two and Three and through the steps that were taken to address the survey design, the data collection and analysis methods used to conduct the research study were illustrated. These issues were addressed in light of the basic research objectives and the relevant research questions. The chapter started by providing a basic background about the different research methodologies and strategies and the importance of selecting an appropriate research approach, research methodology and strategy. Afterwards, the basic assumptions of the research paradigms were illustrated and discussed. Based on this discussion, the chapter proved that there are sufficient philosophical and practical reasons for depending on the positivist approach as the research approach for this research. Moreover, the research methodology and stages were discussed with reference to the adopted research philosophy.

Afterwards, issues related to the research data were discussed in detail. The research primary data was discussed and based on this discussion the implementation of the data collection methods was explored in detail. Within this context, the issues related to the research sample design, the research population, the research sample, the sample type, the sample size, unit of analysis, data collection methods, construction of the research questionnaire, stages of data collection from the field, as well as the data analysis and the research ethics were presented and discussed in detail within the chapter.

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CHAPTER 5

DESCRIPTIVE DATA ANALYSIS

Before plumbing the relationship between related constructs (presented in Chapters 6, 7 and 8), the conceptualisation and validation of the constructs are argued for based on the analyses of internal consistency reliability through Cronbach's alpha test using IBM SPSS Statistics for Windows, Release 24.0 (presented in Chapter 5). Specifically, Chapter 5 has three main sections. Section 5.2 presents descriptive results including the demographic characteristics of the participants. Section 5.3 details and validates the study's constructs in the following order: Personal Experience of severe flood hazards (PE), perceived risk probability (PRP), perceived risk consequence (PRC), positive affects (PA) negative affects (NA), subjective knowledge (SK), perceived self-efficacy (SE), trust in public flood risk management (T), protective behavioural intentions (PBI), of risk denial (RD), residential Satisfaction (RS-P: physical attributes of neighbourhood), residential Satisfaction (RS-SE: socio-economic attributes of neighbourhood) and Residential Satisfaction (RS-D: attributes of dwelling). Section 5.2 reports how missing data were treated. In Section 5.4, missing data and outliers are examined, the normality of the data is assessed, and the adequacy of the sample size is evaluated before proceeding with the data analysis. Finally, in Section 5.5., each scale of reliability was evaluated using Cronbach's alpha.

5.1 DESCRIPTIVE STATISTICS OF DEMOGRAPHICS

This section explores the respondents' profiles and provides descriptive statistics of their demographic characteristics. The demographic information collected during the survey consisted of respondents' gender, age, personal annual income, highest qualification achieved, household size, home ownership, distance from nearest major waterway and length of residence. The profile data (Table 5.1), collected during the mail survey held between May and September 2016, were also compared with corresponding data of the resident population in South East Queensland as of 2011 (Australian Bureau of Statistics, 2011). Specifically, 52.6% of the sample were female compared to 51.8 % in the South East Queensland population, 23.3% were aged between 35-49 compared to 21.6% in the population, 19.9% had completed bachelor or higher degree compared to 18.4% in the population, 61.5% of households earned an income of $2500 or less per week compared to 61.2% in the population and 33.4% of households contained 2 persons compared to 35.1% in the population. Therefore, our sample is somewhat representative for the study population, considering the small-scale spatial distribution of flood-prone households within our sample frame (where 97.5% of the participants reported living within 1 km from a major waterway (i.e. river)). There were no significant differences in the proportions of participants living within the two major flood-plain areas included in the study area (57.4% Bremer river catchment in Ipswich, 42.6% Nerang river catchment in Gold coast).

Table 5.1: Demographic Characteristics of the Current Sample (N = 681)

Demographic	Characteristics	Frequency	Valid Percent	Total (%)	Missing (%)
Sex	Male	312	47.4	658	23
	Female	346	52.6	(96.6%)	(3.4%)
Age	<25	7	1.1	653	28
	25-29	64	9.8	(95.9%)	(4.1%)
	30-34	99	15.2		
	35-49	152	23.3		
	50-54	85	13.0		
	55-60	132	20.2		
	>60	114	17.5		
Weekly Income	$0-$999	51	8.0	641	40
	$1000-$1249	67	10.5	(94.1%)	(5.9%)
	$1250-$1499	65	10.1		
	$1500-$1999	91	14.2		
	$2000-$2499	120	18.7		
	$2500-$2999	82	12.8		
	$3000-$3499	80	12.5		
	$3500-$3999	54	8.4		
	$4000 and up	31	4.8		
Education (Highest qualification achieved)	No qualification	352	53.5	658	23
	Advanced Diploma	64	9.7	(96.6%)	(3.4%)
	Vocational	111	16.9		
	University Undergrad	131	19.9		
Home ownership	Owned	515	77.6	664	17
	Rented	149	22.4	(97.5%)	(2.5%)
Household Size	1 - I live alone	175	27.1	646	35
	2	216	33.4	(94.9%)	(5.1%)
	3	116	18.0		
	4	94	14.6		
	5+	45	7.0		
Length of residence	Less than 5 years	129	19.7	656	25
	5 to 10 years	93	14.2	(96.3%)	(3.7%)
	11 to 15 years	116	17.7		
	16 to 20 years	219	33.4		
	More than 20 years	99	15.1		
Distance from nearest major waterway	Less than 250 m	159	23.6	673	8
	251 m to 500 m	243	36.1	(98.8%)	(1.2%)
	501 m to 750 m	146	21.7		
	751 km to 1 km	108	16.0		
	More than 1 km	17	2.5		

As presented in Table 5.1 above, the respondents were almost equally represented in terms of gender (47.4% Male, 52.6% Female). The average age of respondents (≈52.6 years old) is represented as an age group variable of 4.68. A majority of respondents were in the 30-49 age bracket. People above the age of 60—who are generally considered as most vulnerable to flood hazards—were also well represented in the sample. The likely reason for a small percentage of respondents below the age of 25 is that this study was designed to measure perceptions and intentions of household decision-makers (husbands or wives in married-couple households or sufficiently senior family members) as they seemed best placed to comment on reasons for living in flood-liable residential zones. Most survey respondents owned (77.6%), rather than rented (22.4%), their homes. Sample percentages were slightly higher than the ownership rates calculated for the population (Australian Bureau of Statistics, 2011). Most respondents (80.4%) had lived in their homes for more than 5 years. This may explain the reported higher rates of experiencing flood hazards (particularly the 2011-2012 floods). The median length of residence for the total sample ranged from 11-15 years.

5.2 DESCRIPTIVE STATISTICS FOR RESEARCH CONSTRUCTS

In this stage of analysis, frequency statistics, measures of central tendency (including the mean and standard error SE of the mean), and dispersion (including standard deviation SD) statistics for the data were calculated and summarized using IBM SPSS (V 24.0). Standard deviation (SD) indicates how well the mean represents the observed data. A large SD means that the score is spread more widely around the mean, which means that the mean is not a good representation of the data. A small SD proves that the mean is an adequate representation of the data. Similarly, a large SE shows that there is a lot of variation between the means of different samples, which means that the sample is not well representative of the population. Therefore, a small SE indicates that sample means are similar to the population mean, which improves the accuracy of the population reflection. In this study, it can be seen at Tables 5.2 to 5.12 that scores of SD and SE of most of the items are relatively small when compared to their means. As a result, the mean value is a good representative score for each variable in this data. Also, the small values of SE prove that the sample used was sufficiently representative of the population.

5.2.1 Personal Experience (PE)

Survey participants were first asked if they had ever been affected by flooding. If the answer was yes, they were requested to think back to the worst flood they'd been affected by and describe how it affected them. The question was close ended and it was rated on a seven point scale of impact severity. It is worthwhile to note here that the survey was carried out during April 2016 to December 2016, more than five years after the historic flood disaster of 2011-2012 which caused the loss of twenty one lives. Such a loss had not occurred in the previous four decades (i.e. since the 1974 floods). The event was therefore a memorable one, and most households still remembered it during this survey. The experiences of flooding, as recalled by 394 (58.9%), were severe to extremely severe. Given the long residence time of many respondents, more than 85% of householders that responded reported having experienced a flood that was slightly severe to extremely severe. The characteristics of (PE) are presented in Table 5.2. The SD value is 2.01, which is low enough to argue that the mean adequately represents the data. SE value is .078, which indicates that most of the sample means are similar to the population mean.

Table 5.2: Descriptive Statistics of the PE Construct

Item		SE	SD	Valid percent %						
				(1) Not at all Sever	(2)	(3)	(4)	(5)	(6)	(7) Extremely Sever
PE	Severity of past flood experience	.078	2.01	13.3	14.2	13.6	14.6	12.9	16.0	15.4

Source: Output SPSS/Author's survey.

5.2.2 Perceived Risk Probability (PRP)

In the survey, a 4-item question dealt with residents' perception of the probability of their houses flooding in the future. Below- and above-floor inundation levels were rated on a scale from absolutely never, which indicates no probability of inundation, to once a year which indicates high probability or certainty. Of 675 and 674 valid responses to the questions of inside/outside the property inundation (i.e. PRP.1 and PRP.2) respectively, the respective percentages of respondents answering "absolutely never" were 3.0% and 4.7%; whereas of 672 and 673 valid responses to the questions of below/above habitable residential floor inundation (i.e. PRP.3 and PRP.4), respectively, the respective percentages of respondents answering "absolutely never" were 12.6%, and 26.4%. The cumulative percentages of respondents answering "less than 1-100 years" were 91.7%, 85%, 73%, and 57.7% for PRP.1, PRP.2, PRP.3 and PRP.4, respectively (see Table 5.3 below).

Table 5.3: Descriptive Statistics of the PRP Construct

Items		SE	SD	Valid Percent%								
				1-year	1- 2 years	1-5 years	1-10 years	1-20 years	1-50 years	1-100 years	<100 years	Never
PRP.1	Over the surrounding streets (Outside the property)	.086	2.22	9.6	15.3	10.5	12.0	13.0	17.5	13.8	5.3	3.0
PRP.2	Over the front/back yard (Outside the house)	.085	2.21	4.2	13.1	11.4	10.8	14.2	15.1	16.2	10.2	4.7
PRP.3	Over non-habitable spaces	.084	2.16	1.3	7.0	8.8	11.3	13.7	14.1	16.8	14.3	12.6
PRP.4	Over habitable spaces	.083	2.16	0.7	5.2	4.5	8.5	10.5	14.6	13.7	15.9	26.4

Source: Output SPSS/Author's survey.

The SD values ranged between 2.16 and 2.22, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.083 and 0.086, which indicates that most of the sample means are similar to the population mean. The median PRP.1 was "once in 20 years" (13.0%), while the median PRP.4 was "once in 100 years" (13.7%). These results revealed considerable variations in respondents' perceived risk probability to scenarios combining different inundation extents. In particular, respondents reported lower perceptions of risk for inundation scenarios inside their houses (i.e., below/above habitable residential floors inundation: PRP.3 and PRP.4) than for outside their houses (i.e. neighbourhood streets and front/back yards inundation: PRP.1 and PRP.2). Generally, the majority of the responses obtained for the PRP construct indicated that respondents moderately believe that their property could flood in the future (total PRP average is 4.47 ≈ 1-20 years).

5.2.3 Perceived Risk Consequence (PRC)

The extent of perceived potential tangible/intangible damage as a consequence of the flood varied from household to household; significant proportions of respondents (57.1%, 48.4%, 44.9%, 46.5%, 45%, 46.6%, 43.3%, 47.1%, 46.9%) reported a moderate to high degree of PRC.1, PRC.2, PRC.3, PRC.4, PRC.5, PRC.6, PRC.7, PRC.8 and PRC.9, respectively (see Table 5.4 below). The SD value ranged between 1.726 and 1.875, which is low enough to argue that the mean adequately represents the data. SE ranged between 0.066 and 0.073, which indicates that most of the sample means are similar to the population mean. The median for all PRC items was 5 "Moderately Serious"— except for PRC.1 the median was 4 (15.6% of N=666).

Table 5.4: Descriptive Statistics of the PRC Construct

Item	Descriptions	SE	SD	Valid Percent%						
				(1) Not at all serious	(2)	(3)	(4)	(5)	(6)	(7) Extremely serious
PRC.1	Disruption of supplies	.073	1.875	11.3	14.7	15.5	15.6	16.5	15.9	10.5
PRC.2	Damage to public facilities	.067	1.726	7.9	7.8	13.6	19.1	21.7	18.7	11.2
PRC.3	Damage to house/possessions	.069	1.779	8.0	8.3	12.8	15.8	22.7	18.8	13.8
PRC.4	Financial loss	.069	1.787	8.6	8.0	14.7	15.2	21.1	20.2	12.2
PRC.5	Psychological health	.066	1.700	6.6	6.3	15.3	16.8	22.8	19.5	12.9
PRC.6	Physical health	.070	1.808	8.7	7.9	13.9	16.1	20.3	19.0	14.1
PRC.7	Loved ones or pets' safety	.067	1.745	7.8	5.4	14.3	15.8	22.1	20.6	14.0
PRC.8	Disruption of daily life	.071	1.814	7.1	8.7	15.2	16.1	15.5	22.2	15.2
PRC.9	Inconvenience of recovery process after the flood	.071	1.842	10.1	7.5	13.1	16.2	20.4	18.5	14.2

Source: Output SPSS/Author's survey

It is, however, pertinent to note here that policy in South East Queensland and elsewhere in Australia treats the hundred year floodplain as a high risk area, but—as the results above indicate—the majority of householders that responded believed their risk to be medium to very serious. It is also pertinent to note that there is low, but still considerable, variation among the different items within the PRC scale. For example, the concern about the disruption of supplies (food, electricity, drugs, telephone, internet, water, etc.) as a consequence of flood hazards gained higher concern ratings (PRC.1: mean score 6) than other PRC items.

5.2.4 Affective Appraisals

Two dimensions (namely, positive and negative affective responses) were used to measure residents' feelings associated with possible future flooding scenarios. As presented in Table 5.5 below, the SD values for negative affect (NA) items ranged between 1.880 and 1.976, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.073 and 0.076, which indicates that most of the sample means are similar to the population mean. The median for NA.1 and NA.2 items was 5. The median for NA.3 and NA.4 was 4. The variety of responses to NA items indicates the sample as a whole had a fairly moderate to high degree of negative affective responses to possible future flooding scenarios. Regarding positive affect (PA) items, 55%, 56.2%, 56.4% and 59.9% of respondents reported a "not at all" to "somewhat" to degree of PA.1, PA.2, PA.3 and PA.4, respectively (see Table 5.5 below). The mean values for PA items ranged between 3.21 and 3.40. SD ranged between 1.777 and 1.869, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.069 and 0.072, which indicates that most of the sample means are similar to the population mean. The median for all PA items was 3 (15.5%, N=671; 19.2%, N=672; 19.3%, N=668 and 16.8%, N=674 for PA.1, PA.2, PA.3 and PA.4 respectively).

Generally, the results reported above revealed low, but still considerable, variations in respondents' positive and negative affective responses to future flood scenarios. More specifically, respondents reported relatively higher degrees of "very" to "extremely" negative affect than positive affect. It is also pertinent to note here that there is low, but still considerable, variation among the different items within each scale. For example, respondents reported a higher degree of having feelings of fear than for feelings of worry. Similarly, respondents reported a higher degree of having feelings of unity/solidarity than for feelings of pleasurable fascination/excitement.

Table 5.5: Descriptive Statistics of the NA and PA Constructs

Item	Descriptions	SE	SD	Valid Percent%						
				(1) Not at all	(2)	(3)	(4)	(5)	(6)	(7) Extremely
Negative Affect NA										
NA.1	Feeling of fear	.074	1.919	14.3	18.6	15.8	12.6	17.7	10.4	10.7
NA.2	Feeling of uncertainty	.073	1.897	13.4	18.6	17.9	15.0	14.0	10.0	11.2
NA.3	Feeling of worry	.073	1.880	16.3	17.8	18.1	13.8	15.1	9.8	9.1
NA.4	Feeling of helplessness	.076	1.976	16.2	16.3	18.4	10.7	15.9	10.2	12.3
Positive Affect NA										
PA.1	Feeling of safety	.069	1.777	18.6	20.9	15.5	15.9	16.5	7.3	5.2
PA.2	Feeling of unity/solidarity	.070	1.810	18.2	18.8	19.2	13.7	15.3	8.8	6.1
PA.3	Feeling of beauty/sense of nature	.070	1.797	19.6	17.5	19.3	15.7	14.4	7.2	6.3
PA.4	Feeling of pleasurable fascination	.072	1.869	27.9	12.2	16.8	15.4	15.0	7.1	5.6

Source: Output SPSS/Author's survey

5.2.5 Subjective Knowledge (SK)

Self-assessed or subjective knowledge was characterized by the depth of an individual's understanding or awareness of the hazard's genesis, its mechanisms of exposure, and types of adjustments that can avoid its impacts. As presented in Table 5.6 below, most householders who responded stated that they were slightly to moderately aware of occupying a flood-risk zone SK.1 (65.1% of N=672 respondents). Only 9.7% of respondents were completely not aware of occupying a flood-risk zone. The results obtained from SK data also indicated that only 14.0% of respondents were completely not aware of the immediate impacts of flooding in their region. These results could be partly explained by the reported higher rates of experiencing flood hazards. In addition, 25.8% of respondents were very to extremely aware of the potential factors that contribute to flooding. This value decreased to 21.0%, 22.2%, 19.8%, 21.5% for SK.1, SK.4, SK.5 and SK6, but it increased to 26.1% for SK.1.

Table 5.6: Descriptive Statistics of the (SK) Construct

Item	Descriptions	SE	SD	Valid Percent%						
				(1) Not at all aware	(2)	(3)	(4)	(5)	(6)	(7) Extremely aware
SK. 1	Situation: Awareness of living in a flood-risk zone	.074	1.912	9.7	17.2	17.5	14.3	15.1	11.8	14.3
SK. 2	Impact: Immediate impacts of flooding	.072	1.870	14.0	14.9	23.2	16.1	10.9	9.7	11.3
SK. 3	Cause: Potential factors that contribute to flooding	.076	1.969	14.6	18.8	16.4	15.2	9.1	14.1	11.7
SK. 4	Weather / flood alerts and warning systems	.075	1.929	15.5	17.6	21.0	14.6	9.0	10.7	11.5
SK. 5	Official sources of public safety info. (e.g. safe routes, appropriate actions)	.073	1.882	14.3	21.1	12.0	14.0	9.5	9.0	10.8
SK. 6	Safety: Protection level of local flood-control measures	.077	1.984	18.9	16.9	19.8	12.5	10.4	9.5	12.0

Source: Output SPSS/Author's survey

The SD values for SK items ranged between 1.870 and 1.984, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.072 and 0.077, which indicates that most of the sample means are similar to the population mean. The median for all SK items was 3 "somewhat aware"— except for SK.2 and SK.4 the median was 4. The variety of responses to SK items indicates the sample as a whole had a fairly low to moderate familiarity with general flood issues in the region.

5.2.6 Self-efficacy (SE)

Three dimensions of self-efficacy were measured (on a seven-point scale) to understand its role in shaping flood risk perceptions and preparedness intentions. In particular, the belief that the householders can prepare and secure properties ahead of time for a potential flood (PSE. 1) gained rather moderate ratings of self-efficacy (confidence in adopting and enacting risk reduction behaviours) with a mean score of 3.72. To some degree, householders' feelings of powerfulness (i.e. that they are able to protect themselves against future flood threats) were also rated as moderate (PSE. 2: average score 3.62); however, these ratings were slightly higher than the ratings for householders' resourcefulness (PSE. 3: average score 3.54).

Table 5.7: Descriptive Statistics of the (SE) Construct

Item	Descriptions	M	SE	SD	Valid Percent%						
					(1) Strongly Disagree	(2)	(3)	(4)	(5)	(6)	(7) Strongly Agree
PSE. 1	"I am confident that I can efficiently prepare and secure my property ahead of time for a potential flood"	3.67	.076	1.95	15.6	19.8	15.9	12.5	13.9	11.2	11.0
PSE. 2	"I feel powerless. Protecting myself against future flood threats is beyond my ability"*	3.66	.075	1.94	16.3	18.7	16.6	11.0	15.2	12.8	9.4
PSE. 3	"It is easy for me to protect myself against future flood threats because I can rely on my resourcefulness"	3.56	.074	1.91	19.0	16.6	16.2	13.3	15.3	11.7	7.9

Source: Output SPSS/Author's survey
* SE. 2 is a reverse-scored item.

As presented in Table 5.7 above, the mean values for PSE items ranged between 3.56 and 3.67. SD ranged between 1.910 and 1.950, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.074 and 0.076, which indicates that most of the sample means are similar to the population mean. The median for all SK items was 3 "somewhat agree". The variety of responses to PSE items indicates the sample as a whole had a fairly low to moderate degree of self-efficacy. Only 11%, 9.4% and 7.9% of respondents rated their self-efficacy as "extremely high" for the items PSE. 1, PSE. 2 and PSE. 3, respectively.

5.2.7 Trust (T) in Public Flood Risk Management

Four dimensions of trust were measured. In particular, the perceived expertise of flood risk managers gained rather moderate trust ratings (T. 3 mean score of 3.72 on a seven-point scale with 1 indicating no trust and 7 much trust). To some degree, authorities and their sources of information on flood risk (particularly the extent of flood prone zones) were also perceived as credible (T. 4 average score 3.62); however, these ratings were slightly higher than the trust ratings for design and strength of flood defence structures (T. 1: average score 3.54), but equally similar to the trust ratings for effectiveness of land use policies and development controls of flood liable lands (T.: average score 3.62).

Table 5.8: Descriptive Statistics of the (T) Construct

Item	Descriptions	SE	SD	Valid Percent%						
				(1) Not at all	(2)	(3)	(4)	(5)	(6)	(7) Extrem -ely
T.1	The strength and height of the flood defences is based on a thorough and sound risk analysis	.074	1.89	16.0	22.2	13.7	15.4	13.9	9.8	8.9
T.2	Authorities implement and control local land use and development of flood liable lands to effectively reduce the risk.	.076	1.94	17.2	17.8	16.7	14.0	12.8	11.7	9.9
T.3	The technological skills of flood risk managers can efficiently prevent/mitigate all flood risks	.075	1.93	17.6	17.5	13.8	13.5	12.8	13.4	11.4
T.4	Authorities provide credible information sources on flood risk	.076	1.93	18.5	16.7	14.7	13.7	16.4	11.1	9.0

Source: Output SPSS/Author's survey

As presented in Table 5.8 above, the SD values for T items ranged between 1.89 and 1.94, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.074 and 0.076, which indicates that most of the sample means are similar to the population mean. The median for T. 1 and T. 2 items was 3 "somewhat confident" which is lower than the median value of 4 for T. 3 and T. 4 items. The variety of responses to T items indicates the sample as a whole had a fairly low to moderate degree of self-efficacy. Only 8.9%, 9.9%, 11.4% and 9.0% of respondents rated their trust in local flood protections as "extremely high" for the items T. 1, T. 2, T. 3 and T. 4, respectively.

5.2.8 Protective Behavioural Intention (PBI)

As presented in Table 5.9 below, the mean for PBI items ranged between 3.46 and 3.77. SD ranged between 1.77 and 1.96, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.068 and 0.076, which indicates that most of the sample means are similar to the population mean. The median for all PBI items was 3. The variety of responses to PBI items indicates the sample as a whole had a fairly low to moderate degree of willingness to adopt a risk reduction behaviour as a response to possible future flooding scenarios. Only 15.3%, 16.6%,17.1%, 18.1%, 15.9%, 19.1%, 15.1%, 24.9%, 14.4% and 23.6% of respondents rated their PBI as high to extremely high for the items PBI. 1, PBI.2, PBI.3, PBI.4, PBI.5, PBI.6, PBI.7, PBI.8, PBI.9 and PBI.10, respectively.

It is, however, pertinent to note that there is low, but still considerable, variation among the different items within the PBI scale. In particular, the willingness to purchase (or modify) a property insurance policy for natural hazards (PBI. 8) gained higher ratings (mean score 3.77) than other PBI items. Similarly, to some degree, respondents' willingness to move to a no flood risk area (PBI. 1) showed lower ratings (mean score 3.46) than other PBI items.

Table 5.9: Descriptive Statistics of the PBI Construct

Item	Descriptions	M	SE	SD	Valid Percent%						
					(1) Not at all	(2)	(3)	(4)	(5)	(6)	(7) Extrem-ely
PBI. 1	Moving to no flood risky area	3.46	.070	1.81	16.9	16.3	23.4	14.4	13.5	7.1	8.2
PBI. 2	Implementing hydro-isolation of the walls	3.55	.068	1.77	12.9	19.4	22.7	14.3	14.2	8.9	7.7
PBI. 3	Installing more complex water drainage systems around the house	3.53	.071	1.85	15.7	18.3	20.4	14.8	13.6	7.8	9.3
PBI. 4	Moving electricity outlets/meter boxes and air conditioning unit higher	3.56	.072	1.86	15.1	18.7	20.0	15.7	12.3	8.2	9.9
PBI. 5	Assembling an emergency kit (including water, food, a battery powered radio)	3.53	.069	1.79	14.6	18.4	21.5	14.3	15.3	8.2	7.7
PBI. 6	Making a to-do list that is helpful in case of an evacuation or flood	3.55	.073	1.89	15.3	21.2	18.5	12.1	13.8	9.6	9.5
PBI. 7	Acquisition of sandbags or other barriers against water	3.53	.068	1.78	13.4	19.7	21.2	15.0	15.5	6.6	8.5
PBI. 8	Purchasing (or modifying) property insurance policy for natural hazards	3.77	.076	1.96	14.2	19.3	16.0	13.3	12.3	13.2	11.7
PBI. 9	Attending a public meeting about the matter	3.49	.069	1.79	15.8	18.6	18.9	15.4	16.7	7.2	7.2
PBI. 10	Collecting information about flood	3.70	.076	1.95	15.9	17.7	18.2	10.6	14.0	13.5	10.1

Source: Output SPSS/Author's survey

5.2.9 Risk Denial (RD)

Three dimensions of risk denial were measured (on a seven-point scale) to understand its role in shaping flood risk perceptions and preparedness intentions. As presented in Table 5.10 below, the mean for RD items ranged between 4.34 and 4.49. SD ranged between 1.93 and 2.00, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.075 and 0.078, which indicates that most of the sample means are similar to the population mean. The median for all RD items was 5. The variety of responses to RD items indicates the sample as a whole had a fairly moderate to extremely high degree of flood risk denial. Only 12.0%, 9.2% and 9.7% of respondents rated their denial of exposure to flood risk as low for the items RD.1, RD.2 and RD.3, respectively.

Table 5.10: Descriptive Statistics of the RD Construct

Item	Descriptions	M	SE	SD	Valid Percent%						
					(1) Not at all	(2)	(3)	(4)	(5)	(6)	(7) Extrem-ely
RD. 1	"I believe that future flooding will turn out better than expected"	4.34	.078	2.00	12.0	11.2	13.2	12.1	14.2	20.7	16.6
RD. 2	"I expect that future flooding will occur somewhere else, but that it will not bother me"	4.44	.075	1.93	9.2	11.5	14.0	10.9	16.8	21.0	16.0
RD. 3	"I believe that the occurrence of flooding is grossly exaggerated"	4.49	.077	1.99	9.7	10.8	13.2	13.9	12.4	19.2	20.7

Source: Output SPSS/Author's survey

5.2.10 Residential Satisfaction (RS)

5.2.10.1 RS-P: Physical Attributes of the Neighbourhood

Residents were asked to rate their satisfaction with the physical attributes of their neighbourhood RS-P on a seven-point scale, with 1 indicating very dissatisfied to 7 indicating very satisfied at the beginning of the survey. The explanations for satisfaction varied from the convenience of the location, street design and access to important things, to density (level of crowdedness) and cleanness of the neighbourhood. As presented in Table 5.11 below, the mean for RS-P items ranged between 4.42 and 4.55. SD ranged between 1.76 and 1.81, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.068 and 0.070, which indicates that most of the sample means are similar to the population mean. The median for all RS-P items was 5. The variety of responses to RS-P items indicates the sample as a whole had a fairly moderate to high degree of satisfaction with the physical attributes of neighbourhood. Only 8.5%, 7.5%, 8.1%, 7.3%, 7.5% and 8.5% of respondents rated their satisfaction on RS-P items (RS-P.1, RS-P.2, RS-P.3, RS-P.4, RS-P.5 and RS-P.6, respectively) as low.

Table 5.11: Descriptive Statistics of the RS Data

Item	Descriptions	SE	SD	Valid Percent%						
				(1) Not at all	(2)	(3)	(4)	(5)	(6)	(7) Extrem-ely
RS-P: Physical attributes of neighbourhood										
RS-P. 1	Aesthetic: Physical appearance	.068	1.76	8.5	8.2	12.0	14.8	23.0	20.0	13.5
RS-P. 2	Accessibility to neighbourhood (CBD)	.069	1.78	7.5	9.1	12.1	14.2	22.7	19.7	14.8
RS-P. 3	Street design and circulation system	.070	1.81	8.1	8.7	11.4	15.3	21.3	20.7	14.5
RS-P. 4	Density (Level of crowdedness)	.069	1.79	7.3	7.9	12.1	16.7	23.5	16.8	15.8
RS-P. 5	Cleanness of the neighbourhood	.069	1.79	7.5	9.1	12.5	16.0	20.7	20.1	14.0
RS-P. 6	Commercial, public, and other non-residential uses are evenly distributed	.070	1.80	8.5	9.1	12.8	17.3	20.7	17.1	14.5
RS-SE: Socio-economic attributes of neighbourhood										
RS-SE. 1	Quietness of the neighbourhood	.069	1.78	6.3	7.4	14.0	17.6	17.6	19.0	18.1
RS-SE. 2	Safety of the neighbourhood	.070	1.80	6.9	10.3	11.5	16.6	19.4	19.4	15.8
RS-SE. 3	Social interactions with other residents	.071	1.83	8.2	9.8	10.4	19.3	15.9	21.6	14.7
RS-SE. 4	Social mix of the population	.070	1.81	8.1	9.1	10.9	17.8	21.0	17.5	15.7
RS-SE. 5	Travel distance to friends/family	.069	1.79	8.3	9.0	11.1	17.6	21.4	18.5	14.1
RS-SE. 6	Cost of living	.071	1.82	7.3	8.5	11.8	16.4	18.8	18.9	18.3
RS-SE. 7	Travel distance to workplaces	.070	1.80	7.3	5.6	14.7	16.6	18.2	18.1	19.4
RS-D: Attributes of dwelling										
RS-D. 1	Value of the house/rent paid house	.071	1.82	7.4	11.7	15.0	13.7	19.6	18.6	14.0
RS-D. 2	Privacy at home	.070	1.81	6.8	10.8	14.4	14.4	18.6	20.7	14.3
RS-D. 3	Architecture of the dwelling	.071	1.82	7.0	11.1	13.8	15.0	19.0	18.9	15.1
RS-D. 4	Size of the dwelling	.071	1.84	7.3	11.4	11.8	16.0	18.1	19.6	15.6

Source: Output SPSS/Author's survey

5.2.10.2 RS-SE: Socio-economic Attributes of the Neighbourhood

Residents were then asked to rate their satisfaction with the socio-economic attributes of their neighbourhood RS-SE on a seven-point scale with 1 indicating very dissatisfied to 7 indicating very satisfied. The explanations for RS-SE varied from the quietness and safety of the neighbourhood and social interactions with other residents and place attachment, to cost of living and travel distance to workplaces. As presented in Table 5.11 above, the mean for RS-SE items ranged between 4.47 and 4.62. SD ranged between 1.78 and 1.83, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.069 and 0.071, which indicates that most of the sample means are similar to the population mean. The median for all RS-SE items was 5. The variety of responses to RS-SE items indicates the sample as a whole had a fairly moderate to high degree of satisfaction on the socio-economic attributes of the neighbourhood. Only 6.3%, 6.9%, 8.2%, 8.1%, 8.3%, 7.3% and 7.3% of respondents rated their satisfaction on RS-SE items (RS-SE.1, RS-SE.2, RS-SE.3, RS-SE.4, RS-SE.5, RS-SE.6, and RS-SE.7, respectively) as low.

5.2.10.3 RS-D: Attributes of Dwelling

Finally, residents were asked to rate their satisfaction with their dwellings RS-D on a seven-point scale with 1 indicating very dissatisfied to 7 indicating very satisfied. The explanations for RS-D varied from the value, architecture and size of the dwelling to privacy at home. As presented in Table 5.11 above, the mean for RS-D items ranged between 4.38 and 4.48. SD ranged between 1.81 and 1.84, which are low enough to argue that the mean adequately represents the data. SE ranged between 0.070 and 0.071, which indicates that most of the sample means are similar to the population mean. The median for all RS-P items was 5. The variety of responses to RS-D items indicates the sample as a whole had a fairly moderate to high degree of satisfaction on the dwelling attributes. Only 7.4%, 6.8%, 7.0% and 7.3% of respondents rated their satisfaction on RS-P items (RS-D.1, RS-D.2, RS-D.3 and RS-D.4, respectively) as low.

5.3. DATA PREPARATION AND SCREENING

Assessment of data integrity as well as the evaluation of the distributional assumptions of the model are important activities that need to be undertaken before conducting a multivariate analysis of the data. Part of the task of assessing the data integrity is to identify missing records, examine outliers, assess the distribution of variables, and confirm the adequacy of the sample size before proceeding with further analysis.

5.3.1 Missing Data Treatment

Survey data almost always have missing values (De Vaus, 2013). Missing data often create major problems for the estimation of structural equation models (SEMs) and other multivariate statistical methods (Allison, 2003). For example, missing data can introduce potential bias in parameter estimation, weaken the generalizability of the results, decrease statistical power and increase standard errors due to the loss of information and/or inefficient use of the data (Schafer, 1997; Rubin, 1976, 2004; Peng et al., 2006). Hence, most statistical procedures including SEMs are designed for complete data (Graham and Coffman, 2012; Kline, 2015). Before a data set with missing values can be analyzed by these statistical procedures, it needs to be edited. According to Dong and Peng (2013), failing to edit the data properly—in some way into a "complete" data set—can make the data unsuitable for a statistical procedure and the statistical analyses vulnerable to violations of assumptions (Dong and Peng, 2013: p. 2).

Based on the discussion above, the researcher must determine if the missing data introduces bias or poses a problem for statistical power. That is, if particular variables generated particular patterns of missing data, or if certain types of participants produced missing data for particular variables. The patterns of missingness have been divided into missing completely at random (MCAR), missing at random (MAR), and not missing at random (NMAR) (Rubin, 1976). These have been discussed in detail by most of the literature related to missing data (e.g., Allison, 2003; Schlomer et al., 2010; Graham and Coffman, 2012; Dong and Peng, 2013; Little and Rubin, 2014; Kline, 2015; Byrne, 2016).

