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Summary

Rising global temperatures, urban heat islands, and rapid development have made Vulnerability to Heat a particularly pertinent subject for urban dwellers in tropical Malaysia. Segments of the urban population are more at-risk due to a combination of socio-economic, demographic, and spatial characteristics, including Public Housing Communities (PHCs), the focus of this study. There is however limited information on how this community experiences, understands, or responds to heat in their daily lives.

This study examines Vulnerability to Heat in a selected Malaysian PHC using the Intergovernmental Panel on Climate Change (IPCC)'s definition of Vulnerability, comprising the sub-variables Sensitivity and Adaptive Capacity. Indicators collected via a household survey are used to construct the dependent variable Vulnerability to Heat, which is also used to segregate households into tiers of vulnerability. In addition, the independent variables Exposure, Thermal Comfort, and Risk Perception, are constructed and analysed through regressions. Challenges and opportunities within Vulnerability to Heat are explored.

Findings prove that the studied PHC experiences heat related stress in daily life, with implications for quality of life and health. Drivers of vulnerability within the Sensitivity sub-variable include Number of Health Symptoms, Gender Ratio, Household Size, and presence of Children under 5 years old. Drivers of vulnerability within Adaptive Capacity are Access to Cool Spaces, Income, Knowledge of Heat and Health, and Challenges to Adaptation.

Regression of the independent variables against the Number of Heat-health symptoms show that 1) households exposed to more heat, 2) households experiencing worse thermal comfort, and 3) households with greater risk perception; are likely to report more heat-health symptoms. At the Composite Vulnerability level, regression shows 1) households exposed to more heat and 2) households experiencing worse thermal comfort, are likely to have higher vulnerability scores.

Challenges faced by the community include financial constraints, the lack of skills or knowledge, and rules and regulations. Issues of access and overall marginalisation also play a role in Vulnerability to Heat. Opportunities lie in recognising the diversity of household composition in PHC, leveraging the high social cohesion between neighbours, utilising social media as an effective tool for spreading information and awareness, and working with the community to explore creative or low-cost ways to mitigate heat stress.

Policies and interventions should adopt a targeted, data-driven approach to assisting communities affected by heat, focusing on practical and accessible solutions that bring the most benefit.

Keywords

Heat, vulnerability, adaptive capacity, climate change, Malaysia

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Abbreviations

AC	Air-conditioning
ACI	Adaptive Capacity Index
ANSI	American National Standards Institute
AR4	Fourth Assessment Report, IPCC 2007
AR5	Fifth Assessment Report, IPCC 2014
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
BPR	Bantuan Prihatin Rakyat, government cash aid programme
C-alpha	Cronbach's Coefficient Alpha
CVI	Composite Vulnerability Index
E	Exposure Composite Variable
GDP	Gross Domestic Product
GKL	Greater Kuala Lumpur
HVA	Heat Vulnerability Assessments
IHS	Institute for Housing and Urban Development Studies
IPCC	Intergovernmental Panel on Climate Change
KL	Kuala Lumpur
LR	Likelihood Ratio
PERWACOM	Persatuan PERWACOM Prihatin (Women's Association at PPR Hicom)
PHC	Public Housing Community
PPR	Projek Perumahan Rakyat (People's Housing Project)
PPR HICOM	PPR Kg Baru HICOM (selected public housing site)
RP	Risk Perception Composite Variable
SI	Sensitivity Index
SREX	Special Report on Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation, IPCC 2012
TAR	Third Assessment Report, IPCC 2001
TC	Thermal Comfort Composite Variable
UHI	Urban Heat Island

Chapter 1: Introduction

1.1 Background

Malaysia, classified according to the KOPPEN-Geiger climate classification as a tropical humid country, receives heavy rainfall and sunshine year-round. The country has two primary monsoon seasons; the North-East monsoon (November to March) and the South-west monsoon (June to September) (Aflaki et al., 2017; Makaremi, Salleh, Jaafar, & GhaffarianHoseini, 2012). Temperatures average around 26.4°C, with a moderate maximum of 34°C and a moderate minimum of 23°C (Al-Tamimi & Syed Fadzil, 2011).

In the past century, cities in Malaysia have seen an upward trend in temperatures, likely due to a combination of global warming climactic changes, the El Nino effect, and the Urban Heat Island (UHI) effect (Li, X., 2020; Ramakreshnan et al., 2018; Tangang, Juneng, & Ahmad, 2007).

Rapid urbanisation over the past decades compounds the UHI effect. 75% of the Malaysian population is now urbanised, up from 28.4% in 1970 (Nai & Siow, 2022). Greater Kuala Lumpur (GKL) alone, a region encompassing the nation’s capital Kuala Lumpur (KL) and 9 surrounding municipalities, now accounts for at least 20% of the nation’s population of 31 million and a significant portion of its economic activity (Ramakreshnan et al., 2018).

These development pressures, have transformed large swathes of what was once tropical forests or other green areas into dense concrete jungles. Some areas in Kuala Lumpur (KL) documented a temperature rise of 1.5°C over 20 years. These temperature differences are also observed in Greater KL, with temperatures spiking up to 3 °C higher due to the loss of green space and increase in built-up space (Ramakreshnan et al., 2018).

The combination of continuing urbanisation, climactic change, and the Urban Heat Island effect thus places urban communities and environments under increasing pressure from heat-related challenges. These challenges, sometimes described using the term *heat stress*, manifest through poor health, diminished productivity, disrupted ecological processes and more.

In terms of human health, heat stress may show up through a spectrum of effects, ranging in severity from heat rashes, headaches, heat stroke and death (Budd, 2008). Heat affects quality of life in other ways, from disrupted sleep to productivity losses to general discomfort. While people and populations have adapted and continue to adapt to different climates, their thermoregulatory ability decreases with age and onset of illness (Kovats & Hajat, 2008). In addition, the capacity to adapt or respond to heat stress is dependent on other variables like income, location, knowledge, and gender (Soomar & Soomar, 2023). As a result, certain groups like the elderly, children, lower-income groups, outdoor workers, and unhoused populations are more vulnerable. Communities living in low-cost urban housing too are one of the groups at risk.

In response, globally, many heat vulnerability assessments have been developed to understand risks and shape actions to improve resilience. Using a vulnerability framework derived from the Intergovernmental Panel on Climate Change (IPCC), this study examines the factors driving vulnerability to heat stress through the lens of sensitivity and adaptive capacity. Commonly used indicators are investigated, and relationships are drawn, with conclusions presented.

1.2 Problem Statement

There are limited robust or continuous studies in Malaysia on Urban Heat Islands, or heat stress and how it is perceived or experienced by communities in Greater Kuala Lumpur (Ramakreshnan et al., 2018). Overall, the domain remains understudied in Malaysia and warrants further investigation.

Additionally, the Kuala Lumpur City Hall does not have a Heat Management Plan nor a Heat Response Plan, though one is planned for in the next five years. Proposed actions are vague, with an emphasis on greening outdoor spaces and identification of at-risk populations (Kuala Lumpur, 2021). Other Malaysian municipalities also do not have heat action plans.

Public communication and awareness on heat and health is lacking. The Malaysian Ministry of Health's website has various, scattered short pages on heat and health such as one on hot weather and health (Mohamed, 2012) and basic guidelines on treating heat stroke for outdoor workers, athletes, and military personnel (Wahab, Abd Ghani, & Shafie, 2016). The Malaysian Meteorological Department likewise has a static page on Heat Wave (Malaysian Meteorological Department, 2023). Communication