In this study, the missing rate for each single construct is shown in Table 5.12 (Column 3). As suggested in the literature (Kline, 2015: p. 83), it is acceptable in most instances to have a missing data rate of less than 5% when an appropriate procedure is used to handle incomplete cases. Higher rates of data loss present more challenges, especially if the data loss mechanism is not truly random (or at least predictable) (Kline, 2015).

Table 5.12: Statstics of Missing Values in the Study

Constructs	No. of items in the scales	No. (%) cases with missing values	Constructs	No. of items in the scales	No. (%) cases with missing values
PRC	9	**PRC. 1:** 11 (1.6%)	**FBI**	10	**FBI. 1:** 2 (0.3%)
		PRC. 2: 15 (2.2%)			**FBI. 2:** 4 (0.6%)
		PRC. 3: 12 (1.8%)			**FBI. 3:** 5 (0.7%)
		PRC. 4: 10 (1.5%)			**FBI. 4:** 7 (1.0%)
		PRC. 5: 12 (1.8%)			**FBI. 5:** 2 (0.3%)
		PRC. 6: 8 (1.2%)			**FBI. 6:** 6 (0.9%)
		PRC. 7: 13 (1.9%)			**FBI. 7:** 2 (0.3%)
		PRC. 8: 15 (2.2%)			**FBI. 8:** 5 (0.7%)
		PRC. 9: 23 (3.4%)			**FBI. 9:** 6 (0.9%)
					FBI. 10: 9 (1.3%)
E-FH	1	**HE. 1:** 12 (1.8%)	**T**	4	**TLFP. 1:** 19 (2.8%)
PRP	4	**PRP. 1:** 6 (0.9%)			**TLFP. 2:** 23 (3.4%)
		PRP. 2: 7 (1.0%)			**TLFP. 3:** 23 (3.4%)
		PRP. 3: 9 (1.3%)			**TLFP. 4:** 32 (4.7%)
		PRP. 4: 8 (1.2%)			
PA	4	**PA. 1:** 10 (1.5%)	**RS-D**	4	**RS-D. 1:** 8 (1.2%)
		PA. 2: 9 (1.3%)			**RS-D. 2:** 9 (1.3%)
		PA. 3: 13 (1.9%)			**RS-D. 3:** 14 (2.1%)
		PA. 4: 7 (1.0%)			**RS-D. 4:** 14 (2.1%)
NA	4	**NA. 1:** 8 (1.2%)	**RD**	3	**RD. 1:** 13 (1.9%)
		NA. 2: 9 (1.3%)			**RD. 2:** 19 (2.8%)
		NA. 3: 7 (1.0%)			**RD. 3:** 14 (2.1%)
		NA. 4: 7 (1.0%)			
SK	6	**SK. 1:** 9 (1.3%)	**RS-P**	6	**RS-P. 1:** 9 (1.3%)
		SK. 2: 12 (1.8%)			**RS-P. 2:** 11 (1.6%)
		SK. 3: 12 (1.8%)			**RS-P. 3:** 10 (1.5%)
		SK. 4: 11 (1.6%)			**RS-P. 4:** 12 (1.8%)
		SK. 5: 17(2.5%)			**RS-P. 5:** 12 (1.8%)
		SK. 6: 25 (3.7%)			**RS-P. 6:** 15 (2.2%)
SE	3	**PSE. 1:** 10 (1.5%)	**RS-SE**	7	**RS-SE. 1:** 17 (2.5%)
		PSE. 2: 18 (2.6%)			**RS-SE. 2:** 12 (1.8%)
		PSE. 3: 13 (1.9%)			**RS-SE. 3:** 9 (1.3%)
					RS-SE. 4: 11 (1.6%)
					RS-SE. 5: 5 (0.7%)
					RS-SE. 6: 10 (1.5%)
					RS-SE. 7: 7 (1.0%)

Diagnosing randomness of missing data with Little's MCAR (Missing Completely At Random) test (Little, 1988) shows a Chi-Square of 10183.7, (df = 10071), and a significance level of 0.213. This result is not significant at an alpha level of 0.001, thus the missing data may be assumed to be missing at random. Consequently, the widest range of remedies can be used. In this study, the full information maximum-likelihood (FIML) was used as a method for handling missing data. FIML is a model-based method that is used frequently in structural equating modelling (SEM) (Kline, 2015). Unlike data-based methods (e.g. Multiple Imputation MI), FIML does not impute missing values into newly created data sets but rather obtains parameter estimates and standard errors by maximizing the likelihood function of the incomplete data (Schlomer et al. 2010; Dong and Peng, 2013; Li and Lomax, 2017). Under the assumption of multivariate normality and the missing mechanism of MAR, the log likelihood function of each observation i is (Yuan and Bentler, 2000):

$$\mathrm{Log}Li = K_i - \frac{1}{2}\log|\Sigma| - \frac{1}{2}(x_i - \mu)'\,\Sigma^{-1}(x_i - \mu)'$$

where x_i is the vector of observed values for case i, K_i is a constant that is determined by the number of observed variables for case i, and μ and Σ are, respectively, the mean vector and the covariance matrix that are to be estimated (Enders, 2001). The total sample log likelihood is the sum of the individual log likelihood across n cases. The standard ML algorithm is used to obtain the estimates of μ and Σ, and the corresponding SEs by maximizing the total sample log likelihood function(Dong and Peng, 2013) that measures the discrepancy between the observed data and current parameter estimates by using all the available data from the variables being modelled (Li and Lomax, 2017). FIML estimates are obtained through an iterative approach. See Arbuckle et al. (1996) for technical details.

According to Schlomer et al., (2010), FIML has two primary advantages over imputation techniques that make this procedure the most preferred for handling missing data: (a) the imputation procedure and the analysis are conducted within the same step, thus it is much simpler than multiple imputation (MI) and, (b) unlike the expectation-maximization (EM) algorithm, FIML produces accurate standard errors and confidence intervals by retaining the size of the sample (Schlomer et al., 2010). Furthermore, unlike other traditional missing data treatments, when the normality assumption was violated, FIML is demonstrated to (Li and Lomax, 2017): (a) be more efficient, (b) generate smaller parameter estimate bias, as long as the missing mechanism was MCAR or MAR (e.g., Enders, 2001; Wothke, 2000); and (c) generate lower and more consistent model rejection rates (e.g., (Enders and Bandalos, 2001)). However, to correct the bias associated with non-normality, Enders (2001) recommended the use of correction methods, such as rescaled statistics or bootstrap.

5.3.2 Detecting and Addressing Outliers

Outliers, "out-of-range values", are observation points that significantly deviate from the rest (Hawkins, 1980) or from the model suggested by the majority of the point cloud, where the central model is a multivariate normal set (Rousseeuw and Van Zomeren, 1990). Outliers may be caused by: errors in responding by research participants; errors in data entry; poorly-worded survey items; and/or incorrect specification of the population and/or sampling process (Osborne and Overbay, 2004). In addition, 'interesting' outliers could exist in a given population with potentially valuable or unexpected knowledge about certain phenomena and substructures in the data (Aguinis et al., 2013). In general, outliers can falsify statistical tests, increase error variance, bias estimates (especially when using statistical methods that rely on normality assumptions (Cohen et al., 2013), influence model fit and lead to incorrect inference (i.e. incorrect substantive conclusions regarding relationships among variables, which in turn may lead to false acceptance or rejection of hypotheses); they should, therefore, be addressed before continuing with data analysis (Schwager and Margolin, 1982; Bollen and Jackman, 1990; Yuan et al., 2002; Osborne and Overbay, 2004; Hair et al., 2010; Kline, 2015). Gallagher, Ting and Palmer (2008) posit that identification and deletion of outliers can contribute to the multivariate normality required for SEM estimation methods (Gallagher et al., 2008).

Two separate diagnostic approaches (univariate and multivariate analysis) are used to identify outliers. A univariate outlier has an extreme score on a single variable, whereas a multivariate outlier has extreme scores on two or more variables. For the univariate outliers, critical z-score values of 1.96, 2.58 and 3.29 could be used in identifying potential, probable and extreme outliers, respectively (Field, 2013). For this current study, IBM SPSS for windows was used to inspect the frequency distributions of the standardised z-score values for all the variables and there were no extreme univariate outliers, as all the standardised variable values were less than 3.29 (or $|z| < 3.0$ (Kline, 2015)), which is the critical z-score at the $\alpha = 0.001$ level. This critical z-score is appropriate for this study as the sample was considered to be large, with observations >200.

Table 5.13: Top sixty observations farthest from the centroid, for the Dual-process Model (tested in Chapter 6)

Case #	D^2	P	Case #	D^2	P	Case #	D^2	P
626	104.354	0	657	69.728	0.001	352	64.609	0.005
152	97.893	0	17	69.502	0.001	495	64.576	0.005
506	88.407	0	5	69.5	0.001	61	64.416	0.005
497	86.618	0	551	69.491	0.001	423	63.53	0.006
535	85.761	0	444	69.147	0.001	300	63.362	0.006
661	85.618	0	46	68.566	0.002	550	63.244	0.006
380	83.988	0	651	68.489	0.002	440	63.199	0.006
428	82.49	0	173	68.187	0.002	671	63.123	0.006
451	77.745	0	114	68.167	0.002	664	62.814	0.007
522	74.782	0	225	67.695	0.002	19	61.758	0.009
403	74.353	0	452	67.421	0.002	219	61.112	0.01
257	73.731	0	271	67.364	0.002	80	61.014	0.01
544	72.887	0.001	245	66.978	0.003	250	60.822	0.011
669	71.651	0.001	26	66.931	0.003	10	60.6	0.011
581	71.592	0.001	302	66.81	0.003	116	60.366	0.012
151	71.351	0.001	18	66.649	0.003	9	60.337	0.012
442	71.233	0.001	680	66.276	0.003	208	60.335	0.012
633	71.156	0.001	243	65.655	0.004	47	60.061	0.013
361	70.062	0.001	479	65.57	0.004	459	59.936	0.013
32	69.729	0.001	354	64.878	0.004	472	59.688	0.014

*Notes: **Blue shaded cases are the outliers as indicated by the Mahalanobis Distance.*

A multivariate outlier diagnostic approach was undertaken and this utilised an SEM-based multivariate technique called the squared value of Mahalanobis Distance of a case from the centroid (D2) to analyze the data. Mahalanobis Distance (D2), which identifies extreme scores on a combination of two or more variables, was produced by SPSS AMOS version 24.0 for the detection of multivariate outliers in the data set. For example, Tables 5.13 below gives a summary of the top sixty observations farthest from the centroid (ranked from high to low) for the dual-process model in this study. The Mahalanobis measure has numerical properties that allow for significant testing at 0.001 levels (Hair et al. 2010), and according to Tabachnick and Fidell (2007), a critical chi-square (X2) value can be calculated to determine whether any outliers exist in the data set. With 38 variables used (the 37 variables in the survey and 1 additional ID variable) in AMOS for the production of the Mahalanobis Distance for the variables in the dual-process model, the df = 37 and a criterion p = 0.001, the critical X2 = 69.3 . At this point, 24 multivariate outliers, cases 5, 17, 32, 151, 152, 257, 361, 380, 403, 428, 442, 451, 497, 506, 522, 535, 544, 551, 581, 626, 633, 657, 661 and 669, were identified from the 681, and would be deleted from further analysis (in Chapter 6), leaving 657 cases available for subsequent analysis in the dual-process model.

Using the same criterion, of the total 681 cases, 18 cases with critical X2 = 82.72 (df=47, at p = 0.001) would be removed as they are remotely apart from the rest of the cases, thus leaving a sample size of 663 (See Table 5.14) for subsequent analysis of the extended (mediation) model (this model is tested in Chapter 7).

Table 5.14: Top sixty observations farthest from the centroid, for the Extended Model (i.e. Mediation Model tested in Chapter 7)

Case #	D^2	P	Case #	D^2	P	Case #	D^2	P
626	115.35	0	**633**	80.602	0.002	352	75.836	0.006
152	106.132	0	**423**	80.512	0.002	664	75.383	0.007
506	101.858	0	**495**	80.184	0.002	676	75.325	0.007
661	99.065	0	**361**	80.151	0.002	550	74.889	0.008
380	96.353	0	**5**	80.015	0.003	229	74.497	0.008
428	94.926	0	**581**	79.495	0.003	452	74.463	0.009
497	94.574	0	**32**	79.491	0.003	541	74.195	0.009
535	91.539	0	**151**	79.381	0.003	46	74.077	0.009
451	90.949	0	**17**	79.325	0.003	47	73.858	0.01
614	90.908	0	**271**	79.299	0.003	440	73.584	0.01
442	87.486	0	**9**	78.915	0.003	354	73.548	0.01
544	87.225	0	**551**	78.112	0.004	18	73.342	0.011
556	85.987	0.001	**245**	77.808	0.004	671	73.335	0.011
116	84.914	0.001	**444**	77.613	0.004	225	73.129	0.011
657	84.871	0.001	**243**	77.596	0.004	648	73.078	0.011
522	84.2	0.001	**107**	77.569	0.004	479	73.074	0.011
666	84.139	0.001	**257**	77.497	0.004	205	72.408	0.013
403	83.331	0.001	**669**	77.487	0.004	339	71.967	0.014
173	80.871	0.002	**680**	76.507	0.006	10	71.71	0.015
183	80.829	0.002	**651**	75.921	0.006	114	71.625	0.015

*Notes: **Grey shaded cases are the outliers as indicated by the Mahalanobis Distance.*

According to the same criterion of multivariate outlier detection, of the total 681 cases, 18 cases with critical X2 = 54.05 (df=26, at p = 0.001) would be removed as it is remotely apart from the rest of the cases, thus leaving a sample size of 663 for subsequent analysis of the Moderation Model of RS-P (tested in Chapter 8). Using this criterion for the moderation models RS-SE and RS-D, of the total 681 cases, the respective number of removed cases with critical X2 = 54.05 (df=26, at p = 0.001) were 21 and 17 cases, thus leaving a sample size of 660 and 664, respectively.

5.3.3 Assessing Normality

Having inspected the data for missing values and outliers and applying the appropriate remedies, the next and final step in the data preparation and screening process was to test for the presence of significant departures from normality, which is an essential assumption in the use of numerous multivariate analyses techniques, including SEM (Hair et al,, 2010; Bagozzi and Yi, 2012; Kline, 2015; Byrne, 2016). The additional assumptions are that the data are continuous (with observations (scores) measured independently) and that there are no missing data (Kline, 2012).

Normality is referring to the distribution of sample data that corresponds to a normal distribution. A normal distribution of data describes a symmetrical, bell-shaped curve, which has the greatest frequency of scores in the middle with smaller frequencies towards the extremes (Gravetter and Wallnau, 2016). Normality of variables is evaluated by the use of graphical or statistical methods (Tabachnick and Fidell 2007). The simplest way to assess normality is to examine the data graphically by plotting a histogram, a normal Q-Q plot, or boxplot (Tabachnick and Fidell, 2007). In a normal distribution a straight diagonal line will emerge and the plotted data values are compared with the diagonal straight line. Each of the 68 variables in this study was checked for normality using the frequency histogram and the normal probability plot. For example, Figure 5.1 below depicts an illustration of a normal probability plot for one of the variables in this study, PRP 3.

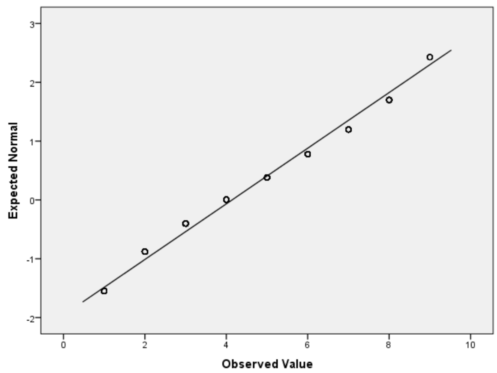

Figure 5.1: Normal Q-Q Plots of PRP.3

Note: This plot revealed a 45-degree line, indicating that departure from normality was acceptable.

Statistically, normality can be assessed to some extent by obtaining skewness and kurtosis levels. The skewness value provides an indication of departure from symmetry in a distribution (Ahad et al., 2011). A distribution, or data set, is symmetric if the median divides the left side and the right side into two identical areas. Skewness is measured with the following equation (Kenney and Keeping, 1962):

$$\text{Skewness} = \sum_{i=1}^{N} \frac{(Xi - \overline{X})^3}{(N-1)s^3}$$

Where $\overline{\boldsymbol{X}}$ *is the mean,* **N** *is the number of data points, and,* **s** *is the standard deviation. A symmetric distribution has a skewness value of zero. Negative values indicate data that are left skewed and positive values indicate data that are right skewed (Ahad et al., 2011).*

Kurtosis, on the other hand, refers to the peakedness of a distribution that measures the extent to which scores are clustered together (i.e., leptokurtic distribution) or widely dispersed (i.e., platykurtic distribution)(Miles and Shevlin, 2001; Cunningham, 2008). That is, data sets with high kurtosis tend to have a distinct peak near the mean, decline rather rapidly, and have heavy tails.

Data sets with low kurtosis tend to have a flat top near the mean rather than a sharp peak (Ahad et al., 2011). Kurtosis is measured with the following equation (Miles and Shevlin, 2001):

$$\text{Kurtosis} = \sum_{i=1}^{N} \frac{(Xi - \bar{X})^4}{(N-1)s^4}$$

*where $\bar{\mathbf{X}}$ is the mean, **N** is the number of data points, and **s** is the standard deviation. The kurtosis for a standard normal distribution is three.*

Absolute value less than or equal to 2 (|skew| ≤ 2) for skewness and less than or equal to 3 (|kurtosis| ≤ 3) for kurtosis are acceptable limits for the condition of normality to be satisfied (Newsom, 2005). Skewness and Kurtosis values close to zero indicate that the distribution is close to normal (Tabachnick and Fidell, 2007). In the present research, univariate normality of the data distribution was inspected using IBM SPSS. As presented in Table 5.15, most of the univariate distributions were considered normal, since the absolute values of skewness (asymmetry) and kurtosis (peakedness) of the variables entered into SEM analyses for the dual process model were below 2 and 3, respectively. The absolute values of skewness and kurtosis of the variables entered into SEM analyses of the mediation and moderation models were also below 2 and 3, respectively.

Table 5.15: Skewness and Kurtosis values of the variables entered into SEM analyses of the Dual Model

Variable	N	Skewness		Kurtosis		Variable	N	Skewness		Kurtosis	
		Statistic	Std. Error	Statistic	Std. Error			Statistic	Std. Error	Statistic	Std. Error
PRP.1	657	.003	.095	-1.033	.190	NA.1	657	.202	.095	-1.135	.190
PRP.2	657	.126	.095	-1.030	.190	NA.2	657	.284	.095	-1.039	.190
PRP.3	657	.295	.095	-.870	.190	NA.3	657	.293	.095	-1.015	.190
PRP.4	657	.631	.095	-.586	.190	NA.4	657	.224	.095	-1.174	.190
PRC.1	657	.068	.095	-1.118	.190	PA.1	657	.316	.095	-.962	.190
PRC.2	657	.364	.095	-.824	.190	PA.2	657	.308	.095	-.972	.190
PRC.3	657	.419	.095	-.747	.190	PA.3	657	.358	.095	-.876	.190
PRC.4	657	.389	.095	-.789	.190	PA.4	657	.339	.095	-1.005	.190
PRC.5	657	.393	.095	-.638	.190	PBI.1	657	.388	.095	-.788	.190
PRC.6	657	.349	.095	-.702	.190	PBI.2	657	.384	.095	-.823	.190
PRC.7	657	.466	.095	-.638	.190	PBI.3	657	.382	.095	-.849	.190
PRC.8	657	.342	.095	-.935	.190	PBI.4	657	.390	.095	-.854	.190
PRC.9	657	.368	.095	-.836	.190	PBI.5	657	.334	.095	-.853	.190
SK.1	657	.329	.095	-.931	.190	PBI.6	657	.370	.095	-1.018	.190
SK.2	657	.241	.095	-1.007	.190	PBI.7	657	.408	.095	-.764	.190
SK.3	657	.302	.095	-1.098	.190	PBI.8	657	.308	.095	-.874	.190
SK.4	657	.400	.095	-.959	.190	PBI.9	657	.208	.095	-1.197	.190
SK.5	657	.451	.095	-.899	.190	PBI.10	657	.219	.095	-1.186	.190
SK.6	657	.382	.095	-1.039	.190	PE	657	-.021	.095	-1.266	.190

5.3.4 Sample Size and Power Analysis

As was discussed in Section 4.3, the issue of sample size in SEM remains an ongoing debate in the literature, with no agreed minimum or maximum sample sizes (Nunnally, 1967; Boomsma, 1982; Bollen, 1989; Bentler and Chou, 1987; MacCallum et al., 1999; Iacobucci, 2010; Fabrigar et al., 2010; MacCallum et al., 2010; Kline, 2011; Wolf et al., 2013; Sideridis et al., 2014). For example, Iacobucci (2010, p. 91), on the one hand, states that when it comes to sample size, "bigger is always better". On the other hand, Fabrigar, Porter and Norris (2010) argue that a satisfactory sample size is the one that approximates the model's statistics to be closely equal to the population parameters. If the sample size is not large, some statistical estimates in SEM, such as standard errors, may not be accurate, and the probability of technical problems in the analysis is greater (Kline, 2015). From this, it was important to consider this issue prior to data collection. In particular, a priori calculation using Soper's (2017) SEM sample size calculator indicates that the number of collected cases exceeds the minimum sample size required for each model in this research analysis to yield adequate power (see Table 4.3).

However, to further ensure that the number of cases in the data set (after handling missing values, unengaged responses and outliers) provided adequate power for the analysis and interpretation of the results, a power analysis test was conducted (see Table 5.16). According to the power analysis approach, the appropriate sample size for each model in this study was estimated based on the number of variables, constructs, and the degrees of freedom, desired power and model fit (MacCallum et al., 1996; Kim, 2005; Preacher and Coffman, 2006). In this study, RMSEA was used to assess the fit, and the desired power of 0.99, 0.95 and .90 were used. There should be sufficient power (> 0.80) in the analysis to reject either perfect fit (Null RMSEA = 0.00) or close fit (Alt. RMSEA = 0.025). Using the computing power and minimum sample size computer software for RMSEA (http://www.quantpsy.org/rmsea/rmsea.htm) and the R programming language for testing the dual process model, minimum sample sizes of 393, 320 and 281 were achieved for the desired power levels of 0.99, 0.95 and 0.90, respectively. The results for the other models are shown in Table 5.16 below. All the available sample sizes (Table 5.16: column 2) for the proposed structural models exceed the minimum recommended sample sizes, and are, therefore, judged to be adequate for testing each structural models. This means enough power existed and the structural equation model was strong enough to detect whether significant effects did actually exist (at alpha= 0.05).

Table 5.16 Computing Sample Size Using RMSEA for Perfect Fit and for Three Desired Power Levels

Structural model		Sample Size (N)	#Observed Variables	Degree Of Freedom	Minimum sample size for test of fit		
					Desired Power = **.99**	Desired Power = **.95**	Desired Power = **.90**
- Dual-process Model		657	37	647	393	320	281
- Extended/ Mediation Model		663	47	1094	293	242	213
- Moderation model:	**RS-P**	663	26	285	625	501	437
	RS-SE	660	26	285	625	501	437
	RS-D	664	26	285	625	501	437

5.4 RELIABILITY ANALYSIS

In this study, scale reliability was evaluated using Cronbach's alpha (coefficient alpha) coefficient on SPSS, giving a measure of how well a set of manifest indicators measure the scale (DeVellis, 2016). As was discussed in Chapter 4, the higher the reliability value, the more reliable the measure and, in most cases, a value of 0.5 to 0.6 would be sufficient to consider a scale as a reliable one and a Cronbach alpha value of more than 0.7 indicates that the scale is more reliable (Hair et al. 2010). Corrected Item-Total Correlation is another way to assess how well one item's score is internally consistent with composite scores from all other items that remain. If this correlation is weak, then that item should be removed and not used to form a composite score for the variable in question. There is no exact standard for the cut-off of Corrected Item-Total Correlation, but a rule-of-thumb is that they should be at least 0.40 (Lounsbury et al., 2006) or 0.30 (De Vaus, 2013).

Table 5.17 shows a summary of item reliability for all the constructs to be used in the structural equation modelling, and it includes the Cronbach's alpha, corrected item-total correlation and Cronbach's alpha if an item is deleted. All alpha were higher than 0.70, which is much preferred. To purify measures of the survey and improve reliability, none of the items was deleted at this stage. Other reliability measures derived from confirmatory factor analysis, such as composite reliability and average variance extracted, will be used after running the confirmatory factor model. These measures will be discussed in depth in the next chapters, Analysis of Data, to confirm the reliability and validity of the scales used. To this end, the reliability coefficients for the thirteen constructs employed in the study exceed the minimum threshold value of .7 and more importantly, are at least equivalent to, or better than, the coefficients reported in comparable studies.

Table 5.17: Reliability analysis: Cronbach's Alpha

Construct	Cronbach's Alpha	Item	Corrected-Item-Correlation	Cronbach's Alpha If Item Deleted
Perceived Risk Probability	.954	**PRP.1**	.880	.942
		PRP.2	.917	.930
		PRP.3	.926	.928
		PRP.4	.827	.957
Perceived Risk Consequence	.955	**PRC.1**	.833	.949
		PRC.2	.812	.951
		PRC.3	.827	.950
		PRC.4	.807	.951
		PRC.5	.813	.951
		PRC.6	.812	.951
		PRC.7	.812	.951
		PRC.8	.840	.949
		PRC.9	.812	.951
Affective Appraisals (Negative)	.925	**NA.1**	.838	.897
		NA.2	.777	.917
		NA.3	.824	.902
		NA.4	.860	.890
Affective Appraisals (Positive)	.941	**PA.1**	.876	.917
		PA.2	.827	.932
		PA.3	.858	.923
		PA.4	.874	.918

Table 5.17 continues on the next page…..

Table 5.17 (continued)

Construct	Cronbach's Alpha	Item	Corrected-Item-Correlation	Cronbach's Alpha If Item Deleted
Protective behavioural Intentions	.959	**PBI.1**	.824	.954
		PBI.2	.790	.956
		PBI.3	.808	.955
		PBI.4	.811	.955
		PBI.5	.789	.956
		PBI.6	.811	.955
		PBI.7	.791	.956
		PBI.8	.822	.954
		PBI.9	.863	.953
		PBI.10	.865	.953
Subjective Knowledge	.928	**SK.1**	.804	.913
		SK.2	.776	.917
		SK.3	.772	.917
		SK.4	.766	.918
		SK.5	.797	.914
		SK.6	.829	.910
Non-protective responses: (Risk Denial)	.920	**RD. 1**	.836	.885
		RD. 2	.850	.874
		RD. 3	.826	.893
Self-efficacy (personal control)		**P. 1**	.815	.885
		P. 2	.837	.867
		P. 3	.827	.875
Trust (Institutional control)	.932	**T. 1**	.839	.912
		T. 2	.827	.916
		T. 3	.839	.912
		T. 4	.858	.906
Residential Satisfaction (physical attributes of neighbourhood)	.943	**RS-P. 1**	.839	.931
		RS-P. 2	.852	.929
		RS-P. 3	.789	.937
		RS-P. 4	.855	.929
		RS-P. 5	.848	.930
		RS-P. 6	.783	.938
Residential Satisfaction (Socio-economic attributes of neighbourhood)	.939	**RS-SE. 1**	.788	.930
		RS-SE. 2	.767	.932
		RS-SE. 3	.825	.927
		RS-SE. 4	.798	.929
		RS-SE. 5	.799	.929
		RS-SE. 6	.795	.929
		RS-SE. 7	.814	.928
Residential Satisfaction (Attributes of dwelling)	.917	**RS-D. 1**	.726	.921
		RS-D. 2	.872	.871
		RS-D. 3	.876	.870
		RS-D. 4	.773	.906

5.5 CHAPTER SUMMARY

In this chapter, as a precursor to the multivariate analysis, an examination of the variables used in the measurement model was presented and descriptive statistics of the population in this study was provided. This was then followed with a discussion of how missing responses and outliers were treated and how both normality assumption and sample size adequacy were checked before proceeding with the data analysis. Finally, the reliability testing of the main constructs was demonstrated. In the next chapters, the preliminary data analysis for hypotheses testing will be discussed.

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CHAPTER 6

SEM ANALYSIS:

The Influence of Cognitive and Affective Risk Perceptions on Protective Behavioural Intentions

(Recursive vs. Non-Recursive Models)

This chapter presents the results from multivariate statistical models used to address the **Research Objective #1**: **To examine how affective and cognitive mechanisms interact to shape risk perceptions and behavioural intentions of flood-prone households.** In particular, this chapter follows a non-recursive (i.e. bidirectional) structural equation modelling (SEM) approach to examine the hypothesis that cognitive and affective processes reciprocally influence each other to (conjointly) shape perceptions and, subsequently, the protective behavioural intentions of flood-prone households. To validate the plausibility of this model, this chapter will then compare it with the traditional (i.e. unidirectional) models in terms of the predictive power for protective behavioural intentions.

6.1 MODEL SPECIFICATION AND IDENTIFICATION

Utilizing the hypothesized model (Figure 3.1) and the research constructs, a structural model consisting of 37 observed variables associated with six latent variables has been specified as illustrated in Figure 6.1 below. Because two of the paths in the model specify two directions of causality (i.e. bi-directionality), the model in this study is non-recursive. Non-recursive structural equation models are more complex, in the sense that they generally take the form of feedback loops (i.e. reciprocal relationships), involving two latent variables (here cognitive and affective processes) that are hypothesized to simultaneously influence each other. The unidirectional arrows represent the causal relationship; that is, the variable at the base of the arrow is hypothesized to "cause" the variable at the head of the arrow. Observed variables are enclosed in boxes and latent variables are circled. To ensure that the model remained over-identified, each latent factor was constrained to one observed variable (i.e. the factor loading for one observed variable in each latent factor was fixed to one). Further to this, all residual coefficients were constrained to 1, thereby making the residual matrix an identity matrix. Finally, the regression coefficient for the residuals of the endogenous latent variables were constrained to 1.

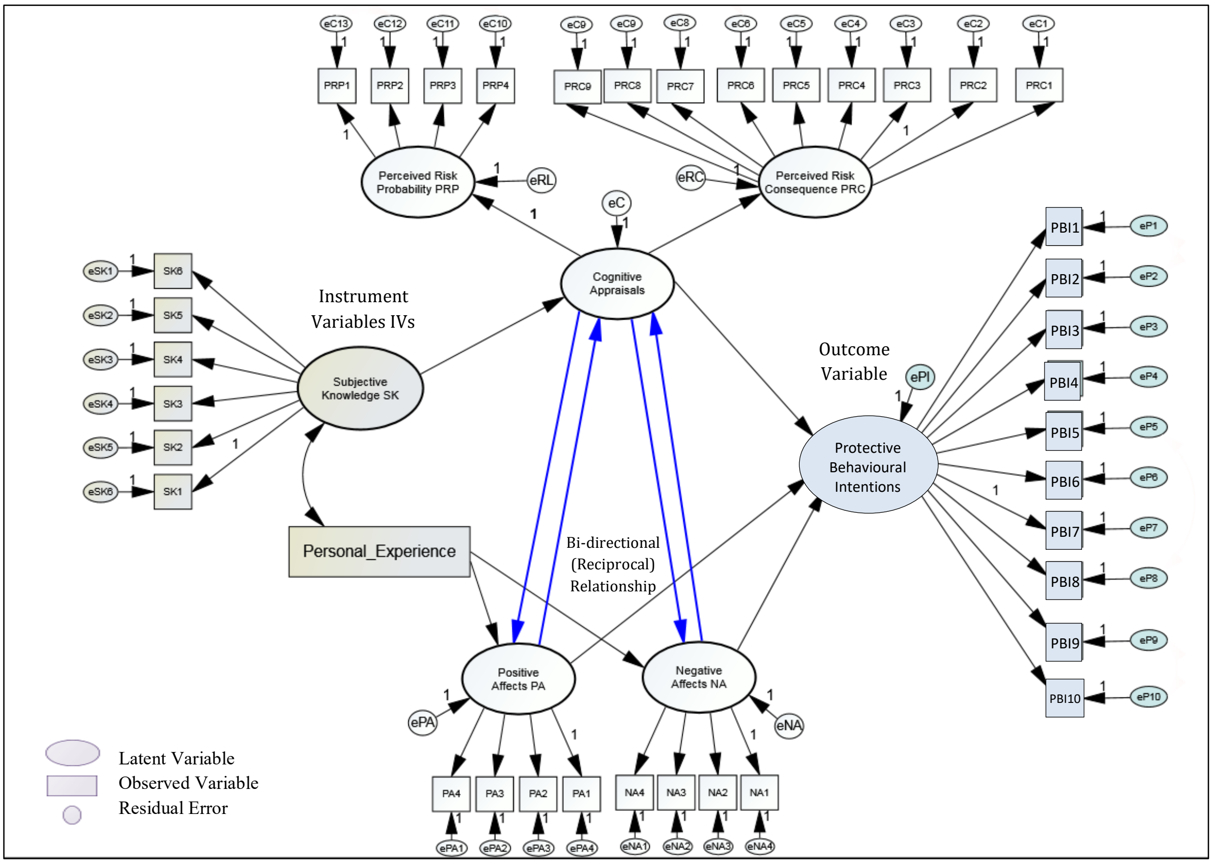

Figure 6.1 The hypothesized dual-process (Cognition ↔ Affect) model with covariance structure analysis

As was discussed in Section 4.7.1, one complication of non-recursive models is empirical identification. Following Finch and French's (2015) recommendations to remedy this complication, subjective knowledge (SK) is introduced as an "instrument variable IV". In particular, it is hypothesized that SK is a valid instrument because it is both theoretically and empirically related to cognitive risk perceptions but only marginally to affective risk perceptions. Subjective, or "self-reported", knowledge is characterized by the depth of an individual's awareness of the hazard's genesis, its mechanisms of exposure, and types of adjustments that can avoid its impacts. Such a level of awareness can largely influence the individual's judgments regarding likelihood and impact of the perceived risk, as found by several investigators (e.g.,Raaijmakers et al., 2008; Botzen et al., 2009a; Lopez-Marrero, 2010).

Personal experience (PE) is introduced as a second IV. There is evidence that PE is theoretically and empirically related to affective risk perceptions, but only marginally to cognitive risk perceptions. To illustrate, in contrast to knowledge about the risk, PE often elicits vivid images of a past risk event. This is particularly attributed to the notion that the salience and severity of previous flood experiences can create strong and instinctive impressions (or emotional reactions) as found by several investigators (e.g. Keller et al., 2006; Grothmann and Reusswig, 2006; Siegrist and Gutscher, 2008; Miceli et al., 2008; Terpstra et al., 2009; Zaalberg et al., 2009;

Terpstra, 2011; Fatti and Patel, 2013). Thus, the main perceptual difference between triggering more negative or positive emotional reactions towards the risk lies in the severity of previous flood experiences.

Furthermore, it is required for the proposed non-recursive model to meet the equilibrium assumption on rational grounds, in order to be more defensible than standard recursive models (i.e. where affective and cognitive processes occur sequentially). The rational ground for this comes substantially from recent neurological evidences demonstrating that affective and cognitive processes in the human brain are more likely to occur simultaneously but not sequentially (Pessoa, 2015). This argument is well supported by some research on risk perception (as discussed in more detail in Chapter 2). However, it is still required to meet the equilibrium assumption on a statistical ground by evaluating the 'stability index' when analyzing the non-recursive model in the following sections. A standard interpretation of the stability index is that values less than 1.0 are taken as positive evidence for equilibrium (Finkel, 1995: p.44).

Other important assumptions that should be considered for a typical application of SEM with maximum likelihood (ML) as an estimation technique are linearity and homoscedasticity. Linearity refers to the linear relationship between variables, whereas homoscedasticity refers to the assumption that dependent variable(s) exhibit equal levels of variance across the range of predictor variables (Hair et al., 1998). The violation of the linearity assumption usually results in under-estimation and further leads to the inflation of Type I and Type II errors (Osborne and Waters, 2002). In addition, obtaining reliable findings based on linear regression requires the variance of regression errors to be stable across observations. Although light heteroscedasticity is acceptable in empirical research, severe violation of the homoscedasticity assumption is likely to increase the Type I error rate (Osborne and Waters, 2002). Heteroscedastic residuals may be caused by non-normality in either variable, greater measurement error at some levels of either variable than others, or outliers (Kline, 2015). To assess linearity and homoscedasticity in this study, scatterplots of standardised residuals vs standardised prediction of the dependent variable were produced and are presented in **Appendix B**. Inspection of bivariate scatter plots resulted in an oval-shaped array of points demonstrating that variables are linearly related and their variances are homogenously distributed. The spread of the residuals was approximately within the same vertical range around the zero horizon line, indicating the constant variance of the regression errors. Thus, for the proposed model above, it is safe to conclude that both linearity and homoscedasticity assumptions are not significantly violated. As a result, it is now possible to move to the next stage, which is model testing by covariance-based (SEM) techniques.

6.2 RESULTS FROM SEM ANALYSIS

To test the proposed dual-process model and its related hypotheses, this thesis follows Anderson and Gerbing's (1988) two-step approach where a measurement model is first estimated using both Exploratory and Confirmatory Factor Analyses. After ensuring the adequacy of the measurement model, a covariance-based (SEM) analysis is utilized to find the best-fitting structural model.

6.2.1 Results from Exploratory Factor Analysis (EFA)

To assess divergent validity, the 37 items that were retained for the hypothesized model in Figure 6.1 were subjected to an exploratory factor analysis (EFA). In particular, after checking the statistical assumptions of EFA in terms of normality (Section 5.3.3) sample size (Section 5.3.4), reliability (Section 5.4), and factorability of the measurement scales, the principal axis factoring (PAF) method was used to extract the variables' underlying factors. As was discussed in Chapter 4, this extraction method seeks the least number of factors which can account for the common bias variance (i.e. communality estimates on diagonal of correlation matrix) of a set of variables. PAF was, therefore, preferred because it accounts for co-variation and it can be used when the assumption of normality has been violated (Fabrigar et al., 1999). The exploratory PAF analysis was conducted considering the eigenvalues greater than one, factor loadings greater than 0.32 (Tabachnick and Fidell, 2001), and Promax with Kaiser Normalization as a rotation method to identify the number of extracted factors. For this study, Promax is expedient because of its speed in larger datasets.

The results from the EFA showed that a total of 74.51% (> 50% (Pett et al., 2003)) variance of the 36 original variables was explained by the 6 extracted factors as shown in the pattern matrix in Table 6.1. The minimum factor loading was 0.665, which is more than the minimum 0.32 (Tabachnick and Fidell, 2001). The signs of the loadings show the direction of the correlation and do not affect the interpretation of the magnitude of the factor loading or the number of factors to retain. In addition, there were no item cross-loadings (i.e., split loadings): each factor defines a distinct cluster of interrelated items. These results, thus, lead us to accept the 6 extracted factors as conceptually proposed to measure the model's constructs

Furthermore, in ensuring the factorability of the data, the inter-item correlations (correlation matrix) amongst the variables (Section 5.5), KMO test of sampling adequacy and Bartlett's test of sphericity were checked for each extracted factor. It is generally recommended that the KMO value should be greater than 0.5 if the sample size is adequate. As presented in Table 6.1 (Column 3), the KMO value for the instruments was ranged between "0.786 to 0.965" all of which are acceptable as a good value. Meanwhile the correlations among the underlying variables of the study measures are confirmed to be significant (at $p < 0.001$) based on the results of Bartlett's test of sphericity. The overall KMO value for the EFA matrix extracted for the CAB model is 0.980—with a significant Bartlett's test (for an Approx. Chi-Square = 25934.193 and DF= 666). Hence, on getting middling to quite meritorious results for the validity, the measurement scales were considered valid and appropriate for further data analysis.

Table 6.1: Tests of divergent validity and dimensionality (Promax Rotated Matrix) of the dual-process model's constructs

Variable	KMO	Bartlett's test	PBI	PRC	SK	PRP	PA	NA
Protective Behavioural Intention	**.965**	Approx. Chi-Square= **6209.420** Df = **45** Sig.= **0.000**						
PBI. 1			.887					
PBI. 2			.838					
PBI. 3			.837					
PBI. 4			.830					
PBI. 5			.825					
PBI. 6			.788					
PBI. 7			.770					
PBI. 8			.767					
PBI. 9			.748					
PBI. 10			.727					
Perceived Risk Consequence	**.963**	Approx. Chi-Square= **5557.102** Df= **36** Sig.= **0.000**						
PRC. 1				.835				
PRC. 2				.835				
PRC. 3				.812				
PRC. 4				.802				
PRC. 5				.798				
PRC. 6				.796				
PRC. 7				.774				
PRC. 8				.758				
PRC. 9				.754				
Subjective Knowledge	**.931**	Approx. Chi-Square= **3029.560** Df = **15** Sig.= **0.000**						
SK .1					.845			
SK. 2					.816			
SK. 3					.815			
SK. 4					.771			
SK. 5					.749			
SK. 6					.701			
Perceived Risk Probability	**.786**	Approx. Chi-Square= **3295.149** Df = **6** Sig.= **0.000**						
PRP. 1						.925		
PRP .2						.864		
PRP. 3						.748		
PRP. 4						.715		
Positive Affects	**.866**	Approx. Chi-Square= **2450.528** Df = **6** Sig.= **0.000**						
PA. 1							-.859	
PA. 2							-.854	
PA. 3							-.839	
PA. 4							-.764	
Negative Affects	**.850**	Approx. Chi-Square= **2084.960** Df = **6** Sig.= **0.000**						
NA. 1								.867
NA. 2								.811
NA. 3								.788
NA. 4								.665

6.2.2 Results from Confirmatory Factor Analysis (CFA)

Satisfied by the initial reliability and validity of the measurement scales, I moved into the confirmatory phase of validating the measurement model. Arbuckle (2016: p. 86) explains that a measurement model is "the portion of the model that specifies how the observed variables depend on the unobserved, or latent, variables". The measurement model thereby specifies the form by which each item loads onto a particular construct or variable (i.e., either with latent or composite variables) (Arbuckle, 2016; Byrne, 2016). According to Hair et al. (2010), a measurement model contributes in two different ways. First, it specifies the indicators (i.e., specific items or survey questions) for each construct and, second, it enables an assessment of construct validity and reliability.

6.2.2.1 Testing CFA Model

CFA involves the estimation of an a priori measurement model, where the observed variables are mapped onto the latent constructs according to theory and prior testing by the researcher. Utilizing the conceptual structures extracted for each construct in the proposed dual-process model of flood risk perception, here the measurement model is specified (Figure 6.2), consisting of 5 first-order reflective latent constructs and one second-order latent variable. The construct of Cognitive risk perception is conceptualised as a first-order reflective latent construct because this thesis focuses on its overall interaction with both negative and positive affective risk perceptions and not how they interact with specific cognitive constructs. The rationale behind this is that an individual's perceived risk relates to the combined measurement of 'perceived probability' and 'perceived consequences' of a possible flood event (as discussed in more detailed in Section 2.2.2). Previous studies have also conceptualised cognitive risk perception as second-order reflective latent constructs (e.g., Zhai and Ikeda, 2008).

For model identification purposes, the "marker variable" technique has been adopted by fixing the variance of each latent exogenous variable to 1. In addition, because each of the latent variables was measured using four or more manifest variables—two of them do not have correlated errors—the CFA model is considered to be identified. By ensuring that the CFA measurement model was adequately identified, the estimation process on SPSS Amos 0.24 was carried out using maximum likelihood (ML) (Jöreskog, 1967, 1969). The Bollen-Stine p-value is employed in this analysis due to the multi-variate non-normality of the data. The Bollen-Stine p-value should be greater than 0.05 at significance level of 0.05.

Furthermore, as was presented in Figure 4.6, this thesis took extra precautions to increase confidence in the replicability of the final (modified) measurement model by cross-validating the model. Therefore, the final sample available (N=657)—after excluding 24 extreme multivariate outliers among the cases—was divided randomly into two subsamples: a calibration sample and validation sample. The calibration sample (N=328)[c] was used in the initial model testing, while the validation sample(N=329)[v] was used to confirm the model. A final CFA was done using the complete sample to obtain more stable estimates of item loadings, discriminant validity, composite reliability (CR) and model fit.

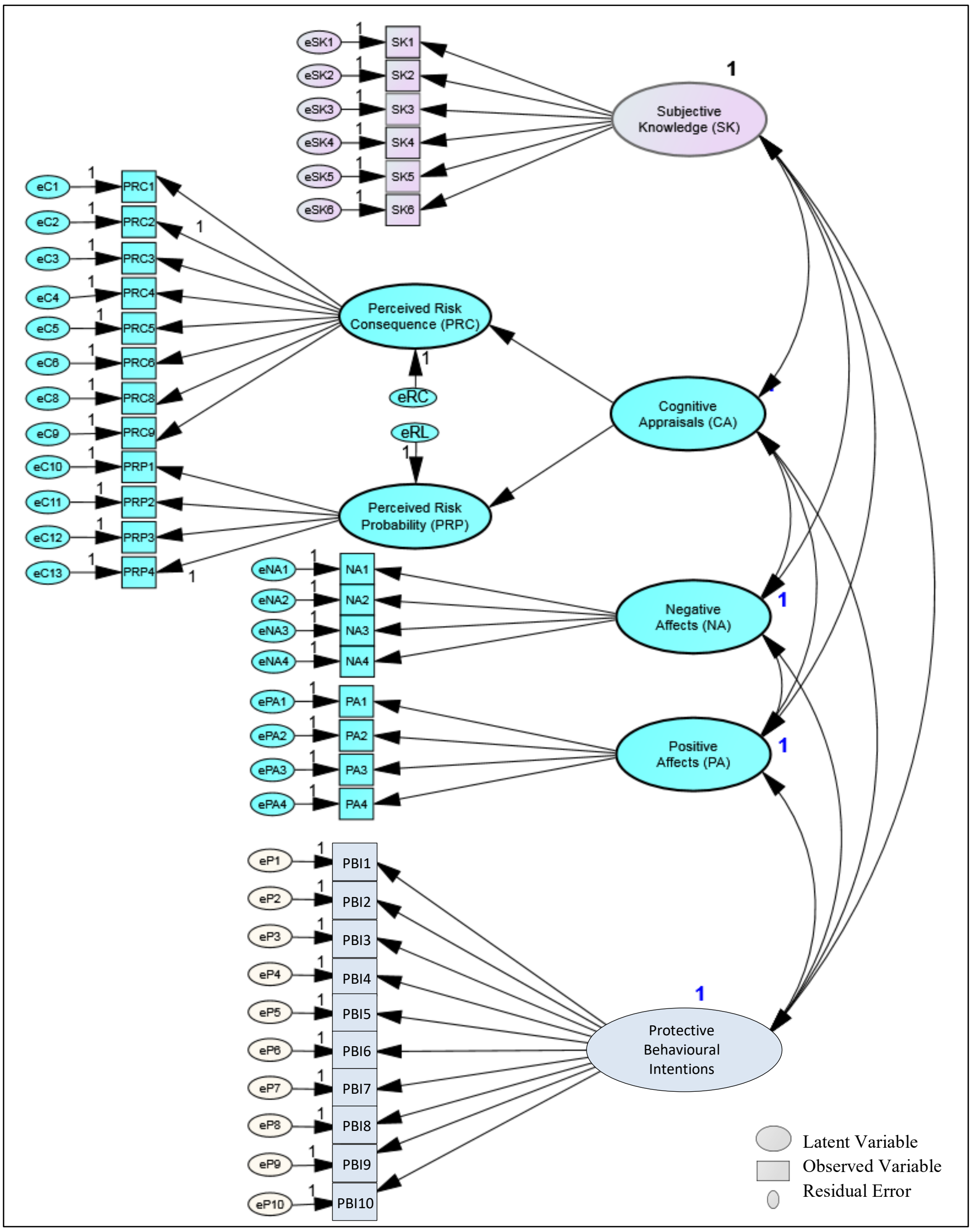

Figure 6.2: The Initial Measurement Model (for the Dual-process Model)

All measures of reliability, validity, and unidimensionality for calibration, validation, and whole sample were separately estimated. In the following sections, convergent validity, item reliability, model fit, and estimates of unidimensionality are reported for calibration, validation, and the whole sample. In contrast, discriminant validity and reliability are reported for the whole sample only (although they were conducted for the calibration and validation samples also) to avoid redundancy.

Table 6.2: Standardized Coefficient weights (ß), Squared Multiple Correlations (SMC) and measurement model fit for the calibration and validation samples

Item	Latent Construct	Calibration Sample		Validation Sample		Whole Sample	
		ß (P-value)[c]	MSC[c]	ß (P-value)[v]	MSC[v]	ß (P-value)[w]	MSC[w]
PBI. 1	←Protective Behavioural Intentions	0.821 (***)	0.674	0.812 (***)	0.659	**0.815** (***)	**0.664**
PBI. 2	←Protective Behavioural Intentions	0.833 (***)	0.694	0.835 (***)	0.697	**0.837** (***)	**0.701**
PBI. 3	←Protective Behavioural Intentions	0.830 (***)	0.689	0.833 (***)	0.694	**0.817** (***)	**0.668**
PBI. 4	←Protective Behavioural Intentions	0.815 (***)	0.664	0.815 (***)	0.663	**0.817** (***)	**0.667**
PBI. 5	←Protective Behavioural Intentions	0.853 (***)	0.727	0.837 (***)	0.700	**0.839** (***)	**0.703**
PBI. 6	←Protective Behavioural Intentions	0.796 (***)	0.634	0.834 (***)	0.696	**0.834** (***)	**0.696**
PBI. 7	←Protective Behavioural Intentions	0.842 (***)	0.708	0.842 (***)	0.709	**0.842** (***)	**0.709**
PBI. 8	←Protective Behavioural Intentions	0.877 (***)	0.769	0.892 (***)	0.796	**0.881** (***)	**0.775**
PBI. 9	←Protective Behavioural Intentions	0.842 (***)	0.708	0.855 (***)	0.731	**0.847** (***)	**0.718**
PBI. 10	←Protective Behavioural Intentions	0.872 (***)	0.760	0.885 (***)	0.783	**0.881** (***)	**0.777**
PRC. 1	←Perceived Risk Consequence	0.944 (***)	0.744	0.886 (***)	0.771	**0.866** (***)	**0.750**
PRC. 2	←Perceived Risk Consequence	0.861 (***)	0.691	0.877 (***)	0.768	**0.850** (***)	**0.722**
PRC. 3	←Perceived Risk Consequence	0.813 (***)	0.662	0.845 (***)	0.714	**0.833** (***)	**0.695**
PRC. 4	←Perceived Risk Consequence	0.822 (***)	0.676	0.853 (***)	0.728	**0.839** (***)	**0.704**
PRC. 5	←Perceived Risk Consequence	0.820 (***)	0.672	0.856 (***)	0.733	**0.848** (***)	**0.720**
PRC. 6	←Perceived Risk Consequence	0.821 (***)	0.674	0.868 (***)	0.753	**0.846** (***)	**0.715**
PRC. 8	←Perceived Risk Consequence	0.827 (***)	0.684	0.868 (***)	0.753	**0.846** (***)	**0.718**
PRC. 9	←Perceived Risk Consequence	0.862 (***)	0.743	0.878 (***)	0.786	**0.874** (***)	**0.764**
SK .1	←Subjective Knowledge	0.846 (***)	0.720	0.827 (***)	0.716	**0.843** (***)	**0.711**
SK. 2	←Subjective Knowledge	0.815 (***)	0.665	0.822 (***)	0.676	**0.836** (***)	**0.699**
SK. 3	←Subjective Knowledge	0.781 (***)	0.609	0.819 (***)	0.671	**0.823** (***)	**0.677**
SK. 4	←Subjective Knowledge	0.856 (***)	0.733	0.846 (***)	0.705	**0.839** (***)	**0.704**
SK. 5	←Subjective Knowledge	0.849 (***)	0.715	0.840 (***)	0.684	**0.823** (***)	**0.678**
SK. 6	←Subjective Knowledge	0.878 (***)	0.771	0.883 (***)	0.780	**0.881** (***)	**0.776**
PRP. 1	←Perceived Risk Probability	0.948 (***)	0.947	0.954 (***)	0.910	**0.951** (***)	**0.905**
PRP .2	←Perceived Risk Probability	0.973 (***)	0.899	0.978 (***)	0.957	**0.792** (***)	**0.628**
PRP. 3	←Perceived Risk Probability	0.896 (***)	0.802	0.899 (***)	0.807	**0.897** (***)	**0.804**
PRP. 4	←Perceived Risk Probability	0.774 (***)	0.599	0.809 (***)	0.655	**0.976** (***)	**0.952**
PA. 1	←Positive Affect	0.905 (***)	0.819	0.921 (***)	0.849	**0.915** (***)	**0.741**
PA. 2	←Positive Affect	0.896 (***)	0.802	0.901 (***)	0.812	**0.917** (***)	**0.841**
PA. 3	←Positive Affect	0.850 (***)	0.722	0.872 (***)	0.760	**0.861** (***)	**0.808**
PA. 4	←Positive Affect	0.913 (***)	0.834	0.925 (***)	0.855	**0.899** (***)	**0.837**
NA. 1	←Negative Affect	0.913 (***)	0.833	0.895 (***)	0.800	**0.899** (***)	**0.809**
NA. 2	←Negative Affect	0.877 (***)	0.769	0.868 (***)	0.753	**0.866** (***)	**0.751**
NA. 3	←Negative Affect	0.803 (***)	0.645	0.847 (***)	0.718	**0.842** (***)	**0.710**
NA. 4	←Negative Affect	0.895 (***)	0.802	0.886 (***)	0.785	**0.904** (***)	**0.817**

6.2.2.3 CFA results using calibration sample

In the first iteration, the factor loadings for each of the 36 items were significantly larger than their standard errors, and the associated t-statistics (critical ratio (C.R) values) exceeded ±1.96 (at $p < 0.05$). All the fit statistics were within the accepted range ($\chi 2/df = 1.604$ RMSEA = 0.043, PCLOSE= .991, CFI= .970 and TLI= .968). However, upon inspection, modification indices (MIs)[c], standardised residuals (SRs)[c], and item content, identified causes of model misspecification so it was decided to embark on post-hoc model fitting. For example, the largest MI was obtained for a pair of manifest variables (PRP_3 and PRP_4 with MI = 115.462), which also produced one standardised residual above 2.58. Based on these results and after assessment of item content, another model was specified by including a correlation between the error terms for these variables. An alternative would be to drop these two items from the model, but I decided to keep all four items in order to represent their respective domains more completely. However, Hair et al. (2010) caution that it is not enough to make changes centred only on modification indices and par change alone, but to consider the theoretical explanation and use of other residual analysis such as standardised residuals. Indeed, the two measurement items, PRP 3 (flooding through the non-habitable spaces in the house) and PRP 4 (flooding through the habitable spaces and their possessions) were somehow considered to measure the same thing (i.e. flooding inside the house), hence, their error terms could be, therefore, co-varied.

Further inspection of the standardised residuals (SRs)c led to the deletion of one item, namely PRC_7 which produced 37 standardised residuals below −2.58 and one above 2.58. Altogether, these changes subsequently improved the fit of the model ($\chi 2/df$ = 1.311, p RMSEA = 0.031, PCLOSE= 1.00, CFI= .985 and TLI= .984) and produced insignificant p-value for the Bollen-Stine bootstrap (P= 0.063 > 0.05), and thus rejecting the null hypothesis that the default model fits the data better is true. To this end the standardised residual covariance matrix (SRCM) from the model output was examined and there were no standardised residual values below −2.58 or above 2.58. A value of |2.58| corresponds to the area beyond the ±2 standard deviations from the average standardized residual or the values lying in the extreme 5% of the distribution. Moreover, all modification indices were below 10. No further refinement or modifications were, therefore, needed.

The results from the final iteration show that all factor loadings for the remaining 36 items are significantly larger than their standard errors, resulting in z-statistic (C.R values) that exceed ±1.96 (at $p < 0.05$). The standardized regression coefficients (ß)c for all items were significant (at $p < 0.001$) and ranged between 0.790 and 0.972 (Table 6.2: Column 3). The squared multiple correlations (SMC) (a measure of statistical variance which is equivalent to the estimated communality (R2) in EFA) were above the acceptable value of 0.3 for all items (Table 6.2: Column 4) and, thus, were retained. These results provided evidence for the unidimensionality of each scale.

6.2.2.4 CFA results using validation sample

The measurement model incorporating the modifications described in Section 6.2.2.3 was retested using the validation sample. Results for the convergent validity from the validation sample are reported in Table 6.2 (Columns 5 and 6). The pattern and size of standardized coefficient weights $(ßs)^v$, and squared multiple correlations $(SMCs)^v$ and the variance explained is almost similar to those in the calibration sample. All the fit statistics were within the accepted range ($\chi 2/df$ = 1.246 RMSEA = 0.027, PCLOSE= 1.00, CFI= .989, TLI= .988 and P-value for Bollen-Stine bootstrap = 0.119), which indicated an excellent fit. All absolute standardized residuals were less than the recommended value (< 2.58), and all modification indices were less than 15. Altogether, these results indicate that the validation sample explains the relationships in the final measurement model well. These results also indicate that the two samples exhibit invariance of form (i.e. using the same mapping of manifest variables to latent variables in two sub-samples is appropriate).

6.2.2.5 CFA results using the whole sample

The path loadings between the item and its corresponding factor were all positive and significant at $p < 0.001$, and the value of the path loading ranged between 0.792 and 0.976 (Table 6.2, Columns 7 and 8). In terms of model fit, all the measures somehow improved with the use of the whole sample due to increased sample size. The RMSEA value equalled 0.022, the p-value associated with the null hypothesis of close fit (1.000) indicates that it could not be rejected. All other fit measures were also above the recommended value ($\chi 2/df$ = 1.321, CFI= .993 and TLI= .992). The proportion of absolute standardized residuals >|2.58| is 0% (0 out of 666), and all modification indices are <15. Composite reliability of study constructs, indicating the internal consistency of multiple indicators for each construct, ranged from 0.892 to 0.960 (Table 6.3), exceeding the recommended threshold suggested by Bagozzi and Yi (1988). Finally, Average Variance Extracted (AVE) for the measures was calculated. All AVE values, ranging from 0.707 to 0.807, exceeded the recommended value of 0.50 (Fornell and Larcker, 1981). This confirmed convergent validity. In addition, the AVE value for each construct was greater than the squared correlation between constructs, indicating that discriminant validity was achieved. The diagonal elements of the correlations represent the square root of the average variance extracted and are all greater than the correlations between the off-diagonal bivariate correlations, also signifying that discriminant validity is satisfactory. To conclude, discriminant validity appears satisfactory at the construct level as well as the item level in the case of all constructs, therefore, the constructs in the proposed model are deemed adequate.

Table. 6.3: Construct reliability, convergent validity and correlations among the latent factors coefficients

Latent Factor	CR	AVE	MSV	PBI	NA	PA	CA-RP	SK
Protective Behavioural Intentions PBI	0.960	0.708	0.661	**0.841**				
Negative Affect NA	0.931	0.771	0.624	0.790	**0.878**			
Positive Affect PA	0.944	0.807	0.618	-0.783	-0.725	**0.898**		
Cognitive Appraisals CA	0.892	0.806	0.661	0.813	0.781	-0.786	**0.898**	
Subjective Knowledge SK	0.935	0.707	0.659	0.730	0.671	-0.662	0.812	**0.841**

6.3 RESULTS FROM STRUCTURAL MODEL ANALYSIS

As the reliability and validity of the measures have been ensured, a covariance-based structural equation modelling analysis (CB-SEM) was conducted using Amos version 24.0 to test the hypothesized "dual-process" model in Figure 6.1.

6.3.1 The Bi-directionality of Cognition and Affect in Predicting PBI

Maximum likelihood estimation was performed on path coefficients between variables in the hypothesized "dual-process" model, thereby giving a measure of causal influence. The statistical significance of each parameter estimate was also computed. Table 6.4 lists the estimated path coefficients along with their corresponding critical ratios and p-values. Path coefficients represent the strength of connection (or influence) conveyed through each pathway. The estimated pathway connection strengths are also summarized graphically in Figure 6.3 below.

Table 6.4: Parameter Estimates and GoF Indices for the (non-recursive) Structural Model

Predictor Constructs	Predicted Constructs	ß (Standardized)	T-test Statistic	p-value[a]
Subjective Knowledge	→ Cognitive Risk Perceptions	**0.536**	13.697	***
Personal Experience	→ Positive Affects	**-0.370**	-10.286	***
Personal Experience	→ Negative Affects	**0.450**	12.823	***
Cognitive Risk Perceptions	→ Protective Behavioural Intentions	**0.405**	4.086	***
Positive Affects	→ Protective Behavioural Intentions	**-0.216**	-8.082	***
Negative Affects	→ Protective Behavioural Intentions	**0.333**	7.236	***
Positive Affects	→ Cognitive Risk Perceptions	**-0.251**	-4.974	***
Negative Affects	→ Cognitive Risk Perceptions	**0.218**	4.589	***
Cognitive Risk Perceptions	→ Positive Affects	**(0.433**	-10.852	***
Cognitive Risk Perceptions	→ Negative Affects	**-0.466**	10.554	***

GOF Indices of the Structural Model

Fit Indices	X^2/df	CFI	TLI	RMSEA	PCLOSE	P for Bollen-Stine bootstrap
Value	1.442	0.989	0.988	0.026	1.00	0.056
Benchmark	≤ 3.00	> 0.95	> 0.95	< 0.05	> 0.05	> 0.05

Note: a:** and *** stand for statistically significant levels of 0.01 and 0.001 respectively Notes: X^2/df (Chi-square/degree of freedom) = normed Chi-square; CFI = comparative fit index; TLI = Tucker-Lewis Index; RMSEA = root mean square error of approximation.

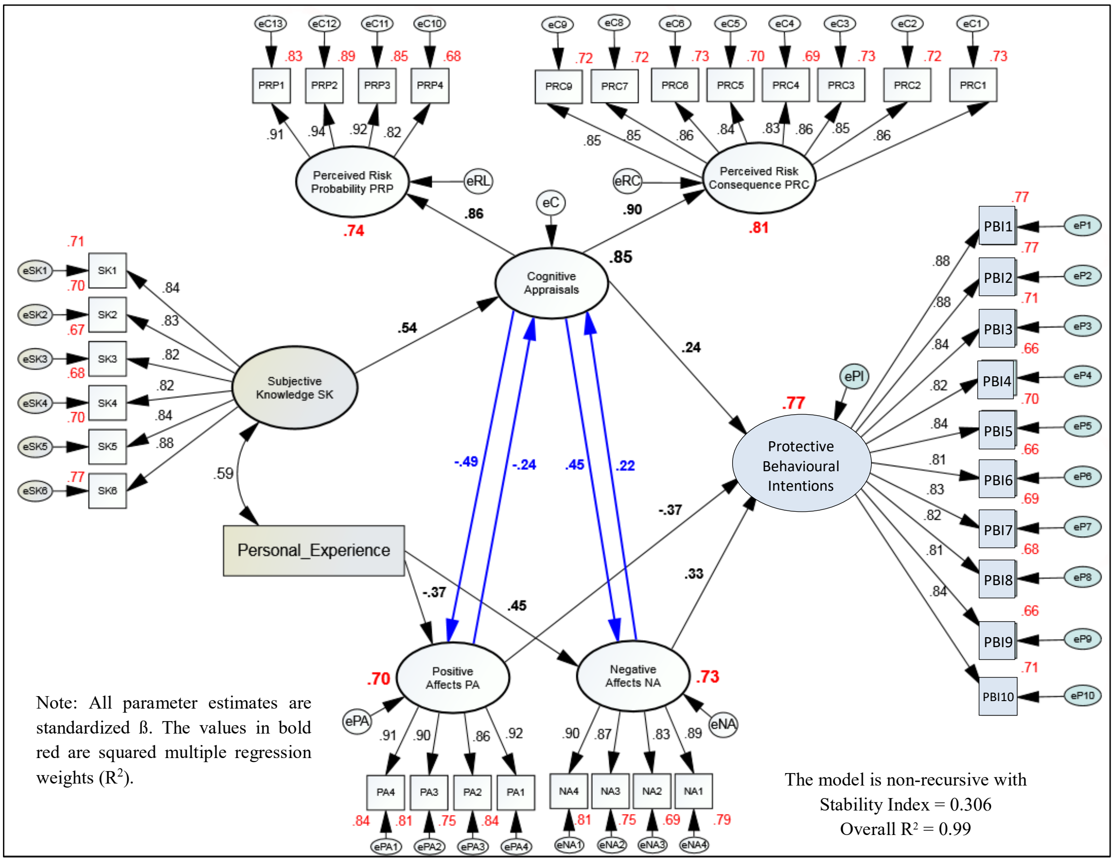

Figure 6.3: Empirical model of (dual-process) flood risk perception with with SEM analysis

The model fit as measured by the absolute goodness-of-fit indices, X2/df and RMSEA, and the incremental fit indices (CFI and TLI), indicated that the structural model had a good fit since all the indices exceeded their respective targeted acceptable levels. Overall, the stability index of the non-recursive model above is 0.214 < 1.00, which satisfies the functional equilibrium assumption (Bentler and Freeman, 1983). As depicted in Table 6.4, all the structural paths are significant and in the direction predicted by the theoretical model. The critical ratios (t-values) are all above 1.96 indicating significant paths at $p < 0.05$ level. The proportion of absolute standardized residuals >|2.58| is 0% (0 out of 703) and all modification indices (MIs) are <15 (after correlating the residual errors of PRP_3 and PRP-4 as was done in the CFA stage). No further refinement or modifications are, therefore, needed.

As depicted in Figure 6.3, the results from the covariance structure analysis indicate that both cognitive appraisals (CA) and negative affect (NA) influence each other significantly and positively with standardized regression weights of $\beta=0.22$ at $p<0.001$ (NA → CA) and $\beta=0.45$ at $p<0.001$ (CA → NA). Initially, these results suggest an interdependent, reciprocal, relationship between CA and NA, confirming what has been predicted by the theoretical dual-process model (see the bi-directional blue arrows in Figure 6.1). To illustrate, it can be concluded that people who express more intense negative affective reactions (e.g., fear, uncertainty, worry and powerlessness) regarding the risk tend to cognitively judge its probability and the extent of damages/consequences to be high (i.e. high intense negative affect triggers more pessimistic risk perceptions). Simultaneously, people who cognitively judge the risk to be high, based on its perceived probability and the extent of damages/consequences, tend to feel more afraid, worried and powerless (i.e. higher levels of risk perception elicit more intense negative affective reactions). Similarly, the coefficient signs suggest that cognitive and 'positive' affective (PA) appraisals of flood risk perception influence each other reciprocally but negatively, with standardized regression weights of $\beta=-0.49$ at $p<0.001$ (CA → PA) and $\beta=-0.24$ at $p<0.01$ (PA →CA). In other words, positive affective reactions trigger optimistic risk assessments. Simultaneously, low risk perception elicits higher positive affective reactions (e.g. feeling of safety, unity/solidarity, beauty of nature, pleasurable fascination or excitement). Again, these results suggest an interdependent, reciprocal relationship between cognitive risk perceptions and positive affect, confirming what has been predicted by the theoretical dual-process model.

Furthermore, to mitigate concerns about the instrument variables (IVs: Subjective Knowledge (SK) and Personal Experience (PE)), their standardised effect on each of the corresponding endogenous variables appears to be equal ($\beta = 0.56$, $p < 0.001$ for the path from SK to CA vs. $\beta = 0.51$, $p < 0.001$ for the path from PE to NA). Moreover, a detailed inspection of the direct and indirect effects (followed by a mediation test with bootstrapping bias-corrected 95% confidence interval procedure in SEM) indicates that the impact of experience on PBI is completely mediated via both negative and positive affect with total indirect effects = 0.127 (at $p= 0.002$) and 0.038 (at $p=0.005$), respectively. Further to this, the impact of experience on CA is completely mediated by NA with a total indirect effect= 0.145 (at $p = 0.001$).

Taken together, these results (partly) support the first hypothesis (H.1) that the perception of flood risk can be represented as a bidirectional (reciprocal) relationship that significantly integrates both cognitively- and affectively-based risk judgements. However, in order to fully test the hypothesis, the fit of the non-recursive model was tested against the strictly recursive models by testing differences in the chi-squared $\Delta\chi^2$, relative fit and Bentler-Raykov squared multiple correlations (R^2), as well as the differences in the Akaike Information Criterion Δ (AIK) and the

Bayesian Information Criterion Δ(BIC), as commonly practiced in research (e.g., Eveland Jr et al., 2005; Linden, 2014). In doing so, two recursive models were developed. In the first recursive model (Figure 6.4) affective appraisals are conceptualized as antecedents of cognition and, in turn, cognition a predictor of PBI (i.e. cognition is conceptualized as a mediator for the affect-intentions relationship). In the second recursive model (Figure 6.5) cognitive appraisals influence affective reactions which in turn predict PBI of flood-prone households. These two recursive models were independently tested and subsequently compared to the reciprocal (non-recursive) model (Figure 6.3: where risk perception is conceptualized as a reciprocal relationship between affect and cognition, and in turn, conjointly predict PBI).

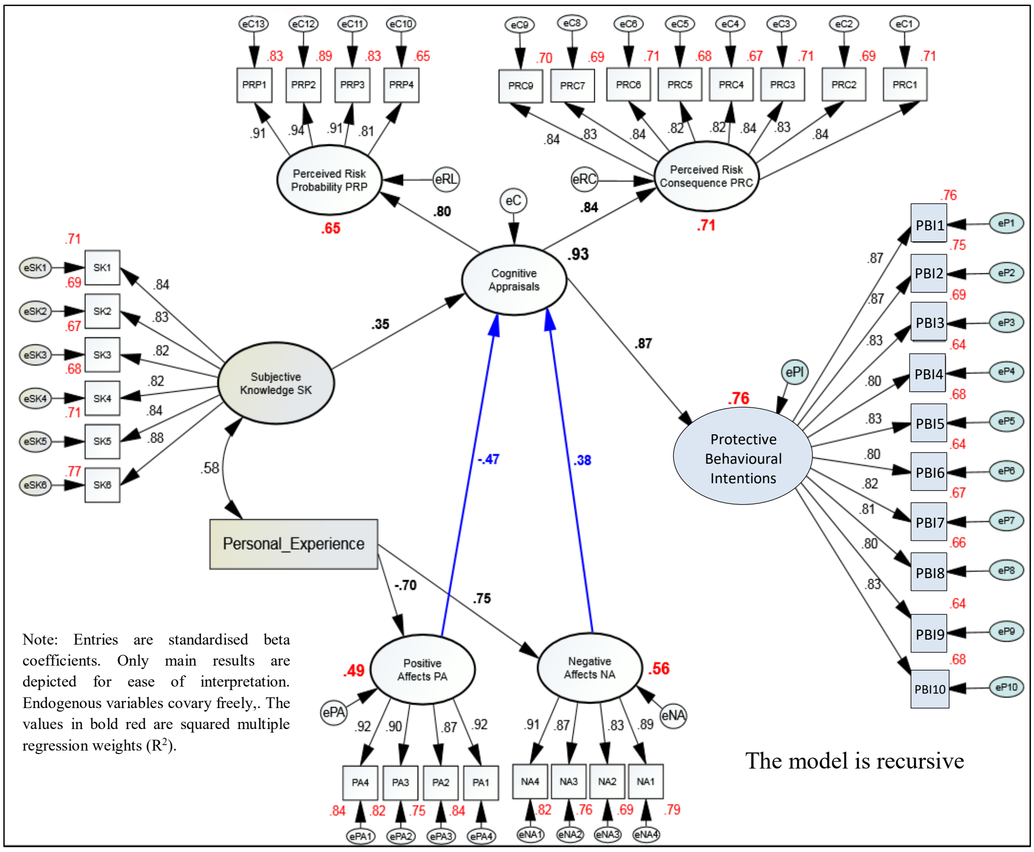

Figure 6.4: Empirical model of (Affect-Cognition– Intentions) relationship with SEM analysis

Table 6.5: Parameter Estimates and GoF Indices for the Recursive Model of Affect-Cognition-Intention

Predictor Constructs	Predicted Constructs	ß Unstandardized	ß Standardized	p-value
Subjective Knowledge	→Cognitive Appraisals	0.312	0.349	***
Persoanl Experience	→Positive Affect	-0.567	-0.701	***
Persoanl Experience	→Negative Affect	0.629	0.748	***
Cognitive Appraisals	→PBI	0.812	0.871	***
Positive Affect	→Cognitive Appraisals	-0.438	-0.467	***
Negative Affect	→Cognitive Appraisals	0.345	0.383	***

GOF Indices of the Structural Model

X2/df	CFI	RMSEA (PCLOSE)	TLI	P Bollen-Stine
1.916	0.978	0.038 (1.00)	0.976	0.056

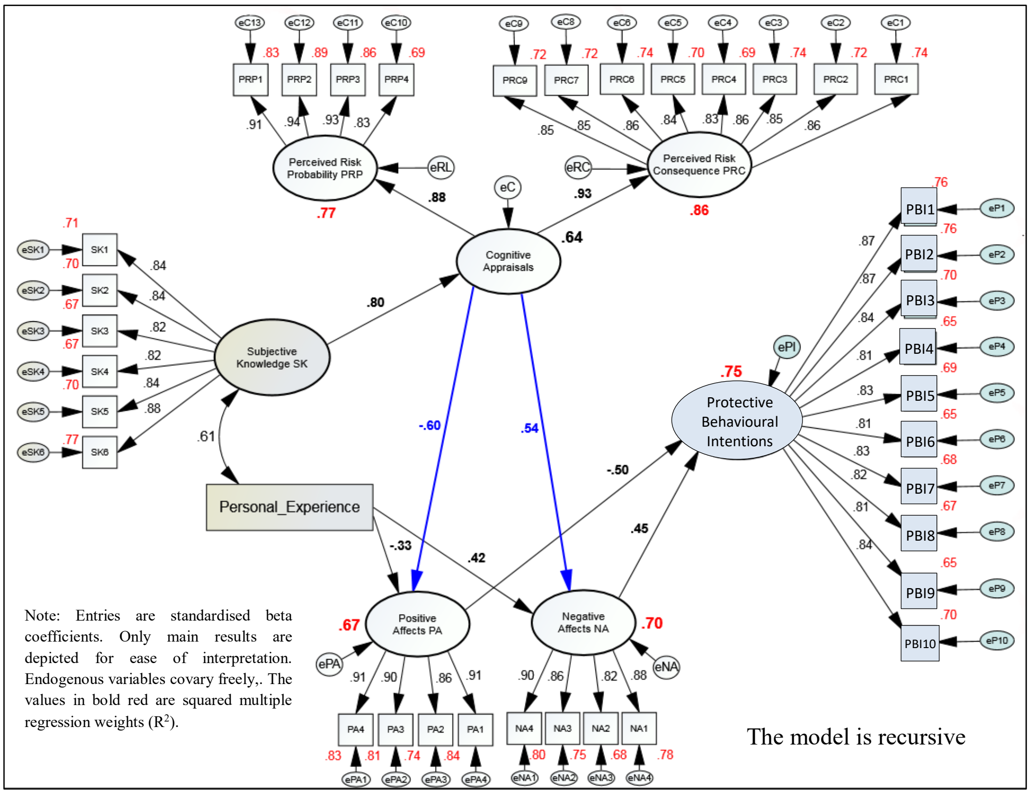

Figure 6.5: Empirical model of (Cognition-Affect-Intention) relationship with SEM analysis

Table 6.6: Parameter Estimates and GoF Indices for the Recursive Model of Cognition-Affect-Intention

Predictor Constructs	Predicted Constructs	ß Unstandardized	ß Standardized	p-value
Personal Experience	→ Subjective Knowledge	0.505	0.619	***
Subjective knowledge	→ Cognitive Appraisals	0.817	0.802	***
Personal Experience	→ Positive Affect	-0.261	-0.333	***
Personal Experience	→ Negative Affect	0.345	0.424	***
Negative Affect	→ Protective Intentions	0.400	0.449	***
Positive Affect	→ Protective Intentions	-0.458	-0.495	***
Cognitive Appraisals	→ Positive Affect	-0.547	-0.603	***
Cognitive Appraisals	→ Negative Affect	0.509	0.541	***

GOF Indices of the Structural Model				
X^2/df	CFI	RMSEA (PCLOSE)	TLI	P Bollen-Stine
1.550	0.987	0.029 (1.00)	0.985	0.056

Based on the results above, a few observations were immediately evident. Both recursive models (Affect-Cognition- Intention: $\chi 2/df$ = 1.916, RMSEA = 0.038, PCLOSE= 1.00, CFI= .978 and TLI= .976) and (Cognition-Affect-Intentions: $\chi 2/df$ = 1.550, RMSEA = 0.029, PCLOSE= 1.00, CFI= .987 and TLI= .985) showed an adequate fit to the data, as was also found for the non-resursive model (cognition ↔ affect: $\chi 2/df$ = 1.442, RMSEA = 0.026, PCLOSE= 1.00, CFI= .989 and TLI= .988). This implies that both the recursive models can well predict the protective behavioural intentions of flood-prone households.

Following the satisfactory results of the model evaluations, the two recursive models were compared with the non-recursive (cognition ↔ affect) model in terms of the explanatory power (i.e. explained variance R^2) for PBI. The results indicated that the dual-process (cognition ↔ affect) model has slightly better explanatory power for PBI ($R^2 = 0.77$) compared to the Affect-Cognition- Intention model with $R^2 = 0.76$, as well as the Cognition-Affect- Intention model with $R^2 = 0.75$. In terms of overall model fit, the non-recursive (cognition ↔ affect) model has a lower $\chi 2$ (610) = 879, $p < 0.001$ – which is preferable than the recursive (Affect-Cognition- Intention) model with $\chi 2$ (614) = 1176, $p < 0.001$, as well as the recursive (Cognition-Affect- Intention) model with $\chi 2$ (613) = 950, $p < 0.001$. In addition, the non-recursive (cognition ↔ affect) model is clearly superior in terms of its relative fit (RMSEA = 0.026) than both proposed recursive models. The differences in the Akaike Information Criterion Δ(AIK)= -304 and the Bayesian Information Criterion Δ(BIC) = -286 are also strongly in favour of the non-recursive (cognition ↔ affect) model, as compared to the recursive (Cognition-Affect- Intention) model. Similarly, the Δ(AIK)= -103 and the Δ(BIC) = -89 are strongly in favour of the non-recursive (cognition ↔ affect) model, as compared to the recursive (Cognition-Affect- Intention) model.

6.3.2 Results from Testing Associations (Direct Path Effects)

The relationships (i.e., associations) between the constructs proposed in the dual-process model will be discussed within the context of previously published research. The association strength (path coefficient) represents the response of the dependent variable to a unit change in an explanatory variable when other variables in the model are held constant (Bollen, 1989). The path coefficients of a structural equation model are similar to correlation or regression coefficients and are interpreted as follows: 1) A positive coefficient means that a unit increase in the activity measure of one structure leads to a direct increase in the activity measure of structures it projects to, proportional to the size of the coefficient. 2) A negative coefficient means that an increase in the activity measure in one structure leads to a direct, proportional decrease in the activity measure of structures it projects to.

In this study, it is hypothesized that cognitive and affective appraisals of perceived risk will each be significantly related with the private protective behavioural intentions PBI of flood-prone households. Figure 6.3 shows that this hypotheses appear to be strongly supported. In combination, the variables of risk perception accounted for 77.0% of the variance explained in PBI. Individually, the results from SEM analysis (Figure 6.3 and Table 6.4) indicate that statistically significant and positive correlations exist between: (1) cognitive appraisals of risk perception and PBI ($\beta = .24$, $t = 4.086$, at $p < 0.001$), and (2) negative affect (i.e. feeling of badness) and PBI ($\beta = .333$, $t = 7.236$, at $p < 0.001$). These results suggest that increased perception of risk and increased tendency to experience intense negative feelings will lead to a higher response to undertake protective measures against flood hazards. Positive feelings had the opposite effect. The results from SEM analysis also indicate that statistically significant but negative correlations exist between the tendency to experience positive affect (i.e. feeling of goodness) and PBI ($\beta = -0.22$, $t = -8.082$, at $p < 0.001$).

6.4 CHAPTER SUMMARY

This chapter tested a novel dual-process model of cognitive and affective risk perceptions predicting behavioural intentions of flood-prone households. In particular, this chapter followed a non-recursive (i.e. bidirectional) structural equation modelling (SEM) approach to examine the hypothesis that cognitive and affective processes reciprocally influence each other to conjointly shape perceptions and, subsequently, protective behavioural intentions of flood-prone households. To validate the plausibility of this model, this chapter compared the non-resursive (i.e. dual-process: cognition ↔ affect) model with the traditional resursive (i.e. unidirectional) models in terms of the predictive power for the protective behavioural intentions of flood-prone households. The results from SEM analysis clearly supported **H #1.1** that: In best predicting protective behavioural intentions of flood-prone households, the relationship between cognitive and affective risk appraisals is expected to be reciprocal. In other words, a bidirectional relationship between cognitive and affective risk appraisals can better predict protective behavioural intentions in comparison with the traditional unidirectional relationships.

The results from testing associations (direct path effects) supported **H #1.2** that: Protective behavioural intentions of flood-prone households is positively related to perceived risk through cognitive routes (i.e. an individual's comprehension of the risk, including its probability of occurrence and the severity of consequences). The results from testing associations (direct path effects) also supported **H #1.3** that: The intensity of negative affect promotes the protective behavioural intentions of flood-prone households, whereas the intensity of positive affect inhibits the protective behavioural intentions of flood-prone households.

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CHAPTER 7

MEDIATION ANALYSIS:

A psychological-oriented decision model of (non)protective behavioural intentions

This chapter extends the analysis of the dual-process model by specifically exploring how a different set of psychological variables influencing perception is processed through both cognitive and affective systems. In this regard, mediation and moderation analyses using SEM are conducted for cognitive and affective routes separately in order to address the ***Research Objectives 2 and 3.***

> **Objective #2:** To examine to what extent a different set of psychological factors influence risk perception processed through both cognitive and affective systems. These factors include previous experience of flooding events, subjective knowledge, self-efficacy (or perceived personal control) and trust in authorities and engineered flood defenses (or perceived institutional control).
>
> **Objective #3:** To examine the extent to which the impact of these psychological factors on protective behavioural intentions of flood-prone households can be mediated through both cognitive and affective risk perceptions.

7.1 MODEL SPECIFICATION AND IDENTIFICATION

Utilizing the hypothesized model (Figure 3.2) and the research constructs, a structural model consisting of 47 observed variables associated with 9 latent variables has been specified as illustrated in Figure 7.1 below. The focus of this study is directed at the psychological (cognitive-affective) variables explaining the link between protective behavioural intentions and particular predictors (namely, personal experience, subjective knowledge, Self-efficacy, and trust in local flood protection measures). The proposed model consists of three building blocks. The first block presents the relationship between protective behavioural intentions construct and its predictors. The second presents affective and cognitive appraisals as intervening (mediating) psychological variables. In the third block, the model was extended to include two specific reactions to the perceived risk: protective and non-protective (i.e. risk denial).

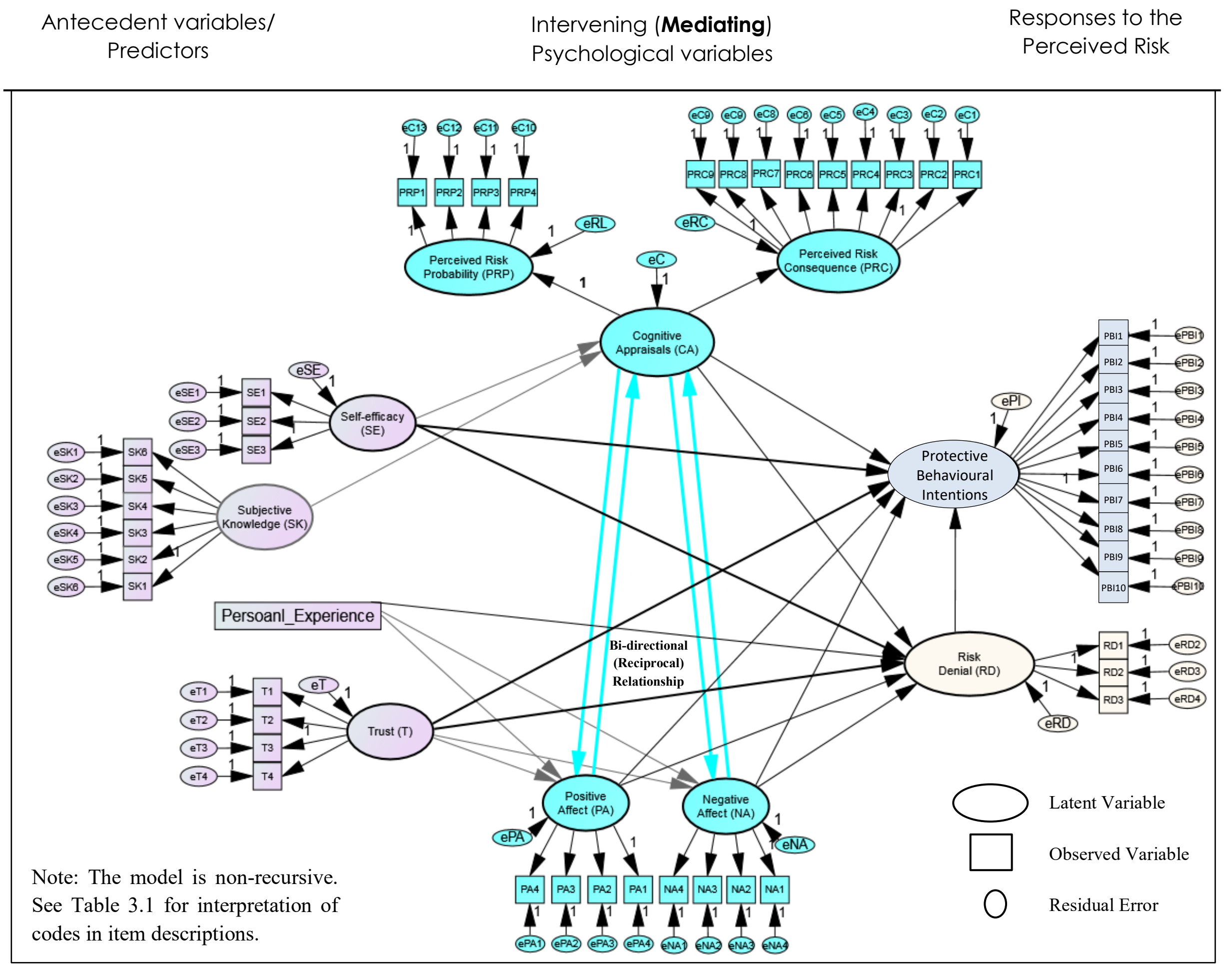


Figure 7.1: Mediation model predicting protective and non-protective (i.e. risk denial) reactions to the perceived risk

The unidirectional arrows represent the causal relationship; that is, the variable at the base of the arrow is hypothesized to "cause" the variable at the head of the arrow, observed variables are enclosed in boxes, and latent variables are circled. Because four of the paths in each mediated model specify two directions of causality (i.e. bi-directionality), the models are non-recursive. Constructs for the mediation model were assigned by setting one factor loading per construct to one in order to identify the model (i.e., marker items). Further to this, all residual coefficients were constrained to 1, thereby making the residual matrix an identity matrix. Finally, the regression coefficient for the residuals of the endogenous latent variables were constrained to 1. Both factor loadings and measurement errors comprised the measurement part of the model. The structural part of the model consisted of construct variances that were allowed to covary. Multiple fit indices were used to judge model fit. However, before discussing the results on direct and mediated relationships, exploratory and confirmatory factor analyses were performed using the whole sample in order to relate unique sets of items to their theoretical constructs as proposed in the mediation model above.

7.2 RESULTS FROM EFA: MEDIATION MODEL

For instruments designed to measure a theoretical construct with the help of a unique set of items, a key question is to what extent such a measurement instrument is valid. To assess divergent validity, the items that were retained for the hypothesized (mediation) model in Figure 7.1 above were subjected to an exploratory factor analysis (EFA). In particular, the EFA technique was used to understand the underlying structure and dimensionality of the observed variables/items. After checking the statistical assumptions of EFA in terms of normality (Section 5.3.3) sample size (Section 5.3.4), reliability (Section 5.4), and factorability of the measurement scales, the principal axis factoring (PAF) method was used to extract the variables' underlying factors. As was discussed in Chapter 4, this extraction method seeks the least number of factors which can account for the common variance (i.e. communality estimates on diagonal of correlation matrix) of a set of variables.

The results of the EFA for the mediation model predicting protective behavioural intentions (PBI) and risk denial (RD) showed that a total of 75.78% (> 50% (Pett et al., 2003)) variance of the 47 original variables was explained by the 9 extracted factors as shown in the pattern matrix in Table 7.1. The minimum factor loading was 0.651, which is more than the minimum 0.32 (Tabachnick and Fidell, 2001). The signs of the loadings show the direction of the correlation and do not affect the interpretation of the magnitude of the factor loading or the number of factors to retain. In addition, there were no item cross-loadings (i.e., split loadings); each factor defines a distinct cluster of interrelated items. These results, thus, lead us to accept the 9 extracted factors as conceptually proposed to measure the mediation model predicting PBI and RD.

Furthermore, in ensuring the factorability of the data, the inter-item correlations (correlation matrix) amongst the variables, KMO test of sampling adequacy and Bartlett's test of sphericity were checked for each extracted factor. It is generally recommended that the KMO value should be greater than 0.5 if the sample size is adequate. As presented in Table 7.1 (Column 2), the KMO value for the instruments was ranged between 0.760 to 0.965, all of which are acceptable as a good value. Meanwhile the correlations among the underlying variables of the study measures are confirmed to be significant (at $p < 0.001$) based on the results of Bartlett's test of sphericity. The overall KMO value for the EFA matrix extracted for the CAB model is 0.978—with a significant Bartlett's test (for an Approx. Chi-Square = 28384.15 and DF= 1035).

Table 7.1: Tests of divergent validity and dimensionality (Promax rotated matrix) of the Mediation model of PBI and RD.

Variable	KMO	PBI	PRC	SK	PRP	PA	NA	SE	T	RD
Protective Behavioural Intentions	**0.965**									
PBI. 1		0.819								
PBI. 2		0.777								
PBI. 3		0.836								
PBI. 4		0.767								
PBI. 5		0.776								
PBI. 6		0.753								
PBI. 7		0.818								
PBI. 8		0.842								
PBI. 9		0.789								
PBI. 10		0.795								
Perceived Risk Consequence	**0.963**									
PRC. 1			0.806							
PRC. 2			0.821							
PRC. 3			0.797							
PRC. 4			0.793							
PRC. 5			0.848							
PRC. 6			0.791							
PRC. 8			0.860							
PRC. 9			0.818							
Subjective Knowledge	**0.931**									
SK .1				0.833						
SK. 2				0.771						
SK. 3				0.775						
SK. 4				0.801						
SK. 5				0.853						
SK. 6				0.830						
Perceived Risk Probability	**0.786**									
PRP. 1					0.697					
PRP .2					0.827					
PRP. 3					0.911					
PRP. 4					0.725					
Positive Affect	**0.868**									
PA. 1						-0.832				
PA. 2						-0.744				
PA. 3						-0.814				
PA. 4						-0.816				
Negative Affect	**0.851**									
NA. 1							0.811			
NA. 2							0.651			
NA. 3							0.767			
NA. 4							0.882			
Self-efficacy	**0.760**									
PSE. 1								0.750		
PSE. 2								0.818		
PSE. 3								0.844		
Trust	**0.862**									
T. 1									-0.820	
T. 2									-0.806	
T. 3									-0.844	
T. 4									-0.909	
Risk Denial	**0.764**									
RD. 1										-0.848
RD. 2										-0.902
RD. 3										-0.835

7.3 RESULTS FROM CFA: MEDIATION MODEL

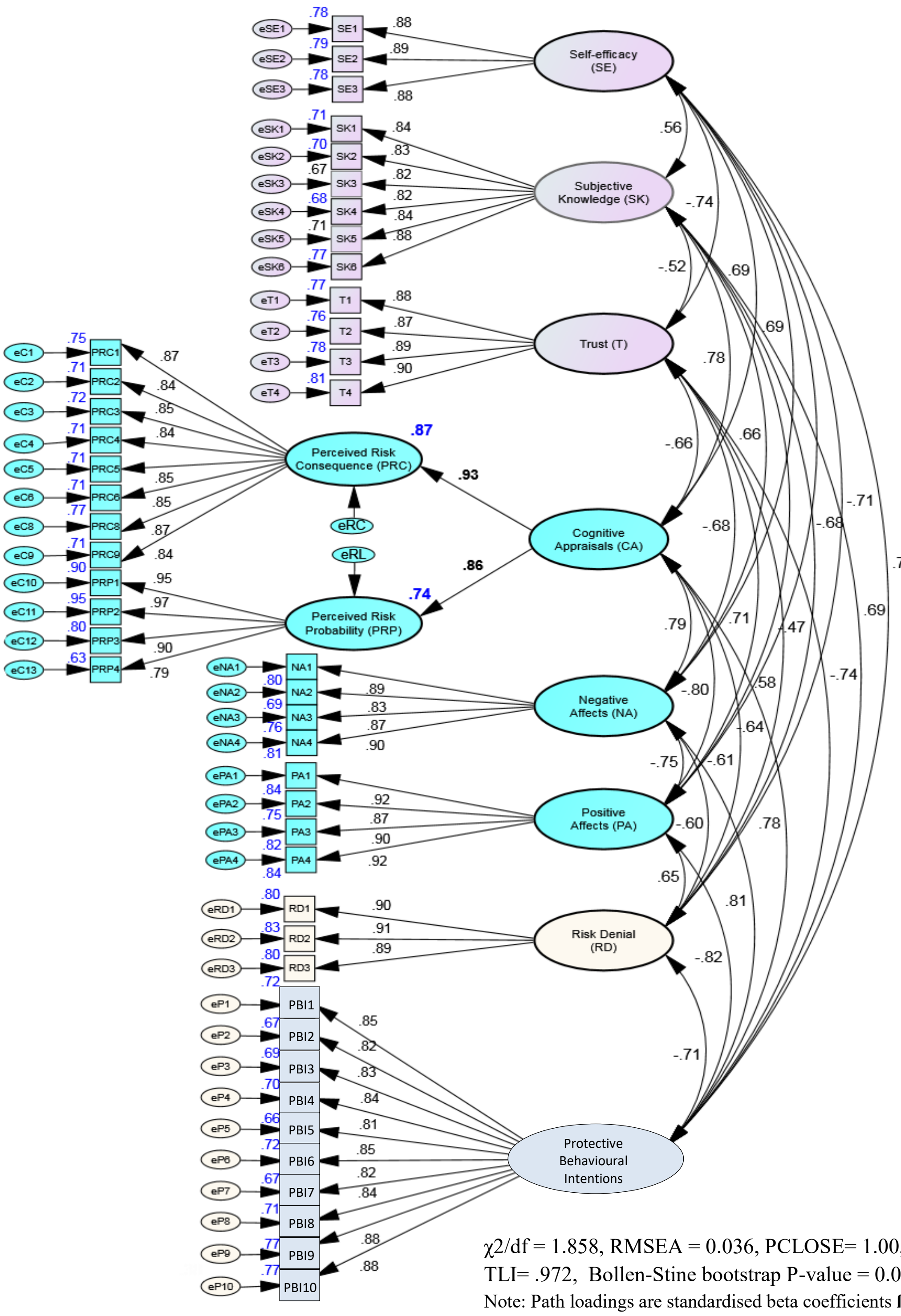
Satisfied by the initial reliability and validity of the measurement scales, the confirmatory phase of validating the measurement models began. Confirmatory Factor Analysis (CFA) involves the estimation of an a priori measurement model, where the observed variables are mapped onto the latent constructs according to theory and prior testing by the researcher.

Utilizing the conceptual structures extracted for each construct in the mediation model (Figure 7.1), here, the measurement model is specified consisting of 7 first-order reflective latent constructs and one second-order latent variable—measuring the "cognitive" appraisals of risk perception (CA) (Figure 7.2). As was recommended in Chapter 4, for model identification purposes, the "marker variable" technique has been adopted by fixing the variance of each latent exogenous variable to 1. In addition, because each of the latent variables was measured using four or more manifest variables—such that two of them do not have correlated errors—the CFA models are considered to be identified.

By ensuring that the CFA measurement models are adequately identified, the estimation process on SPSS Amos 0.24 was carried out using maximum likelihood (ML) (Jöreskog, 1967, 1969). The Bollen-Stine p-value is employed in this analysis due to the multivariate non-normality of the data. The Bollen-Stine p-value should be greater than 0.05 at a significance level of 0.05. Separate CFAs were done using the complete samples for both mediated models to obtain more estimates of item loadings, discriminant validity, composite reliability (CR) and model fit.

In the first iteration, the factor loadings for each of the 47 items were significantly larger than their standard errors, and the associated t-statistics (critical ratio (C.R) values) exceeded ±1.96 (at $p < 0.05$). All the fit statistics were within the accepted range ($\chi 2/df = 1.858$, RMSEA = 0.036, PCLOSE= 1.00, CFI= .974, TLI= .972). However, upon inspection, modification indices (MIs), standardised residuals (SRs), and item content identified causes of model misspecification, so it was decided to embark on post-hoc model fitting. For example, the largest MI was obtained for a pair of manifest variables (PRP_3 and PRP_4 with MI = 260.9). Based on these results and after assessment of item content, another model was specified by including a correlation between the error terms for these variables. This subsequently improved the fit of the model ($\chi 2/df = 1.455$, RMSEA = 0.026, PCLOSE= 1.00, CFI= .986 and TLI= .985) and produced insignificant p-value for the Bollen-Stine bootstrap (P= 0.053 > 0.05), and thus rejecting the null hypothesis that the default model fits the data better is true. To this end the standardised residual covariance matrix (SRCM) from the model output was examined and there were no standardised residual values below −2.58 or above 2.58. A value of |2.58| corresponds to the area beyond the ±2 standard deviations from the average standardized residual or the values lying in the extreme 5% of the distribution. Moreover, all modification indices were below 30. No further refinement or modifications were, therefore, needed.

The results from the final iteration show that all factor loadings for 47 items are significantly larger than their standard errors resulting in z-statistic (C.R values) that exceed ±1.96 (at $p < 0.05$). The standardized regression coefficients ß for all items were significant (at $p < 0.001$) and ranged between 0.794 and 0.975 (Table 7.2: Column 3). The squared multiple correlations (SMC) (a measure of statistical variance which is equivalent to the estimated communality (R^2) in EFA) were above the acceptable value of 0.3 for all items (Table 7.2: Column 4) and, thus, were retained. These results provided evidence for the unidimensionality of each scale.



$\chi 2/df$ = 1.858, RMSEA = 0.036, PCLOSE= 1.00, CFI= .974, TLI= .972, Bollen-Stine bootstrap P-value = 0.048

Note: Path loadings are standardised beta coefficients **ß**. The values in bold blue are Squared Multiple Correlations (**SMC**).

Figure 7.2: Initial Measurement Model (CFA) for the mediation model predicting PBI and RD

Table 7.2: Standardized Coefficient weights (**ß**) and Squared Multiple Correlations (**SMC**) for the mediated models predicting PBI and RD.

Item	Latent Construct	Mediation model	
		ß (P-value)	**SMC**
PBI. 1	←Protective Behavioural Intentions (PBI)	0.849(***)	0.721
PBI. 2	← Protective Behavioural Intentions	0.820(***)	0.673
PBI. 3	← Protective Behavioural Intentions	0.834(***)	0.696
PBI. 4	← Protective Behavioural Intentions	0.834(***)	0.696
PBI. 5	← Protective Behavioural Intentions	0.844(***)	0.664
PBI. 6	← Protective Behavioural Intentions	0.815(***)	0.712
PBI. 7	← Protective Behavioural Intentions	0.819(***)	0.671
PBI. 8	← Protective Behavioural Intentions	0.845(***)	0.713
PBI. 9	← Protective Behavioural Intentions	0.882(***)	0.778
PBI. 10	← Protective Behavioural Intentions	0.880(***)	0.774
PRC. 1	←Perceived Risk Consequence (PRC)	0.866(***)	0.749
PRC. 2	←Perceived Risk Consequence	0.842(***)	0.710
PRC. 3	←Perceived Risk Consequence	0.851(***)	0.724
PRC. 4	←Perceived Risk Consequence	0.841(***)	0.707
PRC. 5	←Perceived Risk Consequence	0.847(***)	0.718
PRC. 6	←Perceived Risk Consequence	0.846(***)	0.716
PRC. 8	←Perceived Risk Consequence	0.876(***)	0.767
PRC. 9	←Perceived Risk Consequence	0.840(***)	0.705
SK .1	←Subjective Knowledge(SK)	0.843(***)	0.711
SK. 2	←Subjective Knowledge	0.836(***)	0.698
SK. 3	←Subjective Knowledge	0.823(***)	0.677
SK. 4	←Subjective Knowledge	0.824(***)	0.678
SK. 5	←Subjective Knowledge	0.839(***)	0.705
SK. 6	←Subjective Knowledge	0.881(***)	0.776
PRP. 1	←Perceived risk probability (PRP)	0.951(***)	0.905
PRP .2	←Perceived risk probability	0.975(***)	0.951
PRP. 3	←Perceived risk probability	0.898(***)	0.806
PRP. 4	←Perceived risk probability	0.794(***)	0.631
PA. 1	←Positive Affects (PA)	0.917(***)	0.842
PA. 2	←Positive Affects	0.866(***)	0.750
PA. 3	←Positive Affects	0.903(***)	0.815
PA. 4	←Positive Affects	0.918(***)	0.842
NA. 1	←Negative Affects (NA)	0.891(***)	0.793
NA. 2	←Negative Affects	0.829(***)	0.687
NA. 3	←Negative Affects	0.873(***)	0.762
NA. 4	←Negative Affects	0.902(***)	0.813
SE. 1	← Self-efficacy (SE)	0.881(***)	0.776
SE. 2	← Self-efficacy	0.890(***)	0.793
SE. 3	← Self-efficacy	0.884(***)	0.782
T. 1	←Trust in Flood Protections (T)	0.879(***)	0.773
T. 2	←Trust in Flood Protections	0.872(***)	0.760
T. 3	←Trust in Flood Protections	0.883(***)	0.780
T. 4	←Trust in Flood Protections	0.901(***)	0.811
RD. 1	←Risk Denial (RD)	0.896(***)	0.803
RD. 2	←Risk Denial	0.910(***)	0.828
RD. 3	←Risk Denial	0.894(***)	0.799

*** represents a significant **ß** at p-value < 0.001.

Composite reliability (CR) of the constructs in the mediation model predicting PBI and RD, ranged from 0.893 to 0.961 (Table 7.3: Column 1), exceeding the recommended threshold suggested by Bagozzi and Yi (1988). This in turn indicates high internal consistency between the multiple indicators/items for each construct in the mediation model. In addition, Average Variance Extracted (AVE) for the latent constructs was calculated. All AVE values, ranging from 0.708 to

0.812, exceeded the recommended value of 0.50 (Fornell and Larcker, 1981). This confirmed convergent validity. In addition, the AVE value for each construct was greater than the squared correlation between constructs, indicating that discriminant validity was achieved. The diagonal elements of the correlations represent the square root of the average variance extracted and are all greater than the correlations between the off-diagonal bivariate correlations, also signifying that discriminant validity is satisfactory. To conclude, discriminant validity appears satisfactory at the construct level as well as the item level in the case of all constructs, therefore, the constructs in the proposed mediation model predicting PBI and RD are deemed adequate.

Table. 7.3: Construct reliability, convergent validity and correlations among the latent factors coefficients for the mediation model predicting PBI and RD

Latent Factor *	CR	AVE	MSV	PBI	SE	RD	CA	T	NA	PA	SK
PBI	0.961	0.710	0.677	**0.842**							
SE	0.916	0.783	0.596	0.772	**0.885**						
RD	0.927	0.810	0.504	-0.710	-0.704	**0.900**					
CA	0.893	0.807	0.643	0.786	0.683	-0.610	**0.898**				
T	0.935	0.781	0.560	-0.748	-0.744	0.584	-0.671	**0.884**			
NA	0.928	0.764	0.659	0.812	0.686	-0.599	0.796	-0.680	**0.874**		
PA	0.945	0.812	0.677	-0.823	-0.676	0.655	-0.802	0.709	-0.754	**0.901**	
SK	0.936	0.708	0.613	0.698	0.555	-0.479	0.783	-0.529	0.668	-0.651	**0.841**

*PBI: Protective behavioural intentions, SE: Perceived self-efficacy, RD: Risk denial, CA: Cognitive appraisals, T: Trust in local flood protections, NA: Negative affective appraisals, PA: Positive affective appraisals, SK: Subjective knowledge.

7.4 RESULTS FROM STRUCTURAL MODEL ANALYSIS

As the reliability and validity of the measures have been ensured, a covariance-based structural equation modelling analysis (CB-SEM) was conducted using Amos version 24.0 to test the hypothesized (mediated) models. However, before analyzing the structural model with maximum likelihood (ML) estimation technique, a typical application of CB-SEM requires considering assumptions that concern linearity and homoscedasticity. To assess linearity and homoscedasticity in this study, scatterplots of standardised residuals vs standardised prediction of the dependent variable were produced and checked. Inspection of bivariate scatter plots resulted in an oval-shaped array of points demonstrating that variables are linearly related and their variances are homogenously distributed. That is, the spread of the residuals were approximately within the same vertical range around the zero horizon line, indicating the constant variance of the regression errors. Thus, it was safe to conclude that the linearity and homoscedasticity were not significantly violated for both mediated models proposed above. After finishing the steps of data screening and assessing the assumptions of multi-variate analysis, it is now possible to move to the next stage which is structural model analysis.

The results from SEM indicate that the mediation model predicting PBI and RD yields a χ^2/df =1.395, RMSEA=0.025, PCLOSE= 1.00, CFI=.988, TLI=.987 and Bollen-Stine *p*-value = 0.091 which is not significant at the level of 0.05. This is an indication that the model fits the data very well—after the inclusion of a correlation between the error terms of PRP3 and PRP4, as was also done in the CFA stage (Section 7.3). Overall, the stability index of the model was 0.122 < 1, which satisfies the functional equilibrium assumption for non-recursive models. However, after the deletion of item PRC7, there were still two pairs of indicators (i.e., PRP4-PRC2 and PRP4-PRC3) that have an absolute value of standardised residual covariance greater than |2.58|. This suggests the existence of multi-collinearity. Thus, one or all of those items should be deleted. However, since the model fits the data well, as indicated by the non-significant Bollen-Stine *p*-value, those items are maintained in this model.

The final modified model shows all paths; however, three paths between the exogenous variable and the endogenous variables are not statistically significant (see regression weights and estimates of significant paths in Table 7.4).

Table 7.4: Unstandardized and Standardized Parameter estimates for the mediation model predicting PBI and RD

Outcome Variables	Predictor Variables	ß Unstandardized (Standardized)	S.E.	T-value C.R.	P-value[a]
Perceived Risk Probability (PRP)[b]	← Cognitive Appraisals	1.00 (**0.905**)	--	--	--
Perceived Risk Consequence (PRC)	← Cognitive Appraisals	0.777 (**0.845**)	0.035	22.186	***
Cognitive Appraisals (CA)	← Negative Affect	0.117(**0.115**)	0.053	2.223	0.026 *
Cognitive Appraisals	← Subjective Knowledge	0.529(**0.476**)	0.043	12.434	***
Cognitive Appraisals	← Positive Affect	-0.218(**-0.203**)	0.055	-3.97	***
Cognitive Appraisals	← Self-efficacy	0.254(**0.243**)	0.04	6.304	***
Positive Affects (PA)	← Cognitive Appraisals	-0.348(**-0.375**)	0.045	-7.795	***
Positive Affect	← Personal Experience PE	-0.217(**-0.270**)	0.027	-7.936	***
Positive Affect	← Trust	0.284(**0.308**)	0.034	8.293	***
Negative Affect (NA)	← Trust	-0.209(**-0.215**)	0.036	-5.792	***
Negative Affect	← Personal Experience	0.295(**0.349**)	0.029	10.314	***
Negative Affect	← Cognitive Appraisals	0.391(**0.400**)	0.046	8.434	***
Protective Behavioural Intentions	← Cognitive Appraisals	0.138(**0.160**)	0.047	2.97	0.003 **
Protective Behavioural Intentions	← Perceived Self-efficacy	0.146(**0.162**)	0.039	3.695	***
Protective Behavioural Intentions	← Positive Affects	-0.216(**-0.233**)	0.042	-5.171	***
Protective Behavioural Intentions	← Negative Affects	0.202(**0.229**)	0.036	5.585	***
Protective Behavioural Intentions	← Trust in Flood Protections	-0.105(**-0.123**)	0.033	-3.148	0.002 **
Protective Behavioural Intentions	← Risk Denial	-0.119(**-0.137**)	0.028	-4.166	***
Risk Denial (RD)	← Trust	-0.049(**-0.050**)	0.058	-0.853	0.393 NS
Risk Denial	← Positive Affect	0.337(**0.314**)	0.069	4.871	***
Risk Denial	← Self-efficacy	-0.525(**-0.504**)	0.062	-8.425	***
Risk Denial	← Negative Affect	0.072(**0.071**)	0.061	1.178	0.239 NS
Risk Denial	← Cognitive Appraisals	0.023(**0.0230**)	0.08	0.285	0.775 NS

Note: **a** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant. **b**: This variable (i.e. PRP) is constrained to 1 for model identification purposes.

The final modified model also indicates that there are varying explanations for the dependent variables. The square multiple correlations (SMC) of a variable show the proportion of its variance that is accounted for by its predictors (determinants) (Arbuckle, 2016). As illustrated in Table 7.5, in combination, four determinants (i.e. subjective knowledge (SK), self-efficacy (SE), positive affect (PA) and negative affect (NA)) account for the variance in cognitive risk perceptions (CA), with a high degree of explanation (SMC = 0.84). In addition, the variance in affective risk perceptions are highly explained by three predictors (i.e. trust in local flood protections (T), severity of past flooding experiences (PE) and cognitive appraisals (CA)) with SMC=0.74 for negative affect and SMC=0.73 for positive affect. Most importantly, the results indicated that the variance in protective behavioural intentions (PBI) is highly explained (SMC= 0.82) by the proposed determinants (i.e. cognitive and affective risk perceptions, T, SE and RD). Finally, the variance in the variable of risk denial (RD) is found to be reasonably (SMC = 0.55) explained by four determinants (i.e. cognitive and affective risk perceptions, T and SE).

Table 7.5: Squared multiple correlations (SMC) for the mediation model predicting PBI and RD

(Predictors) Determinants	Dependent variables	SMC
SK+SE+NA+PA →	Cognitive risk perceptions CAs (Threat Appraisals)	0.84
PE+T+CA →	Affective risk perceptions (Negative Affects NA)	0.74
PE+T+CA →	Affective risk perceptions (Positive Affects PA)	0.73
SE+T+CA+NA+PA+RD →	**Protective Behavioural Intention PBI**	0.82
SE+T+CA+NA+PA →	Risk Denial RD	0.55

*PBI: Protective behavioural intentions, SE: Perceived self-efficacy, RD: Risk denial, CA: Cognitive appraisals, T: Trust in local flood protections, NA: Negative affective appraisals, PA: Positive affective appraisals, SK: Subjective knowledge.

The standardised regression weights are also used since they allow the direct comparison of the relative effect of each independent variable on the dependent variable (Hair et al., 2006). The relative effect (standardised regression weights β) between independent and dependent variables showed stronger paths (with statistical significance) between cognitive risk perceptions CA and SK (β=0.476, p=0.001) in comparison to the paths between CA and PA (β=-0.203, p=0.001), CA and NA (β=0.115, p=0.026) and CA and SE (β=0.243, p=0.001). These results indicated that variance in cognitive risk perceptions (i.e. threat appraisals) is best predicted by the level of subjective knowledge (i.e. critical hazards awareness). The coefficient signs indicated that the higher the subjective knowledge is, the greater the perception of a large chance of flood occurrence with severe consequences becomes, and vice versa. Furthermore, because the standardized regression weight of the cognitive risk perceptions to the flood consequence perception PRC (0.905) is almost equal to that of the flood risk perception to the flood probability perception PRP (0.845), it is reasonable to consider the public flood risk perception to be a combined measure of both probability and consequence perceptions.

Concerning affective risk perceptions, the standardised regression weights (see Table 7.4) showed stronger paths (with statistical significance at p=0.001) from CA to NA (β=0.400) and CA to PA (β=-0.375) in comparison to the paths from PE to NA (β=-0.203, p=0.001) and PE to PA (β=-0.270, p=0.001), T to NA (β=-0.215, p=0.001) and T to PA (β=0.308, p=0.001). The coefficient signs suggested that the higher the perception of a large chance of flood occurrence with severe consequences is, the higher the tendency to express negative feelings reading the idea of living in a flood zone becomes, and vice versa. Moreover, the results also indicated that the stronger the trust in local flood protections, the higher the tendency to express positive feelings reading the idea of living in a flood zone becomes, and vice versa. In other words, local residents who have faith in the structural flood defenses and the provision of emergency assistance during a flood elicits strong positive affective reactions (e.g. feelings of security and unity). Similarly, those who trust the local flood protections elicit weak negative affective reactions (e.g. feelings of insecurity and helplessness).

For the variance in protective behavioural intention (PBI), the standardised regression weights (see Table 7.6) showed stronger paths (with statistical significance at p=0.001) from NA to PBI (β=0.229) and PA to PBI (β=-0.233) in comparison to the paths from CA to PBI (β=0.160, p=0.003), SE to PBI (β=0.162, p=0.001), T to PBI (β=-0.123, p=0.002), and RD to PBI (β=-0.137, p=0.001). These results emphasized the relevance of affective risk perceptions in predicting individuals' intentions to undertake precautionary measures to reduce the risk, confirming the results obtained from the analysis of Cognition-Affect-Intention relationship in Chapter 6. The results also confirmed the combined effect of cognitive and affective perceptions on protective behavioural intention (PBI) formation. Furthermore, the coefficient signs suggest that the stronger the self-efficacy (i.e. perceived personal control) is, the higher the willingness to undertake private precautionary measures to reduce the risk becomes, and vice versa. In contrast, coefficient signs indicated that the higher the trust in local flood protections the lower the willingness to undertake private precautionary measures is, and vice versa. Concurrently, risk denial significantly decreases the willingness to undertake private precautionary measures. Hence, it can be said that a significant positive influence on PBI occurs when the procedural threat level is high and concurrently, when the trust (i.e. perceived institutional control) level is low, when the procedural self-efficacy (personal control) level is high, when the risk denial level is low, when the level of negative affect is high and more significantly when the level of positive affect is low.

Finally, the relative effect (standardised regression weights β) showed stronger paths (with statistical significance at $p= 0.001$) from SE to RD ($\beta=-0.504$) and PA to RD ($\beta=0.314$). The rest are rather weaker with non-statistical significance (see Table 7.4). The coefficient signs indicated that a high level of risk denial is explained by the low levels of perceived self-efficacy and concurrently by the strong tendency to express high, intense, positive affective reactions. A possible explanation for this is that feeling positive will lead people to believe that they are less prone to risk or the outcomes of a risky choice (i.e. living in a flood zone), therefore denying the presence/effect of risk. Another explanation may suggest that risk denial is a psychological response or a coping mechanism with the low satisfaction with/confidence in level of personal control over the risk. However, the results also suggest that the tendency to express negative affective reactions does not significantly influence the denial of the presence/effect of risk. Most importantly, cognitive risk perception as a measure of threat appraisal does not appear to significantly influence risk denial.

Furthermore, from the parameter estimates, it can be seen that the trust in flood protection measures does not have a significant direct impact on the denial of the presence/effect of risk. However, trust may significantly influence risk denial via affective appraisals. This suggests that affect mediates the relationship between the trust variable and the risk denial variable. As was discussed in Chapter 4, a mediator variable is defined as a third variable that intervenes in the relation between an independent variable and a dependent variable, transmitting the effect of the independent variable on the dependent variable. It does this in such a way that the direct relationship between the independent and dependent variable is no longer significant after its introduction (Baron and Kenny, 1986). The complete examination of all possible mediation paths in the proposed model is presented in the next section.

7.5 RESULTS FROM SEM MEDIATION ANALYSIS

The bootstrapping method (Bollen and Stine, 1990, Preacher and Hayes, 2004, Shrout and Bolger, 2002) with bias-corrected bootstrap 95% confidence interval (CI) was used to measure the mediating variable effects and significance. The bootstrapping analysis revealed direct, partial and total effects with standard errors and significance. An indirect effect is significant if the 95%

confidence interval (i.e., at the α-level of this study) does not contain zero. Bias-corrected confidence intervals were used, as indirect effects usually have a skewed distribution. Effect size was calculated as the ratio of the indirect effect (ab) to the total effect of dependent variable on the independent variable (Preacher and Kelley, 2011). The total effect is the sum of indirect effect and the direct effect c' + ab (c is the direct effect without mediator, whereas c' the direct effect with mediator, see Chapter 4 for more details).

For the proposed dual-process model, a detailed inspection of the direct and indirect effects (followed by a mediation test with bootstrapping bias-corrected 95% confidence interval procedure in SEM) indicates that the impact of subjective knowledge on protective behavioural intentions (PBI) is in fact fully mediated by the cognitive appraisals of risk perception, with a total indirect effect = 0.218 at p = 0.001. Most importantly, the impact of subjective knowledge on the negative and positive affective appraisals is also fully mediated by the cognitive appraisals, with total indirect effects= 0.233 (at p = 0.001) and -0.362 (at p=0.002).

Mediation results for the extended dual-process model (Table 7.6) showed that there were significant total and direct effects of self-efficacy (SE) on PBI, and the total indirect effect through the hypothesized mediator (cognitive appraisals (CA)) was also significant. The specific indirect effects showed that CA (Est = 0.035, P=0.015, 95% CI: 0.007 to 0.082, ES = 0.076) partially mediated the relationship between SE and PBI. The direction of the mediated paths indicated that higher perceived self-efficacy (i.e. perceived personal control) leads to higher cognitive risk perceptions, which has a positive influence on the willingness to undertake precautionary measures to reduce the risk. Additionally, mediation analyses showed that there were significant total and direct effects of trust (T) on PBI, and the total indirect effects through the hypothesized mediators (negative affect (NA) and positive affect (PA)) were also significant. The specific indirect effects showed that NA (Est = -0.04, P=0.001, 95% CI: 0.077 to -0.019, ES = -0.268) and PA (Est = -0.06, P= 0.004, ES = -0.361, 95% CI: -0.106 to -0.025) each uniquely mediated the relationship between T and FBI, but with different effect sizes. Simple contrasts indicated that the specific indirect effect through PA was most influential, explaining 36% of the total effect of T on PBI. The direction of the mediated paths indicated that: (a) higher trust in flood protection measures leads to lower negative affective appraisal, which has a negative influence on preparedness intentions (i.e. willingness to undertake private protection measures); (b) higher trust in flood protection measures leads to higher positive affective appraisal, which also has a negative influence on preparedness intentions.

Table 7.6: Bootstrapping results: mediation analysis

Relationship	Total effect (c)		Direct effect (c')		Indirect effect(ab)			ES	Partial/Full Mediation
	Est.	*p*	Est.	*p*	Est.	CI: upper to lower	*p*		
SE → **CA** → PBI	0.195	***	0.146	***	0.035	0.007 to 0.082	0.015	0.076	Partial
PE → **PA** → RD	-0.100	0.010	-0.018	0.670	-0.08	-0.119 to -0.042	0.001	0.800	Full
T → **NA** → PBI	-0.149	***	-0.105	0.002	-0.04	-0.077 to -0.019	0.001	0.268	Partial
T → **PA** → PBI	-0.166	***	-0.105	0.002	-0.06	-0.106 to -0.025	0.004	0.361	Partial
T → **PA** → RD	0.117	0.003	0.050	0.387	.100	.058 to 0.147	0.001	0.830	Full

Notes. 5000 bootstrap samples. α = .05. ES (effect size) = indirect effect/total effect. *** p-value is statistically significant at the 0.001 level (two-tailed)

Mediation results (Table 7.6) also showed that there was significant total effect of T on risk denial (RD), and the total indirect effect through the hypothesized mediator (PA) was significant. The specific indirect effects showed that PA (Est = 0.100, P=0.001, 95% CI: 0.058 to 0.147, ES = 0.83) fully mediated the relationship between T and RD, since the direct effect—with the mediator—

was insignificant (p=0.387). The direction of the mediated paths indicated that higher trust in flood protections leads to higher positive affective appraisal, which has a positive influence on the denial of the presence/effect of risk. Additionally, mediation analyses showed that there were significant total but insignificant direct effects of personal experience (PE) on RD. The specific indirect effects showed that PA (Est = -0.08, P=0.001, 95% CI: -0.119 to -0.042, ES = 0.80) fully mediated the relationship between T and RD. The direction of the mediated paths indicated that severe experience with past flooding leads to lower positive affective appraisal, which has a negative influence on the denial of the presence/effect of risk.

7.6 CHAPTER SUMMARY

This chapter tested the explanatory power of a psychologically-oriented model for flood preparedness intentions. It empirically examined how particular factors influence protective behavioural intentions (whether directly or indirectly through the cognitive/affective route) by using a survey conducted in the southeast region of Queensland. The results underline the crucial role of the combination of high awareness, high perceived risk, high negative affect (i.e. tendency to feel good), high self-efficacy and experience of severe events in the adoption of protective actions, and put this into the broader perspective of motivation for risk mitigation, preparedness and recovery. On the other hand, the combination of high positive affect (i.e. tendency to feel good), high trust in local flood protections, high denial of the presence/effect of the risk is crucially inhibiting the adoption of household flood protection measures. The value of the proposed model, then, resides in its ability to target factors that present barriers to preparedness and address them with effective risk campaign messages. In addition, the model provides valuable insight into the cognitive and affective processes that mediate the relationship between risk response and these key factors.

In particular, the results from testing indirect path effects (with bootstrapping bias-corrected 95% confidence interval procedure in SEM) supported **H #2.1** that: The impact of subjective knowledge (i.e. critical hazard awareness) on protective behavioural intentions is completely mediated through cognitive routes of risk perception. Subjective knowledge increases the level of perceived risk through cognitive routes, which in turn strengthens flood preparedness intentions. The results from testing mediation effects (indirect path effects) also supported **H #2.2** that: The impact of personal experience on flood preparedness intentions is completely mediated through affective routes. In particular, personal experience evokes high levels of (negative) affective reactions, which in turn strengthens flood preparedness intentions. On the other hand, personal experience lessens the tendency to experience (positive) affective reactions, which in turn impedes flood preparedness intentions.

Furthermore, mediation results supported **H #2.3** that: The impact of perceived self-efficacy (i.e. personal control) on flood preparedness intentions is completely mediated through cognitive routes of risk perception. Perceived self-efficacy increases the level of perceived risk through cognitive routes, which in turn strengthens flood preparedness intentions. Mediation results also supported **H #2.4** that: The impact of trust in public flood risk management (i.e. institutional control) on flood preparedness intentions is completely mediated through affective routes of risk perception. In particular, trust lessens the amount of (negative) affective reactions evoked by flood risk, which in turn impedes flood preparedness intentions. Similarly, trust evokes high (positive) affective reactions, which also impedes flood preparedness intentions.

7.7 REFERENCES

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CHAPTER 8

MODERATION ANALYSIS:

Moderating Role of Residential Satisfaction on the Relationship between Risk Perceptions and Intentions

Dealing with the trade-offs between "to act" or "not to act" may lie at the heart of understanding the deeper psychological analyses of benefit and risk perception—where both cognition and affect are hypothesized to function in an interactive way. Benefit perception (i.e. perception of location-embedded benefits) in this study refers to a resident's satisfaction with the physical and socio-economic qualities of their urban environments (i.e. residential satisfaction). Since the conceptualization of residential satisfaction has an implicit relationship with other place-specific biases, such as the spatial optimistic bias (Gifford et al., 2009; Radcliffe and Klein, 2002; Schultz et al., 2014; DeDominicis et al., 2015) applied to environmental risk perception, it may function as a barrier to enacting preventive behaviours in order to cope with an environmental risk. In other words, this thesis predicts that residential satisfaction is a significant moderator of the risk perceptions-intentions relationship.

8.1 RESIDENTIAL SATISFACTION AS A MODERATOR

Taking into consideration the hypothesized relationships (Figure 3.3) among risk perception, protective behavioural intentions (PBI) and the identified moderator variables, the conceptual model for this study was constructed (Figure 8.1). It can be seen from the model that PBI is influenced by perception positioned as an independent variable and residential satisfaction (RS) as a moderator variable. Residential satisfaction, specifically, combines the socioeconomic and physical attributes of the neighbourhood and housing to create three latent variables, which will be separately tested for their moderating effect on the relationship between risk perception and

PBI. Moreover, taking into consideration the integrated measurement scale of risk perception, this chapter specifically explores whether RS exerts its moderating effect on the above-mentioned relationship through the cognitive (Fig. 8.1$_A$) or the affective (Fig. 8.1$_B$) routes, because the effect could be different across these two levels of processing.

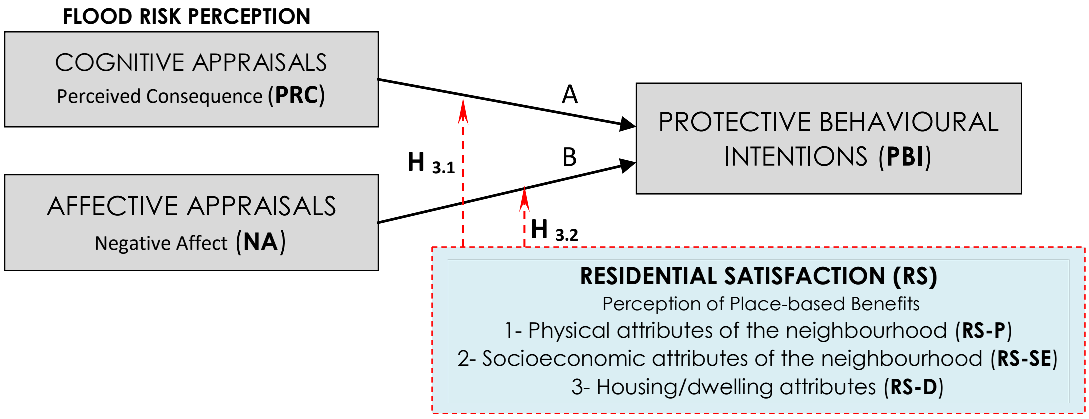

Figure 8.1 Diagram of residential satisfaction (RS) moderation hypotheses

The analytical comparative results of both cognitive and affective models will generate empirical evidence to determine which should be adopted as the level of processing into which moderator variables of RS are to be incorporated. To this end, the investigations of both cognitive and affective models were performed to test the following hypotheses:

Table 8.1: Interaction-moderation Hypotheses

H 3.1	The impact of cognitive risk perceptions on protective behavioural intentions is significantly moderated by perceived benefits (operationalized as residential satisfaction). In particular, risk perception is more strongly positively related to behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to behavioural intentions. **a)** Satisfaction on the physical attributes of neighbourhood (RS-P) negatively moderates the relationship between perceived risk consequences (PRC) and protective behavioural intentions (PBI). **b)** Satisfaction on the socioeconomic attributes of the neighbourhood (RS-SE) negatively moderates the PRC-PBI relationship. **c)** Satisfaction on the Housing/dwelling attributes (RS-D) negatively moderates the PRC-PBI relationship
H 3.2	The impact of affective risk perceptions on protective behavioural intentions is significantly moderated by residential satisfaction. In particular, (negative) affective risk perception is more strongly positively related to behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to behavioural intentions. **a)** Satisfaction on the physical attributes of neighbourhood (RS-P) negatively moderates the relationship between Negative affective appraisals (NA) and protective behavioural intentions (NA-PBI). **b)** Satisfaction on the socioeconomic attributes of the neighbourhood (RS-SE) negatively moderates the NA-PBI relationship. **c)** Satisfaction on the Housing/dwelling attributes (RS-D) negatively moderates the NA-PBI relationship

For each hypothesis, three structural models were tested for the latent interaction effects of the identified moderator variables: 1. socioeconomic attributes of the neighbourhood (RS-P), 2. physical attributes of the neighbourhood (RS-SE) and 3. housing/dwelling attributes (RS-D). The identification of each structural model follows the rules of latent interaction modelling outlined earlier in detail in Section 4.7.3. Specifically, the scale items under each latent variable were first mean-centred and z-standardized in SPSS. This process generated a new set of variables. The interaction-terms were then generated from products of independent and moderator variables. The use of z-scores is recommended in latent interaction modelling because this helps to eliminate multicollinearity between product terms and constituent variables which may undermine results.

To form the product terms, this study applied the "matched pairs" strategy (Marsh, 2012) in which information from the same indicator is not repeated and which requires the number of indicators of each exogenous factor to be the same (see Figures 8.2-7). However, given the unwieldy numbers of indicators for some interaction constructs in this study, the parcelling method (Marsh, Wen, and Hau, 2006) was used in combination with the mean-centring approach. Specifically, the items of the larger latent constructs (i.e., Perceived Risk Consequence PRC and Residential Satisfaction RS) were parcelled to be equal to the number of the smaller latent construct (i.e., 4-item Negative Affect NA). In considering this parcelling approach, it is important to emphasize that parcels were only used as indicators of the latent interactions and that individual items were used as indicators of first-order factors, thus avoiding many potential problems in the use of item parcels as recommended by Marsh et al. (2012). In addition, where parcels were used to form the product indicators in this study the variances of latent variables were fixed as recommended by Jackman and colleagues (2011).

After ensuring the fit of the measurement models (Appendix C), the tests for interaction-moderation hypotheses were executed in AMOS (v. 24) with Maximum likelihood (ML) as an estimation method because it is sufficiently robust in relation to the violation of the normality assumptions under latent interaction modelling (Boomsma, 1983; Hau and Marsh, 2004). Fit indices for each latent interaction model were assessed following guidelines outlined earlier in Chapter 4. The results are shown in Table 8.2-7a. All CFI and TLI values were greater than .95 and RMSEA values were below .08. These values generally constitute good fit. After ensuring the fit of the structural models, the interaction-moderation effect was tested using SEM analysis yielding a set of regression weights, shown in Table 8.2-7b.

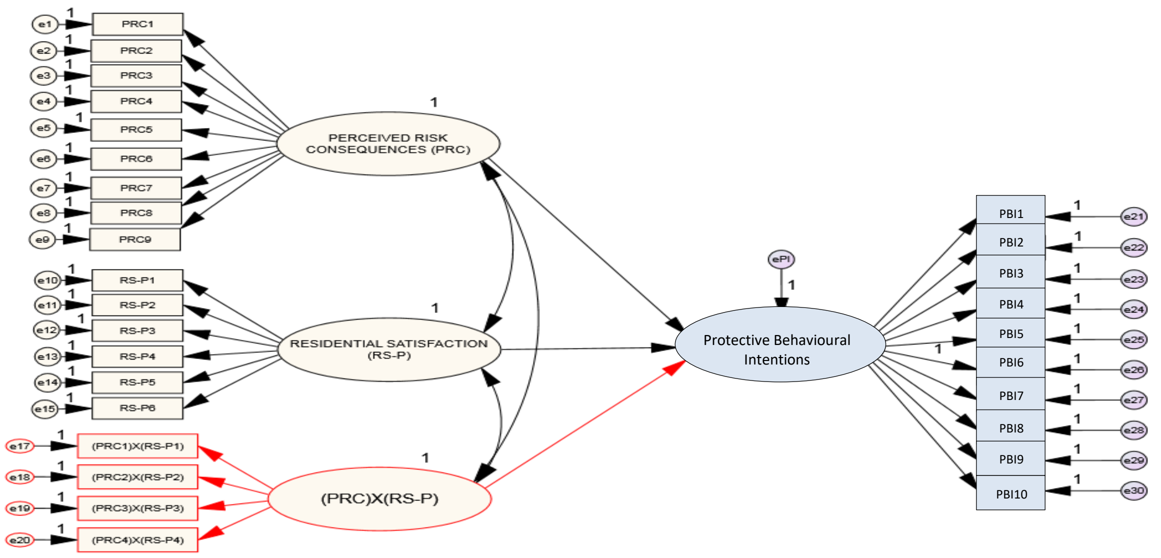

Figure 8.2 A Structural model for the interaction-moderation effect of **RS-P** on the **PRC-PBI** relationship (**Hypothesis 3.1a**)

Table 8.2a: The results for model fit for the structural model testing the moderation effect of RS-P on PRC-PBI

χ2/df	RMSEA	PCLOSE	CFI	TLI	SRMR
1.595	0.030	1.000	0.989	0.987	0.084

8.2b: The regression weights for RS-P on PRC and PBI

Independent V → Dependent V	Estimate (ß)ᵃ	S.E.	T-vale (C.R.)	P-Value ᵇ
PRC → PBI	0.562	0.062	9.138	***
Moderator: RS-P → PBI	-0.032	0.058	-0.55	0.582 NS
Product Term: (PRC)x(RS-P) → PBI	0.027	0.059	0.462	0.644 NS

Note: **a:** ß are the Unstandardized Regression Coefficients **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

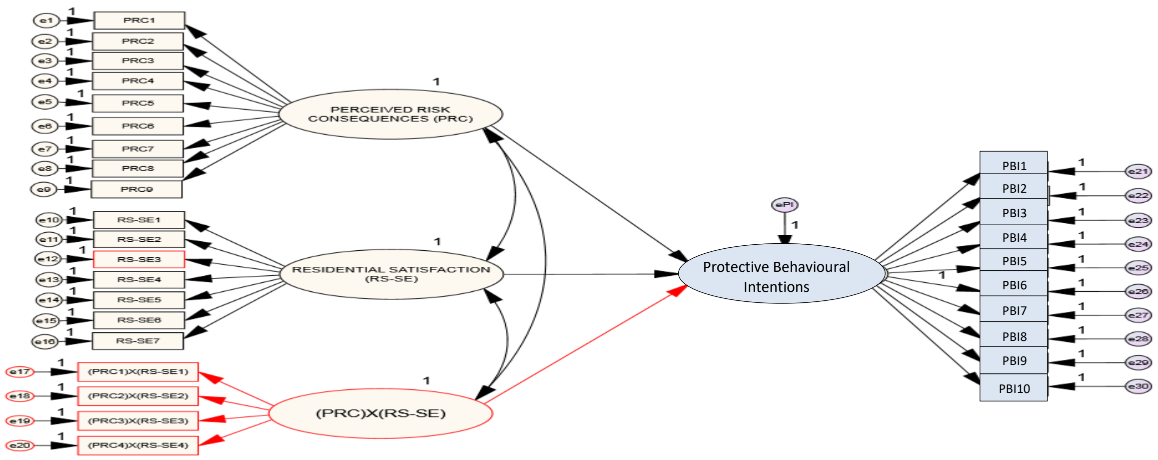

Figure 8.3 A Structural model for the interaction-moderation effect of **RS-SE** on the **PRC-PBI** relationship(**Hypothesis 3.1b**)

Table 8.3a: The results for model fit for the structural model testing the moderation effect of RS-SE on PRC-PBI

χ2/df	RMSEA	PCLOSE	CFI	TLI	SRMR
2.239	0.044	0.995	0.976	0.973	0.096

8.3b: The regression weights for RS-SE on PRC and PBI

Independent V → Dependent V	Estimate (ß)ᵃ	S.E.	T-vale (C.R.)	P-Value ᵇ
PRC → PBI	0.56	0.061	9.123	***
Moderator: RS-SE → PBI	.009	.051	.181	.856 NS
Product Term: (PRC)x(RS-SE) → PBI	.102	.058	1.743	.081 NS

Note: **a:** ß are the Unstandardized Regression Coefficients **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

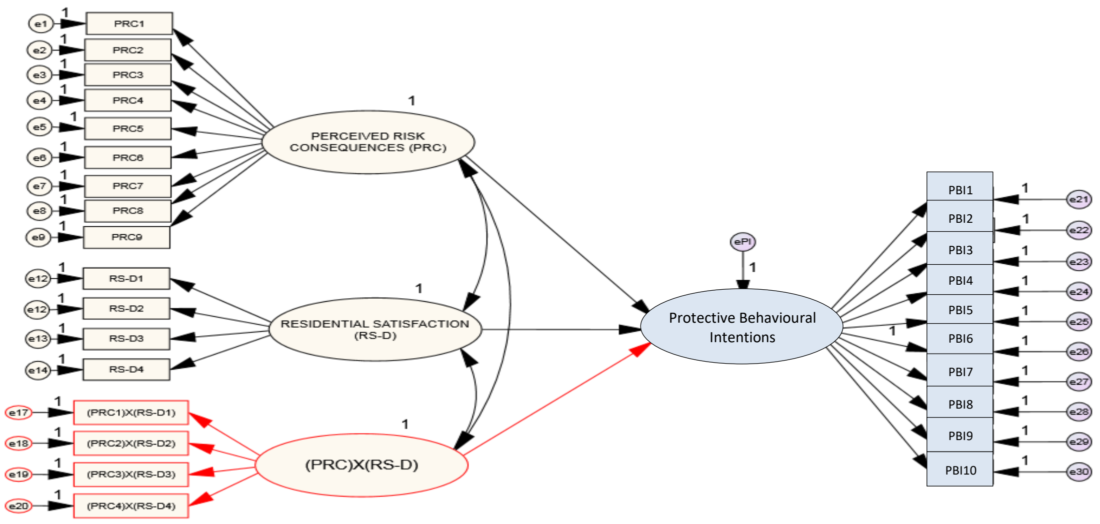

Figure 8.4 A Structural model for the interaction-moderation effect of **RS-D** on the **PRC-PBI** relationship (**Hypothesis 3.1c**)

Table 8.4a: The results for model fit for the structural model testing the moderation effect of RS-D on PRC-PBI					
χ2/df	**RMSEA**	**PCLOSE**	**CFI**	**TLI**	**SRMR**
1.988	0.039	1.000	0.981	0.978	0.085

8.4b: The regression weights for RS-D on PRC and PBI				
Independent V → Dependent V	**Estimate (ß)ᵃ**	**S.E.**	**T-vale (C.R.)**	**P-Value ᵇ**
PRC → PBI	0.563	0.062	9.147	***
Moderator: RS-D → PBI	0.035	0.057	0.622	0.534 NS
Product Term: (PRC)x(RS-D) → PBI	0.012	0.059	0.211	0.833 NS

Note: **a:** ß are the Unstandardized Regression Coefficients **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

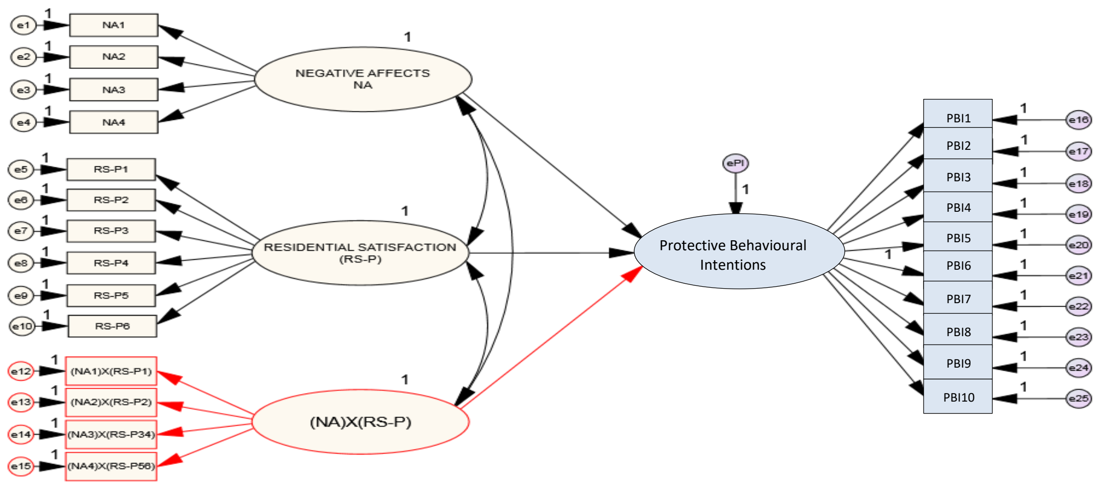

Figure 8.5 A Structural model for the interaction-moderation effect of **RS-P** on the **NA-PBI** relationship (**Hypothesis 3.2a**)

Table 8.5a: The results for model fit for the structural model testing the moderation effect of RS-P on NA-PBI					
χ2/df	**RMSEA**	**PCLOSE**	**CFI**	**TLI**	**SRMR**
1.53	0.028	1.000	0.992	0.991	0.065

8.5b: The regression weights for RS-P on NA and PBI				
Independent V → Dependent V	**Estimate (ß)ᵃ**	**S.E.**	**T-vale (C.R.)**	**P-Value ᵇ**
NA → PBI	0.718	0.035	20.237	***
Moderator: RS-P → PBI	-0.054	0.024	-2.209	0.027*
Product Term: (NA)x(RS-P) → PBI	-0.175	0.051	-3.449	***

Note: **a:** ß are the Unstandardized Regression Coefficients **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

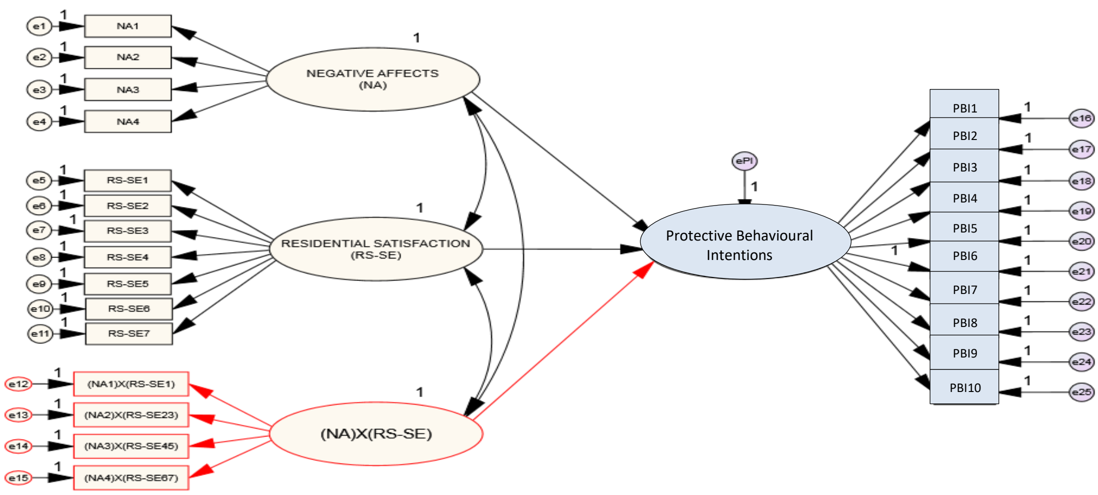

Figure 8.6 A Structural model for the interaction-moderation effect of **RS-SE** on the **NA-PBI** relationship **(Hypothesis 3.2b)**

Table 8.6a: The results for model fit for the structural model testing the moderation effect of RS-SE on NA-PBI					
χ2/df	**RMSEA**	**PCLOSE**	**CFI**	**TLI**	**SRMR**
1.913	0.037	1.000	0.986	0.984	0.061

8.6b: The regression weights for RS-SE on NA and PBI				
Independent V → Dependent V	**Estimate (ß)ᵃ**	**S.E.**	**T-vale (C.R.)**	**P-Value ᵇ**
NA → PBI	0.711	0.035	20.331	***
Moderator: RS-SE→ PBI	-0.051	0.026	-1.976	0.048*
Product Term: (NA)x(RS-SE) → PBI	-0.129	0.049	-2.63	0.009**

Note: **a:** ß are the Unstandardized Regression Coefficients **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

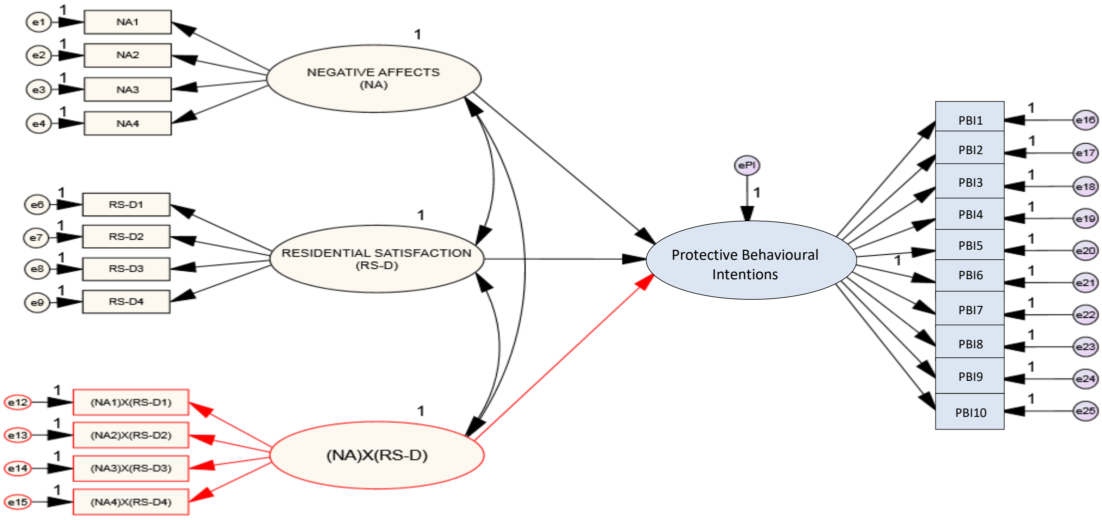

Figure 8.7 A Structural model for the interaction-moderation effect of **RS-D** on the **NA-PBI** relationship **(Hypothesis 3.2c)**

Table 8.7a: The results for model fit for the structural model testing the moderation effect of RS-D on NA-PBI					
χ2/df	**RMSEA**	**PCLOSE**	**CFI**	**TLI**	**SRMR**
1.819	0.035	1.000	0.987	0.985	0.067

8.7b: The regression weights for RS-D on NA and PBI				
Independent V → Dependent V	**Estimate (ß)ᵃ**	**S.E.**	**T-vale (C.R.)**	**P-Value ᵇ**
NA → PBI	0.713	0.035	20.38	***
Moderator: RS-D → PBI	-0.04	0.022	-1.828	0.068 NS
Product Term: (NA)x(RS-D) → PBI	-0.181	0.051	-3.576	***

Note: **a:** ß are the Unstandardized Regression Coefficients: **b:** *** p-value is statistically significant at the 0.001 level (two-tailed), ** p-value is statistically significant at the 0.01 level (two-tailed), * p-value is statistically significant at the 0.05 level (two-tailed), NS p-value is NOT statistically significant.

8.2 HYPOTHESES TESTING

8.2.1 The moderating role of residential satisfaction through the cognitive route

First, this study supposed that there was a moderating effect on the relationship between perceived risk consequences (PRC) and protective behavioural intentions (PBI) through RS-P: satisfaction on the physical attributes of residential places. Table 8.2 refuted this hypothesis **H 3.1a**: the PRC × RS-P interaction effect was not significant (β = 0.027, SE = 0.059, CR =0.462, p = 0.644 > .05); that is, the relationship between PRC and PBI was not moderated under the high or low level of RS-P.

On the other hand, a very slight trend toward significance was found with the moderating effect on perceived risk and protective behavioural intention through satisfaction on the socioeconomic attributes of residential places (RS-SE). Table 8.3 showed a slightly non-significant interaction effect (PRC × RS-SE: β = .102, SE = 0.058, CR =1.743, p = 0.081 > .05), which only gives partial support to the hypothesis **H 3.1b**.

Furthermore, a non-significant effect was found with the moderated path by satisfaction on the housing/dwelling attributes (RS-D). As shown in Table 8.4, the PRC × RS-D interaction effect (β = 0.012, SE = 0.059, CR =0.211, p = 0.833 > .05) strongly refuted the hypothesis **H3.1c**.

To sum up, it was inferred that residents' willingness to undertake private precautionary measures as a response to the cognitively perceived risk was not impeded via factors linked to people's perceived urban environmental qualities, including a satisfaction on the physical and socioeconomic attributes of neighborhood and housing. In other words, residential satisfaction did not moderate the path of (cognitively) perceived risk to protective behavioural intentions of flood-prone households.

8.2.2 The moderating role of residential satisfaction through the affective route

Second, residential satisfaction was predicted to moderate the relation between affective appraisals of risk perception (NA) and protective behavioural intentions (PBI). Specifically, conditions of high satisfaction on the physical attributes of residential places (RS-P) were hypothesized to predict lower PBI than conditions of low RS-P. Table 8.5 validated this hypothesis **H3.2a**: the NA × RS-P interaction effect was significant (β = -0.175, SE = 0.051, CR =-3.449, p < .001); that is, the relationship between NA and PBI was moderated under the high or low level of RS-P. To further explore the nature of this interaction effect, simple slope analyses were performed following the procedure of Aiken and West (1991). Specifically, the unstandardized estimates from the interaction-moderation analysis were inputted into the 2-Way Interaction Tab in the Stats Tools Package (Gaskin, 2016) to plot Figure 8.8. In line with the hypothesis, plotting the interaction revealed that the positive relation between NA and PBI decreases as RS-P increases.

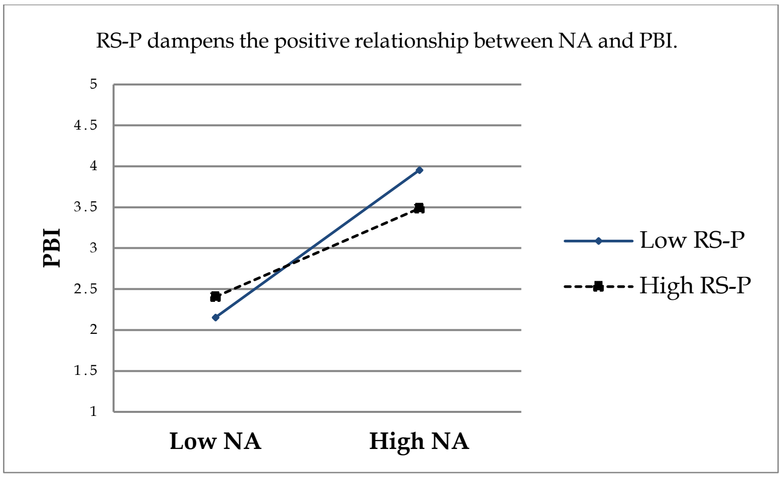

Figure 8.8: Interaction of NA and RS-P predicting PBI, Moderation Analysis, N=644

The same results were also found with the moderating effect on NA and PBI through RS-SE: satisfaction on the socioeconomic attributes of residential places. Table 8.6 showed a significant interaction effect for PRC × RS-SE (β = -0.129, S.E = 0.049, CR =-2.63, p = 0.009 < .01) in predicting PBI, which gives strong support to the hypothesis (**H3.2b**) that RS-SE moderates the positive relationship between NA and PBI. Plotting the interaction revealed that the positive relation between NA and PBI decreases as RS-SE increases (See Figure 8.9).

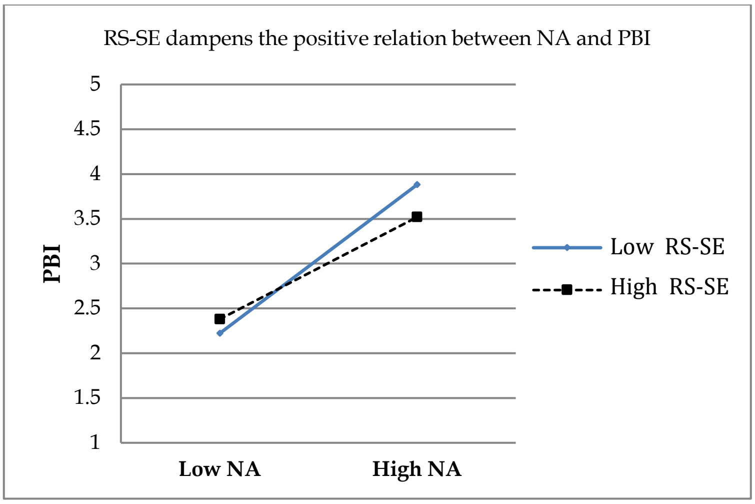

Figure 8.9: Interaction of NA and RS-SE predicting PBI, Moderation Analysis, N=644

Finally, the results from the latent interaction analysis revealed that there was a significant interaction between NA and RS-D in predicting PBI (β = -0.181, SE = 0.051, CR =-3.576, p < .001), see Table 8.7. Therefore, the hypothesis (**H3.2c**) that satisfaction on the housing attributes would function as a moderator between the predictor variable of affectively perceived risk and PBI is supported. Plotting the interaction revealed that the positive relation between NA and PBI decreases as RS-D increases (See Figure 8.10).

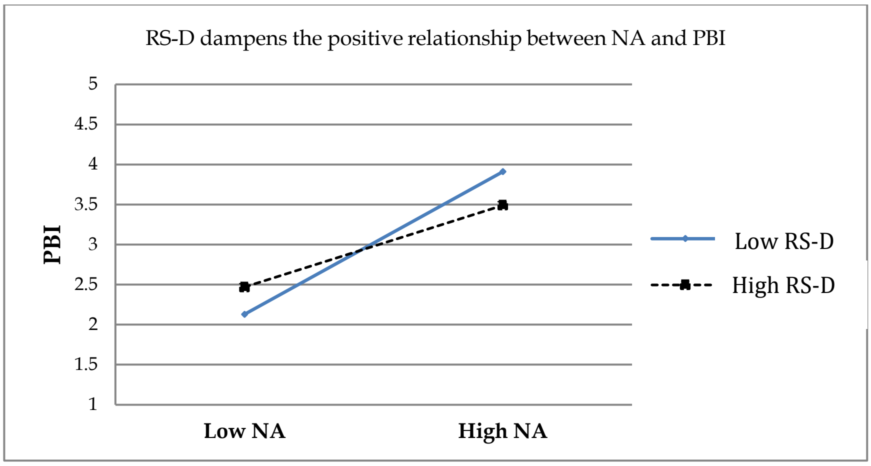

Figure 8.10: Interaction of NA and RS-D predicting PBI, Moderation Analysis, N=644

8.3 CHAPTER SUMMARY

This chapter investigated the moderating role of residential satisfaction on the relationship between risk perceptions and protective behavioural intentions of flood-prone households. It specifically explored whether RS exerts its moderating effect on the perceptions-intentions relationship through the cognitive route (i.e. perceived risk consequence) or the affective route (i.e. negative affect). By using a date from a survey conducted in the southeast region of the state of Queensland in Australia, the results of interaction-moderation underline the crucial role of RS in moderating the perceptions-intentions relationship through the affective route (and not through the cognitive routes of risk perception). Thus, it can be inferred that residents' willingness to undertake private precautionary measures as a response to the affectively perceived risk is promoted via factors linked to their perceived urban environmental qualities (i.e. their satisfaction on the physical and socioeconomic attributes of their neighbourhood and housing). In other words, the simple relationship between affective risk perceptions and risk response varies depending on different levels of residential satisfaction: affective risk perception is more strongly positively related to risk response for lower levels of residential satisfaction, whereas when residential satisfaction is higher, affective risk perception is less positively related to risk response. These findings confirm that residential satisfaction may function as a barrier for enacting protective behavioural intentions in order to cope with the flood risk, especially when the (affectively) perceived risk is higher.

H 3.1 Not Supported	The impact of cognitive risk perceptions on protective behavioural intentions is significantly moderated by perceived benefits (operationalized as residential satisfaction). In particular, risk perception is more strongly positively related to behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to behavioural intentions.
H 3.2 Supported	The impact of affective risk perceptions on protective behavioural intentions is significantly moderated by residential satisfaction. In particular, (negative) affective risk perception is more strongly positively related to behavioural intentions for lower levels of residential satisfaction, whereas when residential satisfaction is higher, risk perception is less positively related to intention.

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CHAPTER 9

SYNTHESIS, DISCUSSION AND CONCLUSIONS

9.1 Routes to Protective Behavioural Intentions

Overall, this thesis reveals a number of interesting findings which in some places lend support to existing empirical enquiries but also offers new and fresh insights in others. From a socio-psychological perspective, this thesis sought to unearth the core factors influencing householders' response to flood risk in a bid to identify how a shift towards greater protection levels can be harnessed. In doing so, and in order to make sense of the results, the findings were related to a framework for understanding household decision making in flood-prone areas of South East Queensland, Australia (Figure 9.1). This framework illustrates the pathways by which household decision making is influenced by dual processes (affective and cognitive) operating at different levels of influence:

1. directly and jointly shaping householders' flood preparedness intentions **(Chapter 6)**; 2. mediating the (indirect) influence of other core factors (personal experience, subjective knowledge, self-efficacy and trust) on householders' flood preparedness intentions **(Chapter 7)**; and, 3. being moderated by the influence of benefit perception (operationalized as "residential satisfaction") on householders' flood preparedness intentions **(Chapter 8)**. Additionally, the framework stresses the relevance of understanding the role and the predictors of householders' non-protective response (i.e. risk denial). In this vein, a shift from non-protective to protective behavioural intentions can be best realized.

PREDICTORS (Influencing Factors) → **MEDIATING PROCESSES (COGNITIVE & AFFECTIVE RISK PERCEPTIONS)** → **REPONSES TO FLOOD RISK**

PREDICTORS (Influencing Factors)

- **Subjective Knowledge**
  Critical hazard awareness impacts positively on householders' cognitive risk perceptions, and their self-efficacy in responding to flood risk. However, critical hazard awareness impacts negatively on householders' trust in public flood protections.

- **Personal Experience**
  While increasing householders' awareness of the risk, self-efficacy and their tendency to express negative affect, the experience of severe flood events decreases individuals' tendency to express positive affect, as well as, their trust in public flood protections.

CONTROLLABILITY OVER THE RISK

- **Self-Efficacy (Perceived Personal control):**
  Limited self-efficacy increases risk denial, but decreases the adoption of protective behavioural measures. Its effect on protective behavioural response is partially mediated through cognitive risk perceptions.

- **Trust (Perceived institutional Control):**
  Trust in the effectiveness of state-provided protection measures impacts negatively on householders' willingness to adopt protective behavioural measures. Its effect on risk denial is fully mediated through positive emotions (trust increases positive emotions, which in turn increase denial).

MEDIATING PROCESSES (COGNITIVE & AFFECTIVE RISK PERCEPTIONS)

- **COGNITIVE ROUTE (Threat Appraisals)**

  Perceived Probability/Consequences

  The combined effect of perceived risk probability and consequences on householders' willingness to adopt protective behavioural measures is significant and positive.
  Cognitive risk perception has insignificant impact on threat denial.
  Cognitive risk perception is a partial mediator for the relationship between perceived self-efficacy and householders' protective behavioural response.

- **NEGATIVE AFFECT:**

  Negative affect (feelings of badness) increase householders' willingness to adopt protective behavioural measures, and their cognitive risk perceptions. Negative affect has an insignificant influence on individuals' attitude towards denial of the presence/effect of the risk.

- **POSITIVE AFFECT:**

  Positive affect (feeling of goodness) decreases householders' willingness to adopt protective behavioural measures and their cognitive risk perceptions. Positive affect has a significant influence on individuals' attitudes towards denying the presence/effect of the risk.
  Positive affect partially mediates the influence of trust and hazard experience on householders' protective behavioural responses.
  Positive affect fully mediates the influence of trust and hazard experience on threat denial.

REPONSES TO FLOOD RISK

- **PROTECTIVE INTENTIONS**
  The potential for protection motivation is reduced by the low cognitive risk perceptions combined with limited self-efficacy rooted in the lack of subjective knowledge about the risk (critical hazard awareness).
  The potential for protection motivation is also reduced by the increased elicitation of positive affect combined with the decreased elicitation of negative affect informed by prior experiences with flood events.
  While being aware of the threat, householders' faith in the effectiveness of state-provided protection measures appears to be lowering their protective behavioural response.

- **RISK DENIAL**
  Variance in the denial of the presence/effect of the risk is best predicted by the limited self-efficacy and the increased tendency to feel good (positive affect) regarding the idea of living in a flood-prone area. Risk Denial has a significant but negative influence on householders' protective behavioural responses.

- **BENEFIT PERCEPTION (RESIDENTIAL SATISFACTION)**
  The impact of affective risk perceptions on protective behavioural responses is negatively moderated by residential satisfaction. In particular, (negative) affective risk perceptions are less related to risk response for higher levels of residential satisfaction, whereas when residential satisfaction is low, affective risk perceptions are more positively related to risk response.

Figure 9.1 Routes to protective behavioural intentions, results from applying a dual-process approach

9.2 The Interplay of Cognition and Affect in Directly and Jointly Shaping Risk Perception and Intentions

First, the results from **Chapter 6** strongly point to the conclusion that a non-recursive model of risk perception (where cognition and affect reciprocally influence each other) provides a better explanatory power for protective behavioural intentions and provides more plausible fit to the observed variance-covariance matrix than the recursive (i.e. unidirectional) models of risk perception. Such findings in fact provide further empirical evidence for the critical role of affect and its interplay with cognition in jointly shaping risk judgement and decision-making (Loewenstein et al., 2001; Trumbo et al., 2016; Linden, 2014; Finucane and Holup, 2006). The findings are generally consistent with recent neurological evidences that clearly lend weight to the notion of separate but interacting cognitive-affective systems in the subcortical and neocortical structures of the human brain (Pessoa, 2008, 2015; Okon-Singer et al., 2015; LeDoux, 1989, 1995, 2012). However, the findings are in contrast with prior research that has shown that affective appraisals can predict cognition (i.e. where affect can be seen as heuristics, fast and associative responses that guide cognition and, subsequently decision-making (Slovic et al., 2004; Klein and Zajac, 2008; Slovic, 2011; Schwarz, 2011; and for research on flood risk perception, see e.g., Miceli et al., 2008; Terpstra, 2011; Siegrist and Gutscher 2008; Poussin et al., 2014 and Keller et al., 2006). The findings are also in contrast with prior research that has shown that affective appraisals are substantially driven by cognitive appraisals (i.e. where affect is only seen as a post-cognitive process (Zeelenberg et al., 2008; Frijda et al., 1989; Smith and Ellsworth, 1985; Böhm and Pfister, 2000; Pfister and Böhm, 2008; Keller et al., 2012; and for research on flood risk perception, see e.g., Zaalberg et al., 2009)).

The results from **Chapter 6** also indicate that cognition and affect not only significantly interact, they are also integrated so that they jointly contribute to householders' protective behavioural intentions to flood risk. Such findings suggest that householders' feelings, as well as their cognitive assessments of the risk (in terms of its perceived probabilities and consequences) operate together, and both have direct impact on householders' response to flood risk. Interestingly, due to having different determinants, these two evaluations diverged and, therefore, a discrepant influence on householders' protective behavioural intentions emerged. Indeed, since flooding can pose a clearly observable physical danger, the personal experience with flooding has been found to significantly trigger affective-based responses that guide or bias cognition completely (as was also found by Terpstra (2011)). Thus, it was much more likely that when a householder personally experienced the likely consequences of flooding (e.g., physical damage), the householder affectively assigned this to his or her psychological experience with prior flood events. Yet, at the same time, the results indicated that when this link has been made salient, it was equally likely that cognitive risk perceptions exert a direct and strong influence on response, especially when uncertainty is reduced (due to increased knowledge of the risk). To this end, consistent with the dual-process theory, the findings confirmed that affective response can directly influence flood preparedness intentions and, simultaneously, cognitive risk perceptions can directly influence flood preparedness intentions.

An explanation of the homogeneous (direct) effects of cognitive and affective systems is that these two systems are interdependent or mutually reliant on each other. However, documenting such direct effects is inconsistent with some previously published studies that found no, or only a statistically weak, relation between cognitive risk perception and response (e.g., Lindell and Hwang, 2008; Miceli et al., 2008; Sjöberg, Moen, and Rundmo 2004; Siegrist and Gutscher, 2006; Bubeck et al., 2013; Väisänen et al. 2016). For example, a regression analysis by Lindell and Hwang (2008) showed that the perceived probability can explain only 1% of the variance in flood preparedness behaviour, and 5.5% of the variance in the purchase of flood insurance. Similarly, a multiple regression analysis by Grothmann and Reusswig (2006) showed that perceived probability and the consequence of flood can only explain an additional 3–6% of the variance in flood mitigation behaviour, which also indicates a weak relation at best. In contrast, the results from this study provide support for the significant role cognitive risk perceptions play in shaping flood protective intentions at the household level (such as raising one's home above the highest flood level, implementing hydro-isolation and more complex water drainage systems, collecting more information about the risk, or taking out flood insurance). This is in line with some previously published studies (e.g., Baan and Klijn, 2004; Plapp and Werner, 2006; Plattner et al., 2006; Terpstra et al., 2011; Terpstra and Lindell, 2013; Babcicky and Seebauer, 2016; Kerstholt et al., 2017). For example, Terpstra (2011) reported that a decrease in Dutch citizens' perceptions of flood likelihood hampers their flood preparedness intentions.

In fact, the positive (direct) association between cognitive risk perception and response—as reported in this study—can be explained by the "motivational hypothesis" (Weinstein et al., 1998), which states that people undertake precautionary measures to reduce the risk they perceive as being high. In light of this, Sjöberg, (2000) claims that "it is simplistic just to assume that a high level of perceived risk carries with it demands for risk mitigation" (Sjöberg, 2000: p. 9). Accordingly, the reasoning behind the "motivational hypothesis" can be used to demonstrate the need for critical hazard awareness raising among the population at risk in order to reduce perceived vulnerability by increasing the level of private mitigation and preparedness (Bubeck et al., 2012). Indeed, consistent with this, the results from Chapter 6 (Table 6.4) indicate that subjective knowledge (i.e. critical hazard awareness) directly increases cognitive risk perceptions ($\beta = 0.536$, $t = 13.6970$, at $p < 0.001$), which in turn positively influences householders' protective behavioural intentions.

In addition, the results from **Chapter 6** supported the predicted (direct) impact of affective appraisals (i.e. feelings attached to the idea of living in a flood-prone area) on the householders' protective behavioural response to flood risk. This is inconsistent with Terpstra's (2011) study, which supported the absence of a direct route from affective appraisals to flood preparedness intentions. Rather, in line with the affect heuristic, Terpstra (2011) provided evidence that supported the indirect route by investigating the mediating role of cognitive risk perception on the relationship between affect and flood preparedness intentions. However, the results from this study are in line with other previous studies (such as Keller, Siegrist and Gutscher 2006; Siegrist and Gutscher, 2006; Grothmann and Reusswig, 2006; Zaleskiewicz et al., 2002; Miceli et al., 2008; Poussin, et al., 2014) which also support the direct impact of affect. For example, Miceli et al. (2008), found that affective appraisals (e.g., fear) were significantly and directly related to householders' willingness to take preventative actions against future floods. Likewise, Poussin, Botzen and others (2014), who conducted a household survey in France, found that the degree of worry felt about potential flooding increased perceived flood damage, which in turn increased the implementation of preparedness measures.

Another way to view the results is devoted to distinguishing the divergent impacts of negative and positive affect on risk perception and intentions. The results from **Chapter 6** showed that positive affect (feelings of goodness) decrease householders' risk perception as well as their protective behavioural intentions. Negative affect (feelings of badness) had the opposite impact. Similar findings were reported by (Terpstra, 2011) who investigated positive versus negative affect attached to previous flood experiences. However, the results from this study appear to conflict with previous studies that investigated positive affect in the context of trauma (e.g., violence (Tugade and Fredrickson, 2004)), crisis (e.g., 9/11 attacks (Fredrickson et al., 2003)) and natural disasters (e.g., tsunami (Tang, 2006), earthquake (Pérez-Sales et al., 2005; Vazquez et al., 2005) and floods (e.g., Babcicky and Seebauer, 2016)). These studies found that positive affect increases people's coping abilities and resilience in dealing with future events. Their interpretations mostly followed the "broaden-and-build theory" (Fredrickson, 2004): positive affect contributes to the ability to cope with stress and negative life experiences because they add to one's physical, intellectual, social and psychological resources, which then allow one to manage threats more effectively.

In short, the results from **Chapter 6** suggest that positive affect leads to lesser risk aversion because people become more optimistic about future outcomes when they are feeling good. The logic behind this is that positive affect signals that the environment is benign and safe, and thus reduces the householder's response to undertake private mitigation and preparedness measures. This is what Giddens (1991) refers to as ontological security, which individuals are placing above their physical security: "preferring to think of their homes as places that are innately safe, they reject the idea of defending them" (Harries, 2008: p.2). This may also be consistent with the notion of 'optimistic bias', originally referred to as 'unrealistic optimism' (Weinstein, 1980), which reflects the tendency of individuals to underestimate the likelihood that they will experience adverse events.

Simultaneously, negative affect tends to make individuals more pessimistic about future outcomes, and this can lead to greater risk aversion by undertaking private mitigation or preparedness measures. The logic behind this is that negative affect signals a ''sense of danger" and alerts people to stop, think, and adopt/adjust their behavioural intentions. In addition, higher levels of preparedness may in part be explained by the desire of individuals to avoid the often unanticipated negative feelings of insecurity, fear and helplessness experienced during a flood event. The severity of personal experience with flood disasters plays a critical role here. Indeed, the results from **Chapter 6** (Table 6.4) showed that the path coefficients from personal experience to positive affective appraisals (β=-0.73, p<0.001) and negative affective appraisals (β=0.45, p<0.001) are significant, but with contradictory signs. The intensity of negative affect increases with the severity of personal experience with flood disasters. Simultaneously, the intensity of positive affect decreases with the severity of personal experience with flood disasters.

9.3 The (Indirect) Influences from Knowledge, Trust, Self-efficacy and Experience:

The mediating role of cognitive and affective risk perceptions

The findings from **Chapter 7** revealed a generally high perception of risk amongst the householders in flood-prone areas of South East Queensland, Australia, based on their subjective knowledge of the risk. Such high levels of risk perception were then found to positively predict householders' protective behavioural intentions. This suggests that if householders are aware of, familiar with, and understand the dangers associated with a prospective flooding event, they will adjust properly to it, as also found by several empirical studies (e.g. Terpstra et al. 2009; Miceli et al. 2008; Grothmann and Reusswig 2006; Botzen et al., 2009a; Burningham et al., 2008; Dzialek et al., 2013). However, such a causal relationship between knowledge (or critical risk awareness) and preparedness contrasts with other studies stressing that knowledge levels are not always great predictors of how people behave (Blake, 1999; Bubeck et al., 2012; Eriksen and Gill, 2010; Kollmuss and Agyeman, 2002; Miceli et al., 2008; Scolobig et al., 2012). In fact, it is even clear from the results of this study that some participants tend to favour non-protective responses or are reluctant to engage in mitigation behaviour, despite an acute awareness that they are at substantial risk of flooding and the scale of damages that would arise from such adverse events. In seeking to explain this, the SEM results indicated that limited self-efficacy (i.e., the capacity to undertake protective actions), inconsistencies in perceived responsibility for protection, and trust in the effectiveness of state-provided protection measures are crucially important, as also stressed by (Wachinger et al., 2013).

In particular, the findings from **Chapter 7** reveal that participants are unwilling to take protective action based on a high-arousal of positive affect (i.e. feeling of goodness about prospective flooding events) which appears strongly rooted in their trust in the effectiveness of state-provided protection measures, particularly engineered flood defenses. Similarly, it is clear that householders' trust levels are negatively influencing their feelings of badness (i.e. their concern about the probability of a flooding event taking place in the future). Any reduction in a householders' risk perception will undoubtedly influence the take-up of preparedness measures in a negative way. Evidence supporting this overall relationship can be found in studies carried out by Dzialek et al. (2013), Grothmann and Reusswig (2006), Hung (2009), Scolobig et al. (2012), Terpstra (2011), Viglione et al. (2014), Fox-Rogers et al., (2016) and Babcicky and Seebauer (2016). In short, the findings indicate that if householders rely on the efficacy of state-provided protection measures they will take less precautionary action themselves. However, such findings appear to contrast with the findings of, for example, Reynaud et al. (2013) who found a positive relationship between the level of confidence in the city to efficiently manage flood risks and the presence of a pump in the household. Richert et al., (2017) also found that reliance on public flood protection has a positive effect on private flood mitigation. Similarly, Poussin et al. (2014) found a positive effect of the feeling of being protected by public measures on the number of structural measures implemented. Taken together, it can be concluded that the relationship between reliance on public flood protection and private protective response is still unclear and requires further investigation.

In illustrating the mediation mechanism, the findings from **Chapter 7** showed that trust in local authorities makes a difference in the respondents' feelings about the risk, which then alters their willingness to undertake preparedness and mitigation measures: the higher their level of trust, the lower their feeling of badness, the higher their feeling of goodness and thereby the lower their tendency to undertake protective behavioural intentions to flood risks as a result of living in flood-prone regions. Again, while this reflects a rational positive evaluation of their way of operating (i.e. private flood preparedness may be redundant if public agencies conduct adaptation, such as successfully building levees to prevent floodwaters reaching people's doorsteps), it also signals a tendency to overestimate the efficacy of state-provided protection measures and possibly a tendency to delegate self-responsibility. In a concurrent manner, it may be that some residents do not feel endangered because they assume that the management of flood risk is the task of the local services, and they rely on their (experienced) efficiency and (supposed) ''unlimited capacities'' (Scolobig et al. 2012). Thus, the problem of encouraging household flood preparedness could be compounded by the fact that householders may be over-reliant on structural flood defences. Not only are these structural measures, such as dykes, highly visible, but householders in the flood-prone areas of South East Queensland also have been consistently told by the local governments that they are quite safe due to these measures. A combination of the presence of prominent structural measures and being consistently told of the effectiveness of these measures could, via the action of the risk compensation bias, reduce people's perceived need for private preparedness. This bias arises because people make judgments about their risk based on their perception of how safe the environment appears to be. To this extent, the visibility of structural mitigations and civic risk management agencies consistently reminding people of their existence and their ability to offer protection (which people may overestimate) can result in people seeing their environment as safe and as negating any need for them to prepare (Kerstholt et al., 2017).

This thesis also acknowledges that there is a problem in considering the concept of trust in structural mitigation measures, as there is always an element of "residual" risk given that carefully engineered flood defenses "cannot prevent damage if a flood exceeds the capacity of a structure designed to prevent it" (Takao et al., 2004: 777). With this in mind, it is clear that at-risk populations may have excess confidence in the structural measures available, which reduces affective perceptions of risk and fosters an unwarranted resistance to the adoption of preparedness measures at the individual level—a phenomenon commonly known as the 'levee effect' (Bradford et al., 2012; Ludy and Kondolf, 2012; Scolobig et al., 2012). As such, the recommendations here are in line with several authors who have argued that flood risk communication strategies need to be more specific in explaining that "no structural protection measure is infallible", precisely because of the (largely recognized) unpredictability of certain types of floods (Scolobig et al., 2012: 515). This means, for example, that local authorities should communicate clearly that structural devices do not provide total safety (see also Grothmann and Reusswig 2006). This is admittedly not going to be easy, as such an admission of the inability to provide total safety—even when a lot of money is assigned to engineering works—would undoubtedly create problems for those responsible for delivering structural components of flood risk management programs and strategies, particularly when such communication is to take place at various stages throughout the entire process of generating flood risk management programmes (Fox-Rogers et al., 2016).

Besides the negative indirect effect of trust—partly mediated through affective risk perceptions—the findings from this study also suggest the concept of threat denial as an explanation for residents' lack of risk-mitigation action. Specifically, threat denial has been found to inhibit people's motivation to prepare for a prospective flooding event, thus corroborating the findings of other scholars (e.g., Grothman and Reusswig 2008; Zaalberg et al. 2009). Indeed, the figures reported in Chapter 5 suggest that in a location where there are good reasons for most householders to know that they reside in a high flood risk area (the officially reported risk level rating is high and there is a recent history of significant flood threat), there are grounds for considering that up to about 38% of householders are in denial about their flood risk to a high degree. To explain this, the perception of limited self-efficacy (as the extent to which respondents perceived impediments for carrying out flood preparedness actions) is particularly noteworthy. In this regard, the results suggest that if the threat is seen as uncontrollable due to the inability to effectively exercise influence over it, people are more likely to cope with the hazard by denying its existence.

Evidence supporting that denial as an adaptive coping mechanism or a defensive reaction to risks appraised as serious but not self-controllable can be also found in studies carried out by others (e.g., Grothman and Reusswig 2008; Zaalberg et al. 2009). Alternatively, denial may be initiated as an emotion-focussed process to reduce an individual's level of anxiety, distress or any psychological harm resulting from uncontrollable threat situations. This means that people in denial try to avoid, or simply ignore, any information that might challenge their images in an unsafe situation (Ager 2008; Baytiyeh and Naja, 2016). Such a process can be viewed as a maladaptive defence mechanism if it inhibits, interferes with, or prevents available adaptive coping actions being taken. Indeed, the results from this study elucidate the fact that participants are unwilling to take protective action based on their tendency to deny the presence/effect of the risk combined with their perceived inability to cope with it.

Although the relation between awareness and risk denial was not one of the objectives of this study, one would expect that awareness should be directly (negatively) correlated with denial. Interestingly, the bootstrapping results showed that the effect of critical hazard awareness on denial was fully mediated via self-efficacy (Est = -.170, P=0.001, 95% CI: -0.263 to -0.105). The direction of the mediated paths indicated that higher awareness leads to higher self-efficacy, which has a negative influence on the denial of the presence/effect of risk. As such, people need to believe in the existence of the threat and to learn about how to be protected. In fact, perceived self-efficacy (as an integral component of coping appraisal) has been found to be negatively correlated with threat denial, but positively with protective behavioural intentions. Several authors have also highlighted the robustness of 'coping appraisal' in particular as an explanatory factor in this regard (Bubeck et al., 2013; Grothmann and Reusswig, 2006; Poussin et al., 2014; Terpstra, 2011; Babcicky and Seebauer, 2016; Richert et al., 2017; Sullivan-Wiley and Gianotti, 2017). For instance, Grothmann and Reusswig (2006: 107) observe that understanding whether or not people decide to protect themselves against a flood is predominantly decided on the basis of the coping appraisal, as self-efficacy was correlated with non-protective responses in their study. Similar findings are reported by Poussin et al. (2014), who found that threat self-efficacy is one of the most powerful predictors of risk mitigation behaviour amongst the French case studies they surveyed. Bubeck et al.'s (2013) empirical work also supports this contention, with self-efficacy emerging as a significant predictor of whether individuals adopt structural building measures.

Furthermore, the perception of limited self-efficacy amongst about 35% of the participants appears strongly rooted in people's belief that authorities will provide adequate protection against any threat. In this regard, detailed inspections of the mediating effect of self-efficacy on the relationship between trust and risk denial show significant indirect estimates (Est = 0.287, P=0.001). The direction of the mediated paths indicate that trust in local authorities and their mitigation measures lead to a lower perception of self-efficacy, which in turn increases the denial of the presence/effect of the risk. As such, flood-risk communication strategies disseminated within communities where structural protection measures (e.g. dams) are constructed, should be tailored to communicate the fact that "no structural protection measure is infallible" and that self-efficacy is paramount if the take up of preparedness measures is to succeed. In particular, this thesis lends support to others who have highlighted the need for detailed guidance to be provided to at-risk communities, not only in terms of the preparedness measures available, but also through the provision of detailed information about how they are actually implemented in practice and what are the means to act (through trainings, material resources, or both) (Bubeck et al., 2013; Fox-Rogers et al., 2016; Sullivan-Wiley and Gianotti, 2017. Moreover, the findings suggest that funds which may be ring-fenced to provide financial assistance to roll out the provision of mitigation measures (e.g. flood gates) could be redirected towards providing direct assistance to people to help them to implement measures which they feel they cannot do by themselves. In short, strengthening levels of self-efficacy amongst individuals at risk is, therefore, paramount in order to decrease the level of denial and concurrently increase the level of preparedness.

In addition to the need to bolster coping appraisals to stimulate a shift from non-protective to protective actions within our case study area, the results also signal the need to understand individuals' affective risk perceptions, which appear strongly rooted in people's past experiences of floods. Throughout the data, positive affect (i.e. a feeling of goodness regarding prospective floods or the idea of living in a flood-prone zone) emerged as a significant predictor for risk denial, with the highest explanatory power in the proposed model for the unwillingness to undertake flood-risk preparedness measures as indicated by the standardized coefficients (see Table 7.4). In contrast, the results show that if levels of negative affect (i.e. feeling of badness) are high, there will be a greater demand for risk reduction, thus stimulating higher levels of preparedness and vice versa. This general line of argument has been supported empirically in several studies on negative affective response (see Harries, 2008; Miceli et al., 2008; Zaleskiewicz et al., 2002; Takao et al., 2004). However, no significant correlation was found between householders' (negative) affect and their denial of the presence/effect of the risk of flooding. Risk denial is rather found to be a result of positive affective risk perceptions which induce feelings such as safety, hopefulness, excitement and sense of beauty/power of nature. In this vein, it seems reasonable to link risk denial to what has been called "unrealistic optimism" (Weinstein, 1980), particularly when an individual claims to be safe and less subjected to risk than others (Sjöberg, 2000)—a case that cannot be absolutely right if living in a designated flood zone). To this end, if the tendency to show intense positive emotions functions like "unrealistic optimism" in promoting risk denial and inhibiting the adoption of protective measures, attention must be paid to risk messages that trigger positive affective risk perceptions.

For example, "fear appeal" messaging (Witte 1992; Witte and Allen 2000; Kievik et al. 2009; Kievik and Gutteling, 2011), which uses emotive language that plays down the positive emotional content of a risk message —while playing up the personally relevant and high efficacy messaging (i.e. an individual's perceived capability to avert the threat)— can successfully capture people's attention and raise concern in some cases. This can be effective in producing the lowest level of risk denial, which in turn can be efficient in achieving the behavioural change. This general line of argument has been supported empirically in several studies on careful design of risk appeal messaging (see Witte and Allen 2000; Ruiter, Abraham, and Kok, 2001; Feinberg and Miller, 2011; Kievik and Gutteling, 2011; Linden, 2014; O'Neill and Nicholson Cole, 2009; O'Neill et al., 2016; Kerstholt et al., 2017). However, more research is needed to investigate the direct correlation between positive affect and the denial of risk presence/effect. For example, future research may focus on contrasting the differentiated effects of discrete positive emotional states, since the valence-based scale adopted by this study cannot sufficiently explain emotion-specific functions on risky decision making because not all positive affects are equal in the responses they produce.

Furthermore, the influence of previous flood experience on affective responses is noteworthy, with those who have not been severely flooded previously (much) more likely to feel good that they live in a safe environment and consequently be (much) less prepared. Thus, it seems that for residents to engage in risk mitigation and preparedness actions, the level of negative emotions emanating from previous flooding must be high (see also Burn, 1999; Siegrist and Gutscher, 2006; Terpstra 2011; Gotham et al. 2017). Here, the severer the previous experience of the risk, the greater the feeling of badness aroused, the greater the severity of the threat perceived, and the greater the susceptibility to the threat perceived, the stronger the willingness to engage in self-protective behaviours becomes. Apart from increasing the feeling of vulnerability and the way people personalize hazards and their consequences, the results also show that disaster experience enhances the perceived self-efficacy (i.e. "You could be on your own" (Becker, et al. 2013). As such, the ways in which preparedness behaviour is influenced by disaster experience are related to levels of vulnerability and efficacy. For instance, personal experience of harm may be here explained by a lack of precautions, which can lead to fear of its recurrence, and a need to avoid experiencing negative emotions and take actions to change the situation. However, no significant direct correlation between experience and protective behavioural intention was found in this study, thereby contrasting the results of other researchers (Grothmann and Reusswig 2006; Harries 2012; Kreibich et al., 2005; Lindell and Hwang 2008; Osberghaus 2015; Richert et al., 2017; Siegrist and Gutscher 2008) Osberghaus, 2017; Sullivan-Wiley and Gianotti, 2017; Richert et al., 2017). Instead, the results of this study lend support to the indirect effect of personal experience (mediated via risk perception) on self-protective behaviours, which is also highlighted by other researchers (such as Botzen et al., 2009b; Miceli et al., 2008; Terpstra 2011; Bubeck et al. 2012).

Thus, the severity of disaster experience can affect the strength of its relationship to risk perceptions. Those who have experienced mild forms of a hazard, for example, may tend to underestimate subsequent danger and show less tendency to express negative emotions regarding prospective events, with an attitude that Mileti and O'Brien (1992) describe as ''normalization bias", whereby people interpret the mild impacts of the early experience as the norm and believe that future severe impacts can also be avoided. In other words, people may find themselves underprepared by anticipating floods of the same magnitude as a previous event, thereby neglecting the possibility that the risks to property and individuals associated with a future flood might be much greater (Hopkins and Warburton, 2015). As such, flood-risk communication strategies disseminated within communities with robust flood histories should be tailored to communicate the fact that future events may not replicate those of the past.

9.4 The Moderating Role of "Residential Satisfaction" Through Cognitive and Affective Risk Perceptions

The analyses of **Chapter 8** also yield some interesting results regarding the moderating effect of benefit perception in the relation between flood risk perception and intention to enact protective behaviours to cope with flood risk. In fact, dealing with the trade-offs between "to act" or "not to act" may lie at the heart of understanding the deeper psychological analyses of benefit and risk perception. Benefit perception (i.e. perception of location-embedded benefits) in this study refers to a resident's satisfaction with the physical and socio-economic qualities of their urban environments (i.e. residential satisfaction). Since the conceptualization of residential satisfaction has an implicit relationship with other place-specific biases, such as spatial optimistic bias (Gifford et al., 2009; Radcliffe and Klein, 2002; Schultz et al., 2014; Dominicis et al,. 2015) applied to environmental risk perception, it may function as a barrier for enacting protective behaviours in order to cope with a location-related risk. This effect should be stronger where the threat is actually more concrete, i.e., in a higher compared to a lower perceived risk level. Given its connection with the risk-benefit trade-off, residential satisfaction may also act as an automatic defensive response to accept higher flood risk in exchange for location-embedded benefits (He.X 2009). In other words, this restraining effect may reflect a sort of ignorance among flood-prone householders to the hazardousness of their locations in exchange for perceived benefits.

Accordingly, it was predicted that residential satisfaction may function as a negative moderating variable on preventive behaviours when related to high flood-risk perception. The moderation analyses carried out in **Chapter 8** empirically confirm this hypothesis. More specifically, the results reflect a general tendency of residential satisfaction to reduce the strength of the positive relation between risk perception and preventive behaviours. This finding adds to a growing body of literature (e.g. Bradford et al., 2012; He.X, 2009; O'Sullivan et al., 2012; De Dominici et al., 2015; Bonaiuto et al., 2016) examining the effect of relevant constructs such as place attachment and perceived location-embedded benefits on risk perception and behavioural response. However, the analytical comparative analyses in the present thesis supported the predicted moderating impact of residential satisfaction on the affective route to flood preparedness (but not the cognitive route). To illustrate: negative affective risk perceptions (feelings of badness: e.g. worry and fear) were less related to risk response for higher levels of residential satisfaction, whereas when residential satisfaction was low, feelings of badness were more related to risk response. In other words, residential satisfaction dampened the positive relationship between householders' affective risk perceptions and their protective behavioural intentions. The findings here suggest that the affective perception of risk, even if generally related to a tendency to enact protective behaviours to cope with the risk, is not enough to engage people to behave preventively at higher levels; in fact, another affect-based variable, namely residential satisfaction, may interact with affective risk perception and negatively moderate its effect.

Acting as an affect-based and place-specific social-psychological cue, residential satisfaction can be, therefore, considered a useful concept to explain householder failures to take preparatory risk mitigation actions. This suggests that residential satisfaction must be clearly understood in order to develop more effective programs to manage the development in floodplains, and to provide the necessary information to improve floodplain residents' understanding of the hazardousness of their locations.

To conclude, by considering the role of residential satisfaction the present research contributes to “disaster-related theory” by providing an empirical study explaining at-risk citizens’ coping behaviours. The present research also provides support to the “theory of places” (Stokols and Shumaker, 1981) recently applied in risk research (e.g., De Dominici et al., 2015). Environmentally related variables and their impacts on at-risk citizens’ behaviours should be conceived as place-situated phenomena and should be adequately studied, taking into account the specific situations they are embedded in.

9.5 The Dual-process Approach to Risk Perception and Intentions: Implications for Risk Communication

Generally speaking, this study suggests that both affective and cognitive appraisals underlying risk perception play a role in decisions about how to deal with future flood risks. That is, while cognitive appraisals clearly tell part of the story about the mechanisms by which individuals make efficient (analytically-based) risk judgements, affective appraisals must also enter the narrative to provide a more complete picture. This may have practical relevance in developing interventions to inform residents about future flooding risks. For example, with respect to risk communication, many authors have emphasized the importance of incorporating the two modes of risk perception, cognition and affect (e.g., Slovic et al., 2004; Finucane and Holup, 2006; Marx et al., 2007; Visschers, 2007; Zaalberg et al., 2009; Linden, 2014; Rakow et al., 2015; Oh et al., 2015; Bosschaart et al., 2016). In a congruent manner, the current thesis recommends that in order to create effective social, behavioural and psychological interventions, persuasive risk messages crafted in the course of public communication campaigns, should take into account the inherent interrelatedness between the affective and cognitive processing modes. Importantly, risk communicators should also take into account the way in which these two modes have an interactive effect on one’s intentions to undertake various flood preparations (e.g., to seek more information about the risk, to take a risk reduction or prevention action, or even to take part in a collective action to ameliorate the risk situation).

However, risk communicators need to think carefully about how to design, combine and deliver both affective and cognitive contents of risk messages. For example, fear-based messages (which use emotive language that plays up the negative emotional content of a risk message) can successfully capture one’s attention and raise concern leading to greater preparedness . In some cases, however, attempts to change risk protection behaviour through fear-based messages with scary, dramatic or shocking imagery can be ineffective (Witte and Allen, 2000). Where fear-based messages are presented without clear steps for risk reduction, maladaptive responses (e.g., defensive denial) fatalism, helplessness and psychological distancing can be elicited (O’Neill and Nicholson Cole, 2009; Ruiter, Abraham, and Kok, 2001; Feinberg and Miller, 2011; Linden, 2014; O'Neill et al., 2016; Kerstholt et al., 2017). Indeed, recent researchers have found that greater self-reported worry about flooding do not necessarily predict greater uptake of protective behaviours (Bradford et al., 2012 Harries, 2012). Thus, it has been recommended that communication strategies should not aim to evoke fear in vulnerable communities (Bradford et al., 2012, Harries, 2012). Instead, when considering affect-rich messages, it is important that risk communicators consider whether they represent unwarranted manipulation and a hindrance to informed decision making (Rakow et al., 2015).

In this vein, Witte and Allen (2000) suggest that fear-appeals are only effective if they trigger only a moderate amount of fear (i.e. not alarmist in nature) and provide recipients with feasible risk reduction steps. In other words, it is recommended that risk communication strategies should be designed in a way that the arousal of moderate levels of "fear" prompts the balance between both affective and cognitive processes underlying the perception of risk (Bosschaart et al., 2016). Providing a clear presentation of technical (non-emotional) information can also be effective in achieving such a balance by reducing the undue influence of emotive messages and so facilitating more informed decision making (Rakow et al., 2015). It is also important to provide recipients with sufficient information on potential solutions, which is consistent with the idea that a message is more persuasive when negative affect about one's vulnerability is coupled with positive thoughts and high efficacy messaging (Das, de Wit, and Stroebe, 2003). For example, Linden (2014) argued that strong fear appeals with high efficacy messaging (i.e. an individual's perceived capability to avert the threat) can produce the highest level of behavioural change.

Furthermore, based on the findings of this study and others (e.g., Zaalberg et al., 2009; Linden, 2014), risk communicators should try to emphasize the association between hazard experience, emotion elicitation and risk preparedness. For example, in case people have no experience with a hazard because of the low frequency of occurrence (which is the case for most natural hazards including flood hazards), risk communication could focus on producing vicarious experiences through experimental manipulation with, for example, visual images and high-end virtual environments (Terpstra et al., 2009; Zaalberg et al., 2009; Bosschaart et al., 2016). Indeed, the effectiveness of visual images in changing risk perceptions is supported by data from Keller, Siegrist, and Gutcher (2006) who found that showing people photographs of flooded houses increased their perception of the danger of living in a flood zone (compared with those shown pictures of other houses), even though all participants in this study received information and warnings about flood risk. Similarly, Zaalberg et al. (2009) suggested the use of 3D-technology that produces a high-end virtual environment to mimic a disaster experience that is experienced as "real", personally relevant and emotionally arousing, which in turn can be efficient in achieving the behavioural change. In the context of designing a flood-risk education program to enhance 15-year-old students' flood-risk perception and coping appraisal, Bosschaart et al. (2016) also recommend the use of serious games and 3D flood simulations that are based on theoretical understandings from learning theory, information processing, and risk communication (Bosschaart et al., 2016).

Simultaneously, based on the findings of this study and others (e.g., Rakow et al., 2015), risk communicators should try to emphasize the association between subjective knowledge, risk perception (i.e. analytical/cognitive evaluations of hazards) and the likelihood of taking precautions or changing behaviour. To illustrate, residents in flood-prone areas may have accumulated information (about the hazard's genesis, its mechanisms of exposure, and types of adjustments that can avoid its impacts) that is stored in memory and accessed when needed. That is, what individuals believe they know about a risk domain is their subjective knowledge of the risk itself. Indeed, there is evidence that provides support for the influence of subjective knowledge in risk perception formation and subsequently the adoption of voluntary risk reduction activities, including such key measures as safe construction, retrofitting, and household preparedness (see e.g., Thieken et al. (2007). Consistent with this, specific information that is acquired can also alter an individual's perceived risk leading to the elicitation of intense affective responses, sometimes positive and often negative, and thereby more highly motivated behaviours.

The extant literature in expertise has consistently demonstrated that effective disaster risk communication and education strategies can sufficiently increase risk awareness and knowledge (e.g., (Burningham et al., 2008; Krasovskaia et al., 2007, Maidl and Buchecker, 2015; Bodoque et al., 2016). However, risk communicators should know how to tailor the communication of scientific knowledge about the genesis of hazard, its mechanisms of exposure and types of adjustments that can avoid its impacts. For example, getting the right level of detail when communicating quantitative risk estimates presents a sizable challenge: "Imprecise communications breed ambiguity, but precise communications can be difficult to understand" (Rakow et al., 2015). Messages delivered at multiple levels of precision or numeracy may be an effective means of reducing ambiguity and misunderstanding, and messages need to take account of the two-dimensional (cognitively- and affectively-based) risk conceptualization. The affective content of messages must be carefully combined with the analytical content: "when emotions (affect) run high, the phenomenology and the numbers can be expected to take a back seat while emotions (affect) drive people's behaviour" (Rakow et al., 2015). However, the importance of understanding emotions was also highlighted in a comparative empirical study on communication strategies focusing on residents' responses to flood warnings in four European countries (O'Sullivan et al., 2012). In line with the findings of Höppner et al. (2012), they found that one-way risk communication had limited effects, because it failed to address the multi-dimensional determinants of people's behaviour, including affect.

In short, the proposed dual-process model in this study may allow risk communicators to see and understand the balance and connections between an individual's desire for accurate, clear and sufficient information to analytically judge the risk, as well as his/her desire to make decisions in an effortless and intuitive manner, whereby affective states (i.e. feelings or goodness or badness) are used. The affective part of the model looks at how individuals elicit differential (positive and negative) affective responses to the intensity levels of their past flood experiences and, more generally, to the idea of living in a flood zone. The cognitive part of the model looks at how individuals analytically judge the risk in terms of its probability occurrence and consequences, based on their mental models, strongly held beliefs, memories or accumulated information about the hazard's genesis and its mechanisms of exposure. In other words, the affective part represents an in-depth processing of the information, and is more deliberate and time consuming. The overall model states that at-risk households will use both affective and cognitive mechanisms in their risk judgements. Risk communicators with knowledge of these processing mechanisms, abilities and interest can determine how to best present complicated information to the public and generally adapt more effective disaster risk communication and education strategies to them.

To conclude, from a dual-process perspective, facilitating the interactive processing of both cognitive and affective mechanisms underlying individuals' perception of risk is key to providing more nuanced understanding of risk perception formation, and possibly fostering more public engagement in resilience-building activities and disaster risk management.

9.6 The Use of SEM: A Contribution to Methodology of Flood Risk Perception Research

Structural equation modelling (SEM) is a very powerful multivariate statistical analysis technique that is used to analyze structural relationships between multiple sets of variables. Over the last decade, SEM has attracted increasing attention among academicians and practitioners in different fields, including flood risk perception research (e.g., Zhai and Ikeda, 2008; Zaalberg et al., 2009; Terpstra, 2011). However, in previous flood risk perception studies the applications of SEM are still limited to simple path models that analyze simple patterns of direct and indirect relationships. Acknowledging the high potential of SEM methodology, this thesis extends the application of more sophisticated techniques (i.e. non-recursive model, mediation and moderation analyses) in the study of flood risk perception and preparedness. Performing such techniques can provide a better understanding of the mechanisms underlying the complex associations between variables, which is indispensable for advancing theories and practices.

9.7 Some Final Thoughts and Research Directions

First, the purpose of this thesis was to explore the functional relationships between cognitive and affective constructs in the context of flood risk perception. However, it should be noted that results of the current study are based on a national sample of Australian respondents and thus it remains unclear to what extent results are generalizable to other contexts. Future research is advised to further focus on other countries as well as other domains of risk for a better understanding of risk perception and how this influences intentions and possibly actual protective actions. Indeed, the measures developed herein represent a valid and highly reliable set of survey items that could be applied to a wide range of populations at risk. Variations in study contexts can yield additional support for the developed framework and approaches of this thesis —which can help to further specify factors influencing risk perception and their interrelations. However, as risk perception has itself been found to be specific to culture and place (Douglas and Wildavsky, 1982; Weber and Hsee, 1999; Rippl, 2002), it is also to be expected that risk perception and preparedness intention formations may differ broadly between countries. Thus, in understating factors influencing risk perception it is also important to consider the unique historical, social, political, environmental, cultural and other location-specific contexts of the country under study.

Another direction for future research is to examine the interactive impact for cognitive and affective processes underlying individual risk perception on non-protective behavioural intentions such as wishful thinking, denial or fatalism. It is also important to distinguish between people's judgments, intentions and actual protective behaviours in respect to risk situations. Future research is also advised to examine the dual-process model specified herein beyond the psychological analyses of an individual’s risk perception, and take into account a broad range of social, economic, political, environmental, cultural and physical aspects, which could influence puplic risk perception to a great extent as well. The conceptualization of "risk perception" should be a multi-disciplinary undertaking which connects insights from domains besides psychology in order to create more in-depth characterizations.

It is pertinent to mention here that this thesis has primarily focused on contrasting the differentiated effects of positive versus negative emotional states. However, a valence-based scale cannot sufficiently explain emotion-specific functions on risky decision making because neither all positive nor all negative affects are equal in the responses they produce. For example, previous studies on fear and anger suggest that, although both affective reponses are negatively valenced, fear leads to risk-avoidance while anger leads to risk-seeking behaviour, presumably because the former is associated with pessimistic risk evaluations whereas the latter is associated with optimistic assessments (Lerner and Keltner, 2000). To gain a coherent understanding of the cognitive consequences of affect, it is therefore critical to not only investigate beyond differential effects of general positive versus negative emotional states, but also differentiate between the effects of discrete emotional states that vary in their concomitant certainty and consequential effect on risk judgement.

In this vein, there are also strong grounds for questioning whether it is possible to extract an individual's actual feelings and thoughts (his or her real perception about effectiveness of the preventive measures, his/her capacity to implement them, and the actual intention of preparedness) from this questionnaire survey. However, it is true that major affective and cognitive studies on disaster and risk management have used these sorts of field survey techniques and questionnaires. Second, the study uses feelings, perceptions, beliefs, attitudes and intentions expressed during the survey which could be static and hence would have predated and caused the protective response. Perceptions were measured by self-reports which could also be biased.

Second, this thesis tested the explanatory power of a psychologically-oriented model for protective behavioural intentions of flood-prone households. It empirically examined how particular factors influence flood preparedness intentions (whether directly or indirectly through the cognitive or affective routes). The results underline the crucial role of the combination of high awareness, high vulnerability, high negative affect (i.e. tendency to feel good), high self-efficacy and prior experience events in the adoption of protective actions and put them into the broader perspective of motivation for risk mitigation, preparedness and recovery. On the other hand, the combination of high positive affect (i.e. tendency to feel good), high trust in the effectiveness of local flood protections, and high denial/acceptability of the presence of risks is crucially inhibiting the adoption of household flood protection measures. The value of the proposed model, then, resides in its ability to target attitudes and perceptions that present barriers to preparedness and to address them with effective risk campaign messages. In addition, the model provides valuable insight into the cognitive and affective processes that mediate the relationship between these key factors and risk responses. However, the proposed model is assuming a more or less structured, sequential decision process underlying the adoption of flood protection measures. The merely good degree of explanation by this model indicates that it might be useful to include factors such as outcome expectancy and coping-efficacy, communication and feedback which suggest that decision-making processes can lack sequential characteristics or can be seemingly chaotic. By inclusion of these factors and processes— leaving assumptions about structure and logic in human behaviour even further behind—future studies might yield better levels of explanations.

Third, the present thesis represents a systematic and structured starting point to study a new research topic, that is, the moderating role of an affect-based and place-specific social-psychological cue such as residential satisfaction in the relation between flood risk perception and the related protective behavioural intentions. The basic counterintuitive insight of this research comes from the notion of the strong relation between residential satisfaction and the risk-benefit trade-off (He. X, 2009). In this vein, residential satisfaction may act as an automatic defensive response to accept higher flood risk in exchange for location-embedded benefits. Accordingly, it was predicted that residential satisfaction may function as a negative moderating variable on preventive behaviours when related to high flood risk perception. The moderation analyses carried out in the present research empirically confirm this hypothesis. Despite the encouraging results, this thesis presents some limitations. For example, the effect sizes of the interactions found in the present research are slightly small, and further research is needed in order to address the issue of understanding how strong the effect of residential satisfaction in mitigating the positive relationship between risk perception and related protective behavioural intentions is. Another important avenue for future conceptual and empirical investigations can be devoted to shedding more light on the psychologically parallel mechanisms by which the interaction between residential satisfactions and risk perception can be represented through cognitive routes, on the one side, and through affective routes, on the other side. More generally, the study of the relation among residential satisfaction and risk perception can also be approached within a broader reciprocal interplay, where their reciprocal causal status is different (e.g., residential satisfaction being considered as a dependent variable rather than a moderator); for example, recent findings (He. X, 2009) showed that residents' satisfaction with their home location is directly related to one's willingness to undertake some preventive behaviours to enhance their resilience.

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APPENDICES

A. Participant Information Statement and Survey Form

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THE UNIVERSITY OF NEWCASTLE AUSTRALIA

Information Statement for the Research Project:
Flood risk acceptance in the context of flood-prone residential land use: A case study
Document Version No.1 Data: DD-MM-2016

Dear Householder,

You are invited to participate in the research project identified above. The research is part of *Lara Altarawneh's* PhD studies at the University of Newcastle, supervised by Assoc.Prof. *Jamie Mackee* and Assoc.Prof. *Thayaparan Gajendran* from the School of Architecture and Built Environment. This study is being funded by the University of Newcastle. An external organisation *(Micromex Research & Consulting)* is being employed to conduct the survey. You have been identified through publicly available databases [Google maps and Gold Coast Council's PD Online mapping services].

Why is the research being done?

The purpose of this study is to examine individual flood risk perception and response in Gold Coast. Your participation in this research will provide valuable information for the formulation of mitigation and planning activities that may help lessen the impacts of future flood events so as to effectively ensure the safety, sustainability and wellbeing of your household/ local community.

Who can participate in the research?

Residents above the age of 18 living in South East Queensland can participate in this study. The resident should have also been involved in the decision-making of acquiring and/or living in the property. However, residents who own property but do not live in the property are not eligible to participate in this study.

What would you be asked to do?

If you agree to participate you will be asked to complete a paper/online or a telephone survey that consists of **5** pages with a total of **14** questions about your perception of flood risks and flood risk information.

What choice do you have?

Your participation in this study is entirely voluntary and you are not under any obligation to complete the postal/online survey. Whether or not you decide to participate, your decision will not disadvantage you. As survey responses will be de-identified for analysis (prize entry details will be maintained in a separate database) you will not be able to withdraw your response after it has been de-identified.

How much time will it take?

The completion of the survey will take approximately **(15-20)** minutes.

***What are the risks and benefits of participating*?**

There are NO anticipated risks associated with participating in this research. If, for any reason, you were unaware or surprised to find that you are living in a flood prone area you can call Gold Coast City Council on **07 5582 8211** to access necessary information, advice, and support about safety and wellbeing in flood affected area. Please indicate to the receptionist that you are a research participant. Additional information is available online at Council's website where you can check flood levels from easy to read maps and information (including your Property Specific Flood Report).

Although it is not envisaged that any negative consequences will occur, the following safeguards have been put in place for the possibility of distress being caused while taking part in the survey:
1- Lifeline Telephone: 13 11 14/ Website: www.lifeline.org.au/
Crisis support chat: www.lifeline.org.au/GetHelp/OnlineServices/crisis-chat
2- beyondblue Telephone: 1300 22 4636 Website: www.beyondblue.org.au"

There are some anticipated benefits associated with participating in this research. First, participating in our survey will provide a platform for you to give your opinions, to voice concerns, and to influence decisions relating to flood risk management. The survey will also enable you to acquire general knowledge about flood risks and the possibilities of private precautionary measures.

Second, all completed questionnaires submitted before **DD/MM/2016** will be entered into a prize draw to win **one of four Gift Vouchers worth $250**. The Harbour Town Gift Card can be redeemed at over 190 stores including outlets, specialty stores and restaurants.

The potential prize winners will be selected in a random computer generated draw (Random Picker) from all eligible entries received. The Prize Draw will be conducted within 2 weeks after the closing day. The prize winners will be notified by phone or email within 2 weeks of the draw. Prizes will be distributed by mail to the address advised by prize winners.

How will your privacy be protected?

Participation is voluntary and responses will be anonymous to ensure privacy. No information will be revealed that will make your responses identifiable to others. The collected data via paper based-questionnaires will be securely stored in a locked cabinet in the Chief Investigator's / Project Supervisor Office at the University of Newcastle.

Micromex Research and Consulting will administer the survey process. Micromex Research is committed to the protection of an individual's privacy. Micromex Research adheres to the Code of Professional Behaviour of the Market and Social Research Society of Australia (AMSRS) and to the 13 Australian Privacy Principles (APP's) that govern the way organisations collect, use, protect and disclose personal information. To read their Privacy-Policy, please see http://www.micromex.com.au/index.php/our-privacy-policy

All participants' paper/online responses would be then combined, statistically coded and data-cleaned, and an SPSS (Statistical Package for Social Science) database produced by Micromex Research and

Consulting. All collected data is expected to be encrypted before being delivered to the UON's research team. The data provided would be de-identified – no respondent names/addresses/phone numbers/email addresses would be provided. Once the data is delivered securely to the UON's research team, the data would be stored in password-protected computer files at the University of Newcastle's network space, including the UNmail system. The data would be then analyzed through Structural Equation Modeling (SEM) and other multivariate analysis techniques via AMOS software (Analysis of Moment Structures).

Once the project is complete the data will be stored for five years in the Chief Investigator's/ Project Supervisor's office in a locked cabinet and then destroyed according to University of Newcastle procedures.

If you decide to enter the prize draw after finishing the survey, you will need to complete a separate paper/online or verbal (in case of participating via a telephone interview) entry form. You will need to provide your phone number or email address so we can notify you if you win. This will keep your survey responses anonymous as contact details will be stored in a separate, unattached cabinet or data set to the survey. These details will be deleted after all vouchers have been claimed.

How will the information collected be used?

Your answers will be completely confidential and will be reported only as a summary without any identification. Non-identifiable data may be shared with other parties (i.e thesis examiners, editors and staff of professional journals) to encourage scientific scrutiny and to contribute to further research and public knowledge, or as required by law. You can request a summary of the results by contacting the researchers after 01 December 2016 on the details given below.

***What do you need to do to participate*?**

Please read this Information Statement and make sure you understand its contents before you consent to participate. Please note that only ONE response per household is requested.

If you would like to participate, please indicate your consent by either:

Option-1
Complete and return the attached questionnaire in the reply paid envelope provided by **DD MM 2016**.

Option-2
Complete the online survey. You can do this by typing the following Web link into your web browser
(www.micromex.com.au/index.php/uon).

If you need to leave the survey at any stage by closing the web browser, you can return to the survey using the same details.

The completion and submission/return of the paper/online survey will be taken as your implied consent to participate.

We understand the events that you may have experienced in the recent past and our research is attempting to address and improve that situation. For this reason we truly appreciate your time and valuable insights and hope that you may able to assist.

Thank you for considering this invitation

Further information
Should you wish to find out any additional information regarding this study, please do not hesitate to contact any of the researchers:-

Assoc. Prof. Jamie Mackee Project Supervisor School of Architecture and Built Environment Faculty of Engineering and Built Environment The University of Newcastle (UON) University Drive Callaghan NSW 2308 / Australia Tel: +61 2 4921 7451 Fax: +61 2 4921 6913 Email:Jamie.Mackee@newcastle.edu.au	**Assoc. Prof. Thayaparan Gajendran** Project Supervisor School of Architecture and Built Environment Faculty of Engineering and Built Environment The University of Newcastle (UON) University Drive Callaghan NSW 2308 / Australia Tel : (+61 2) 4921 5781 Fax: (+61 2) 4921 6913 Email: thayaparan.gajendran@newcastle.edu.au	**Lara Altarawneh** Architect & PhD Student School of Architecture and Built Environment Faculty of Engineering and Built Environment The University of Newcastle (UON) University Drive Callaghan NSW 2308 / Tel : (+61 4) 23728279. Email: lara.altarawneh@uon.edu.au

Complaints about this research

This project has been approved by the University's Human Research Ethics Committee, Approval No. **H-2016-0005.** Should you have concerns about your rights as a participant in this research, or you have a complaint about the manner in which the research is conducted, it may be given to the researcher, or, if an independent person is preferred, to the Human Research Ethics Officer, Research Office, The Chancellery, The University of Newcastle, University Drive, Callaghan NSW 2308, Australia, telephone (02) 49216333, email **Human-Ethics@newcastle.edu.au.**

Survey for the Research Project:

Flood risk acceptance in the context of flood-prone residential land use: A case study

Document Version NO.1/ Date: 13 May 2016

Thank you for participating!

Please complete and return this questionnaire by **DD MM 2016** using either the reply paid envelope provided, or you can complete it **online** by typing the following Web link into your web browser: **(www.micromex.com.au/index.php/uon)**

Your participation in this research will help us to better understand individual flood risk perception and response in South East QLD. This understanding can lead to mitigation and planning activities that in other areas have been shown to help lessen the impacts of future flood events, ultimately ensuring the safety of your household and local community.

This questionnaire consists of 5 pages with a total of 14 questions. Please answer questions as they relate to you. For most answers, tick/cross the box(es) most applicable to you or fill in the blanks. There are no correct or incorrect responses; We just want your personal point of view.

The completion of the questionnaire will take approximately (15-20) minutes.

Research **STUDY**

THE UNIVERSITY OF NEWCASTLE AUSTRALIA

UoN HREC Approval Number: H-2016-0005

Q1. About how long have you lived in this neighbourhood? (PLEASE TICK ONE & ONLY ONE)

☐Less than 5 years. ☐ 5 to 10 years. ☐ 11 to 15 years. ☐ 16 to 20 years. ☐ More than 20 years.

Q2. Please rate how satisfied you are with your current home location, for the following items: (PLEASE SELECT ONE ANSWER PER ROW)

	Not at all satisfied				*Very satisfied*
1. Physical appearance of the neighbourhood (i.e. Is it aesthetically pleasant?)	☐	☐	☐	☐	☐
2. Accessibility to the neighbourhood (i.e. is it well-connected with important parts of the city?)	☐	☐	☐	☐	☐
3. Street design and circulation system (i.e. width, streetscape, lighting of streets, street furniture, pedestrian accesses... etc.)	☐	☐	☐	☐	☐
4. Density (i.e. level of crowdedness in the neighbourhood)	☐	☐	☐	☐	☐
5. Cleanness of the neighbourhood	☐	☐	☐	☐	☐
6 .Provision of parks and other amenities within the neighbourhood	☐	☐	☐	☐	☐
7. Quietness of the neighbourhood	☐	☐	☐	☐	☐
8. Safety of the neighbourhood	☐	☐	☐	☐	☐
9. Social interactions with other residents in neighbourhood	☐	☐	☐	☐	☐
10. Social mix of the neighbourhood population	☐	☐	☐	☐	☐
11. Travel distance to friends, family or other social relationships	☐	☐	☐	☐	☐
12. Cost of living	☐	☐	☐	☐	☐
13. Travel distance to workplaces	☐	☐	☐	☐	☐
14. Price or rent you paid for your house.	☐	☐	☐	☐	☐
15. Privacy at home.	☐	☐	☐	☐	☐
16. Architecture of the dwelling (Physical characteristics of building interiors and exteriors)	☐	☐	☐	☐	☐
17. Size of the dwelling.	☐	☐	☐	☐	☐

Q3. How far away from a waterway (river, lake, etc.) is your home? (PLEASE TICK ONE & ONLY ONE)

☐Less than 500m ☐501m to 1 km ☐1.1 km to 2 km ☐2.1 km to 5 km ☐More than 5 km

Q4. How often do you undertake activities (e.g. swimming, fishing, boating, walking, dining, etc.) at water front? (PLEASE TICK ONE & ONLY ONE)

☐Never ☐Annually ☐ 2 or 3 times a year ☐ Monthly ☐Fortnightly ☐Weekly ☐Daily

Q5. Have you ever experienced flooding in your current home? (PLEASE TICK ONE & ONLY ONE)

☐No (GO TO Q.7) ☐Yes.

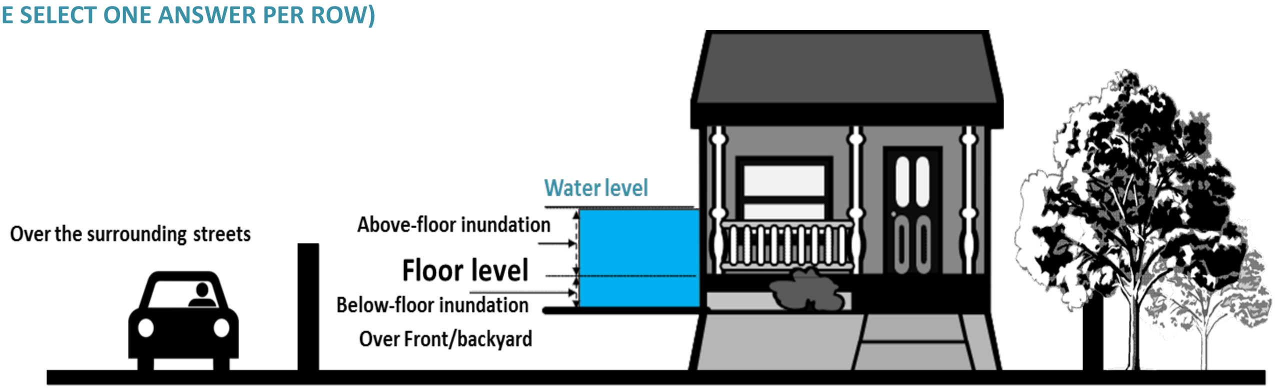
Q6. If Yes, thinking of the worst flood you've experienced in your current home, how serious were the effects of the flood upon the personal safety of householders? (PLEASE TICK ONE & ONLY ONE)

☐Not at all serious ☐Slightly serious ☐Serious ☐Very Serious ☐Extremely Serious

Q7. Please rate how familiar you are with the following items. (PLEASE SELECT ONE ANSWER PER ROW)

	Not at all familiar				*Very familiar*
1. Your property is situated in (or anywhere near) a flood zone	☐	☐	☐	☐	☐
2. The potential factors that contribute to flooding in the region	☐	☐	☐	☐	☐
3. The official sources of public safety information (e.g. household emergency plan, evacuation procedures, etc.)	☐	☐	☐	☐	☐
4. Weather or flood alerts and warning systems	☐	☐	☐	☐	☐
5. Public flood risk management— e.g., the protection level provided by local flood defences such as levees or dams	☐	☐	☐	☐	☐
6. How to prepare and plan for floods	☐	☐	☐	☐	☐

Q8. How often, if at all, do you think your home will be flooded in the future, for the following cases? (PLEASE SELECT ONE ANSWER PER ROW)



	Once a **year**	Once in **2** years	Once in **5** years	Once in **10** years	Once in **20** years	Once in **50** years	Once in **100** years	Once in **more** than **100** years	**Never**
1. Over the surrounding streets *(i.e. outside your property)*	☐	☐	☐	☐	☐	☐	☐	☐	☐
2. Over the front/back yard *(i.e. inside your property but not entering the house);*	☐	☐	☐	☐	☐	☐	☐	☐	☐
3. -In the garage and non-habitable spaces of your house *(i.e. below the front steps of your house);*	☐	☐	☐	☐	☐	☐	☐	☐	☐
6. Through habitable floors and their possessions *(such as furniture, whitegoods, clothing, curtains, floor coverings, and other).*	☐	☐	☐	☐	☐	☐	☐	☐	☐

Q9. Imagine there will be a flood in your area. How concerned are you regarding the following? (PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all Concerned				*Extremely Concerned*
1. Substantial damage to public facilities (roads, parks, etc.)	☐	☐	☐	☐	☐
2. Disruption of electricity, telephone, internet or water supplies.	☐	☐	☐	☐	☐
3. Substantial damage to your house or possessions.	☐	☐	☐	☐	☐
4. Pollution, soiling of the house.	☐	☐	☐	☐	☐
5. Financial loss (e.g. residential property values).	☐	☐	☐	☐	☐
6. You and/or your family will face a life-threatening situation (e.g. drowning, injuries, hypothermia, and animal or venomous bites).	☐	☐	☐	☐	☐
7. Psychological health	☐	☐	☐	☐	☐
8. Your daily life (job and other daily routines) will be disrupted.	☐	☐	☐	☐	☐
9. Inconvenience of recovery process after flood (e.g. problems with rebuild, clean-up, or relocation).	☐	☐	☐	☐	☐

Q10. Could you indicate how you feel now, at this moment, when you think of the risk of flooding in your area? (PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all				*Extremely*
1. I feel frightened	☐	☐	☐	☐	☐
2. I feel helpless	☐	☐	☐	☐	☐
3. I feel uncertain	☐	☐	☐	☐	☐
4. I feel worried	☐	☐	☐	☐	☐
5. I feel safe	☐	☐	☐	☐	☐
6. I feel the beauty and force of nature	☐	☐	☐	☐	☐
7. I feel excited	☐	☐	☐	☐	☐
8. I feel solidarity with my community	☐	☐	☐	☐	☐

Q11. To what extent do you intend to do the following in the near future ? (PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all likely				*Extremely likely*
1. Assembling an emergency kit (including water, food, a battery powered radio, a first aid kit, etc.).	☐	☐	☐	☐	☐
2. Collecting information about flood consequences, evacuation routes, and safe/high locations.	☐	☐	☐	☐	☐
3. Making a to-do list that is helpful in case of an evacuation or flood (household plan).	☐	☐	☐	☐	☐
4. Making agreements with family, friends, and neighbors on how to help each other in case of evacuation/flooding.	☐	☐	☐	☐	☐
5. Acquisition of Sandbags or other barriers against water	☐	☐	☐	☐	☐
6. Elevating the ground floor (at least 1 m) or having garages or simple basements/cellars as the ground floor	☐	☐	☐	☐	☐
7. Implementing hydro-isolation of the walls to avoid water contact in inundated ground	☐	☐	☐	☐	☐
8. Moving electricity outlets/meter boxes and air conditioning unit higher.	☐	☐	☐	☐	☐
9. Attending a public meeting about the matter	☐	☐	☐	☐	☐
10. Purchasing (or modifying) property insurance policy for environmental hazards.	☐	☐	☐	☐	☐

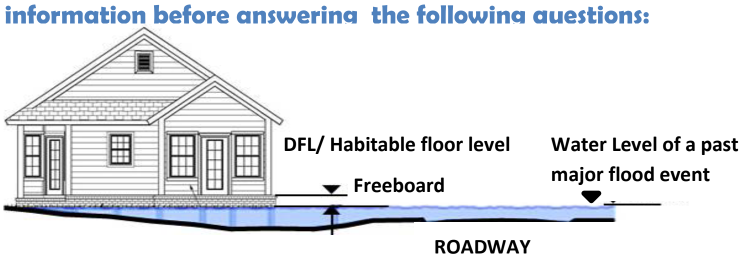
Q12. Considering your own circumstances, How confident do you feel that

(PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all responsible				*Extremely responsible*
1. You can efficiently prepare and secure your property ahead of time for a potential flood?	☐	☐	☐	☐	☐
2. You are powerless. Protecting your household against future flood threats is beyond your ability?	☐	☐	☐	☐	☐
3. It is easy for you to protect yourself against future flood threats because you can rely on your resourcefulness?	☐	☐	☐	☐	☐

I would like to provide you with some information before answering the following questions:

Designated Flood Levels (DFLs) are an important tool in the management of flood risk. They are derived from a combination of a past major flood event and a 'freeboard' gap, which is usually about 300 millimeters.



Q13. How confident are you that ..... (PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all confident				*Extremely confident*
1) ... the strength and height of the flood defences in your local area is based on a thorough and sound risk analysis?	☐	☐	☐	☐	☐
2) … the flood defences in your local area are maintained properly?	☐	☐	☐	☐	☐
3) … the technological skills of flood risk managers can efficiently prevent/mitigate all flood risks on your local area?	☐	☐	☐	☐	☐
4) … the authorities in your area have sufficient knowledge about flood protection?	☐	☐	☐	☐	☐

Q14. Please indicate how strongly you agree or disagree with all the following statements

(PLEASE SELECT ONE ANSWER ON EACH ROW)

	Not at all responsible				*Extremely responsible*
1. "I believe that future flooding will turn out better than expected"	☐	☐	☐	☐	☐
2. "I expect that future flooding will occur somewhere else, but that it will not bother me"	☐	☐	☐	☐	☐
3. "I believe that the occurrence of flooding is grossly exaggerated".	☐	☐	☐	☐	☐

Would you mind providing us some information about your house/ household.

All information provided will remain confidential and only used for the purpose of this study

1) Are you. . .
☐Male ☐Female

2) What is your age?
☐<18 ☐18-20s, ☐30s, ☐40s,
☐50s, ☐60s, ☐70s or over

3) How many people, including yourself, live in your household? Number____________

4) For analysis purposes, how much is your total ANNUAL household income before taxes?
☐$0-$24,999 ☐25,000-49,999
☐50,000-74,999 ☐75,000-99,999
☐100,000-124,999 ☐125,000-149,999
☐150,000-174,999 ☐175,000-$199,999
☐200,000 and up

5) What is the highest level of education that you have completed?
☐Primary school
☐High school
☐Junior College/ diploma
☐University undergraduate
☐Post graduate

6) Do you, or anyone else in your household, require assistance due to disability or long-term injury or illness?
☐Yes ☐No

7) Which of the following best describes the home where you are currently living?
☐ I/We own/are currently buying this property
☐ I/We currently rent this property

8) Is your home wooden?
☐Wooden ☐Non-wooden

9) The building age is… :
☐0-10 years ☐11-20 years
☐21-30 years ☐>30 years

10) Do you expect to undertake any further development on your land in the future?
☐None
☐Minor extensions/ alterations
☐New dwelling
☐Dual occupancy (granny flat)
☐Subdivision
☐Other_____________________________________

PLEASE ADD ANY OTHER COMMENTS, QUESTIONS OR QUERIES YOU MAY HAVE ABOUT THIS QUESTIONNAIRE.

____
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THANK YOU <u>SO</u> MUCH FOR PARTICIPATING.

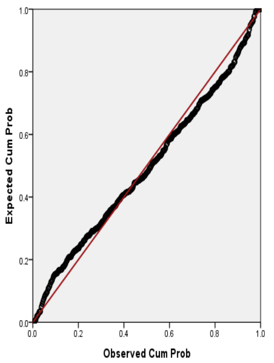
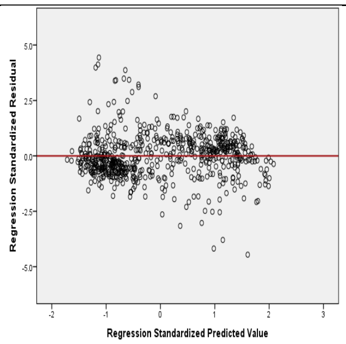
Don't forget your GIFT CARD entry

and GOOD LUCK!!

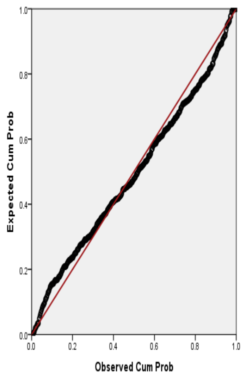
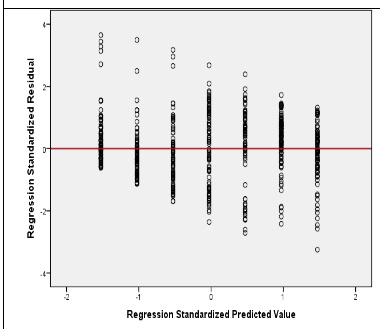
Appendix B.

Linearity, Homoscedasticity and Multicollinearity Tests

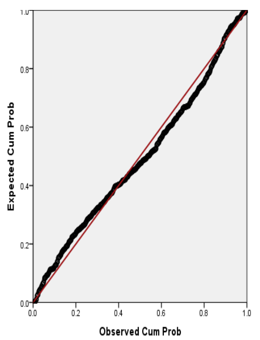
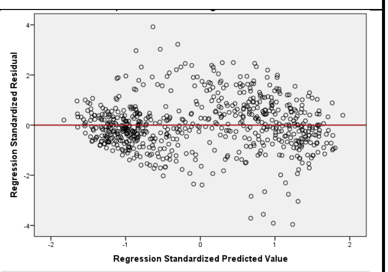
Subjective Knowledge → Cognitive Appraisals

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	VIF
	3724.7	0.00	1.00	1.00
	Residual scatterplot			
				

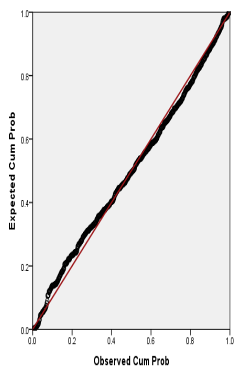
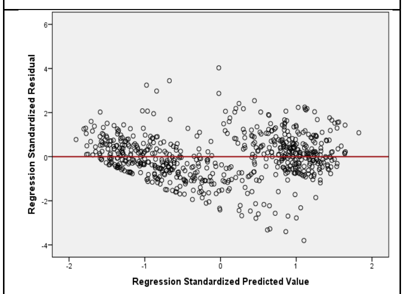
Experience → Affective Appraisals

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	VIF
	1062.1	0.00	1.00	1.00
	Residual scatterplot			
				

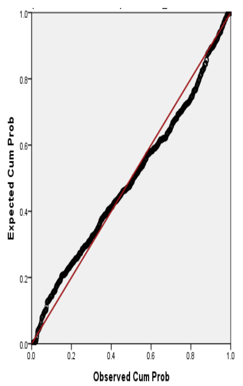
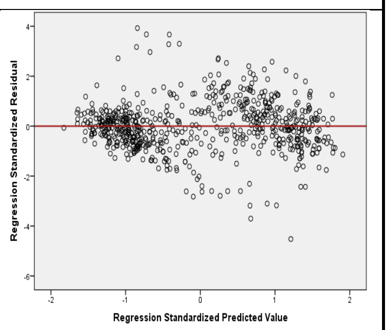
Cognitive Appraisals → Negative Affects

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	F
	1957.6	0.00	1.00	1.00
	Residual scatterplot			
				

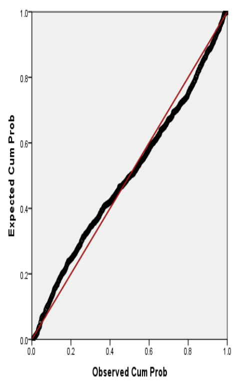
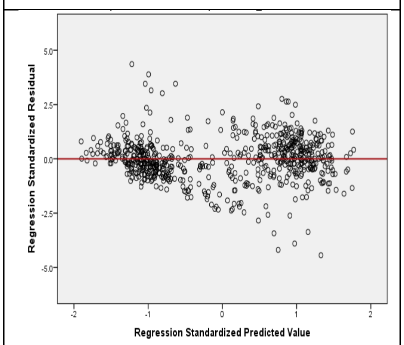
Cognitive Appraisals → Positive Affects

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	VIF
	1862.1	0.00	1.00	1.00
	Residual scatterplot			
				

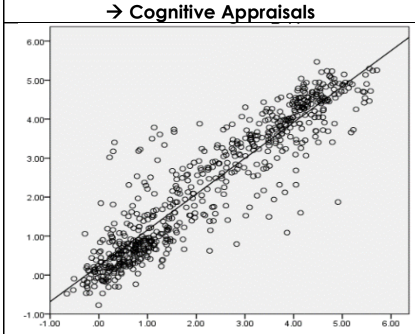
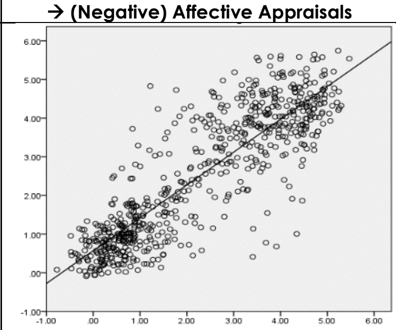
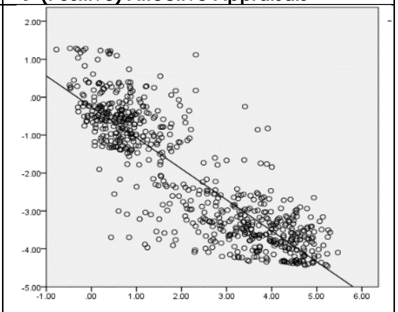
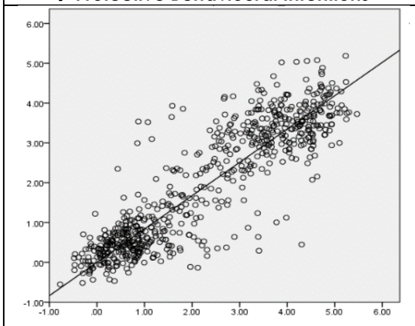
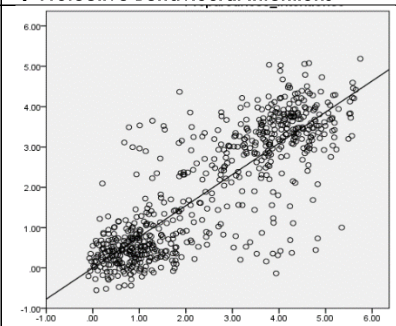
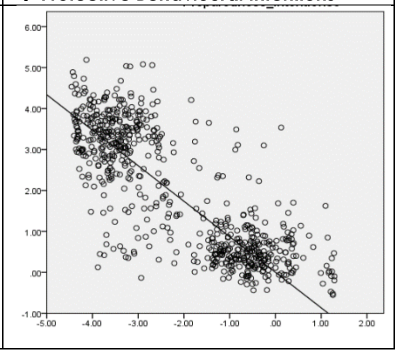
Cognitive Appraisals → Protective Behavioural Intentions

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	VIF
	2471.2	0.00	1.00	1.00
	Residual scatterplot			
				

Affective Appraisals → Protective Behavioural Intentions

Normal probability plot of the regression standardized residuals	Linearity (ANOVA)		Collinearity Statistics	
	F	Sig.	Tolerance	VIF
	1064.2	0.00	1.00	1.00
	Residual scatterplot			
				

Linear Curve Estimations

Knowledge → Cognitive Appraisals	Cognitive Appraisals → (Negative) Affective Appraisals	Cognitive Appraisals → (Positive) Affective Appraisals
		
Cognitive Appraisals → Protective Behavioural Intentions	**(Negative) Affective Appraisals → Protective Behavioural Intentions**	**(Positive) Affective Appraisals → Protective Behavioural Intentions**
		

Appendix C.

1. The measurement models for the latent interactions of PRC and RS

Three measurement models for PRC and RS were estimated to ensure their fit prior to estimating the structural models (see Figure A.8. 1-3). These models yielded $\chi 2/df < 3$, RMSEA < 0.08, PCLOSE= 1.00, CFI > 0.95 and TLI > 0.95 which all constitute good fit to the data. The latent interaction terms (PRC x RS1), (PRC x RS2) and (PRC x RS3) do not have means, variances, or covariance with other parameters in each corresponding model and therefore should not affect the fit of the measurement models for NA and RS (Muthén, 2012; Maslowsky et al., 2014). The results from estimating the measurement models revealed that all the factor loadings were significantly larger than their standard errors, resulting in z-statistics (C.R values) that exceed ±1.96 (at $p < 0.05$). The standardized regression coefficients ß for all items were significant (at p <0.001) and ranged between 0.794 - 0.975 (Table C.1. 1), 0.794 - 0.975 (Table C.1. 2) and 0.794 and 0.975 (Table C.1 3) for the measurement models of RS1, RS2 and RS3, respectively. The squared multiple correlations (SMC) (a measure of statistical variance which is equivalent to the estimated communality (R2) in EFA) were above the acceptable value of 0.3 for all items in each model, thus were retained. These results provided evidence for the unidimensionality of each scale in these models. To this end, the standardised residual covariance matrix (SRCM) from the output of each model was examined and there were no standardised residual values below −2.58 or above 2.58. A value of |2.58| corresponds to the area beyond the ±2 standard deviations from the average standardized residual or the values lying in the extreme 5% of the distribution. Moreover, all modification indices were below 30. No further refinement or modifications were, therefore, needed for the three measurement models of PRC and RS.

Table C.1 Standardized Coefficient weights (**ß**) and Squared Multiple Correlations (**SMC**) for the moderated models of RS in predicting behavioural intentions.

Item	Latent Construct	NA and RS_1 Model		NA and RS_2 model		NA and RS_3 model	
		ß (P-value)	SMC	ß (P-value)	SMC	ß (P-value)	SMC
PBI. 1	←Protective Behavioural Intention	0.849(***)	0.721	0.845(***)	0.714	0.845(***)	0.714
PBI. 2	←Protective Behavioural Intention	0.820(***)	0.673	0.817(***)	0.668	0.817(***)	0.668
PBI. 3	←Protective Behavioural Intention	0.834(***)	0.696	0.830(***)	0.689	0.830(***)	0.689
PBI. 4	←Protective Behavioural Intention	0.834(***)	0.696	0.833(***)	0.694	0.833(***)	0.694
PBI. 5	←Protective Behavioural Intention	0.844(***)	0.664	0.811(***)	0.658	0.811(***)	0.658
PBI. 6	←Protective Behavioural Intention	0.815(***)	0.712	0.843(***)	0.710	0.843(***)	0.710
PBI. 7	←Protective Behavioural Intention	0.819(***)	0.671	0.816(***)	0.667	0.816(***)	0.667
PBI. 8	←Protective Behavioural Intention	0.845(***)	0.713	0.843(***)	0.711	0.843(***)	0.711
PBI. 9	←Protective Behavioural Intention	0.882(***)	0.778	0.896(***)	0.803	0.896(***)	0.803
PBI. 10	←Protective Behavioural Intention	0.880(***)	0.774	0.894(***)	0.799	0.894(***)	0.799
PRC. 1	←Perceived Risk Conseq. PRC	0.829(***)	0.687	0.829(***)	0.688	0.829(***)	0.688
PRC. 2	←Perceived Risk Conseq. PRC	0.829(***)	0.687	0.829(***)	0.688	0.829(***)	0.688
PRC. 3	←Perceived Risk Conseq. PRC	0.873(***)	0.762	0.873(***)	0.762	0.873(***)	0.762
PRC. 4	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
PRC. 5	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
PRC. 6	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
PRC. 7	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
PRC. 8	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
PRC. 9	←Perceived Risk Conseq. PRC	0.902(***)	0.813	0.902(***)	0.813	0.902(***)	0.813
RS. 11	← Residential Satisfaction RS_1	0.881(***)	0.776	---	---	---	---
RS. 12	← Residential Satisfaction RS_1	0.890(***)	0.793	---	---	---	---
RS. 13	← Residential Satisfaction RS_1	0.884(***)	0.782	---	---	---	---
RS. 14	← Residential Satisfaction RS_1	0.879(***)	0.773	---	---	---	---
RS. 15	← Residential Satisfaction RS_1	0.872(***)	0.760	---	---	---	---
RS. 16	← Residential Satisfaction RS_1	0.883(***)	0.780	---	---	---	---
RS. 21	← Residential Satisfaction RS_2	---	---	0.900(***)	0.810	---	---
RS. 22	← Residential Satisfaction RS_2	---	---	0.900(***)	0.810	---	---
RS. 23	← Residential Satisfaction RS_2	---	---	0.900(***)	0.810	---	---
RS. 24	← Residential Satisfaction RS_2	---	---	0.900(***)	0.810	---	---
RS. 25	← Residential Satisfaction RS_2	---	---	0.995(***)	0.921	---	---
RS. 26	← Residential Satisfaction RS_2	---	---	0.954(***)	0.991	---	---
RS. 27	← Residential Satisfaction RS_2	---	---	0.920(***)	0.910	---	---
RS. 31	← Residential Satisfaction RS_3	---	---	---	---	0.995(***)	0.921
RS. 32	← Residential Satisfaction RS_3	---	---	---	---	0.954(***)	0.991
RS. 33	← Residential Satisfaction RS_3	---	---	---	---	0.920(***)	0.910
RS. 34	← Residential Satisfaction RS_3	---	---	---	---	0.960(***)	0.847

*** represents a significant **ß** at p-value < 0.001.

2. The measurement models for the latent interactions of NA and RS

Three measurement models for the latent interaction of NA and RS were estimated to ensure their fit prior to estimating the structural models (see Figure A.8. 4-6). These models yielded $\chi 2/df < 3$, RMSEA < 0.08, PCLOSE= 1.00, CFI > 0.95 and TLI > 0.95 which all constitute good fit to the data. The latent interaction terms (NA x RS1), (NA x RS2) and (NA x RS3) do not have means, variances, or covariance with other parameters in each corresponding model and therefore should not affect the fit of the measurement models for NA and RS. The results from estimating the measurement models revealed that all the factor loadings were significantly larger than their standard errors, resulting in z-statistics (C.R values) that exceed ±1.96 (at $p < 0.05$). The standardized regression coefficients ß for all items were significant (at $p <0.001$) and ranged between 0.794 - 0.975 (Table C.2, Columns 3 and 4), 0.794 - 0.975 (Table C.2. Columns 5 and 6) and 0.794 and 0.975 (Table C.2. Columns 7 and 8) for the measurement models of RS1, RS2 and RS3, respectively. The squared multiple correlations (SMC) were above the acceptable value of 0.3 for all items in each model, thus were retained. These results provided evidence for the unidimensionality of each scale in these models. To this end, the standardised residual covariance matrix (SRCM) from the output of each model was examined and there were no standardised residual values below −2.58 or above 2.58. Moreover, all modification indices were below 30. No further refinement or modifications were, therefore, needed for the three measurement models of NA and RS latent interactions.

Table C.2 Standardized Coefficient weights (**ß**) and Squared Multiple Correlations (**SMC**) for the moderated models of RS in predicting behavioural intentions.

Item	Latent Construct	NA and RS_1 Model		NA and RS_2 model		NA and RS_3 model	
		ß (P-value)	SMC	ß (P-value)	SMC	ß (P-value)	SMC
PBI. 1	←Protective behavioural Intention	0.848(***)	0.707				
PBI. 2	←Protective behavioural Intention	0.813(***)	0.656				
PBI. 3	←Protective behavioural Intention	0.830(***)	0.719				
PBI. 4	←Protective behavioural Intention	0.837(***)	0.661				
PBI. 5	←Protective behavioural Intention	0.810(***)	0.656				
PBI. 6	←Protective behavioural Intention	0.834(***)	0.700				
PBI. 7	←Protective behavioural Intention	0.810(***)	0.696				
PBI. 8	←Protective behavioural Intention	0.841(***)	0.688				
PBI. 9	←Protective behavioural Intention	0.872(***)	0.760				
PBI. 10	←Protective behavioural Intention	0.872(***)	0.760				
NA. 1	←Negative Affects	0.819(***)	0.756				
NA. 2	←Negative Affects	0.869(***)	0.671				
NA. 3	←Negative Affects	0.902(***)	0.813				
NA. 4	←Negative Affects	0.887(***)	0.786				
RS. 11	← Residential Satisfaction RS_1	0.922(***)	0.819	---	---	---	---
RS. 12	← Residential Satisfaction RS_1	0.936(***)	0.877	---	---	---	---
RS. 13	← Residential Satisfaction RS_1	0.870(***)	0.752	---	---	---	---
RS. 14	← Residential Satisfaction RS_1	0.915(***)	0.837	---	---	---	---
RS. 15	← Residential Satisfaction RS_1	0.905(***)	0.757	---	---	---	---
RS. 16	← Residential Satisfaction RS_1	0.867(***)	0.850	---	---	---	---
RS. 21	← Residential Satisfaction RS_2	---	---			---	---
RS. 22	← Residential Satisfaction RS_2	---	---			---	---
RS. 23	← Residential Satisfaction RS_2	---	---			---	---
RS. 24	← Residential Satisfaction RS_2	---	---			---	---
RS. 25	← Residential Satisfaction RS_2	---	---			---	---
RS. 26	← Residential Satisfaction RS_2	---	---			---	---
RS. 27	← Residential Satisfaction RS_2	---	---			---	---
RS. 31	← Residential Satisfaction RS_3	---	---	---	---		
RS. 32	← Residential Satisfaction RS_3	---	---	---	---		
RS. 33	← Residential Satisfaction RS_3	---	---	---	---		
RS. 34	← Residential Satisfaction RS_3	---	---	---	---		

*** represents a significant **ß** at p-value < 0.001.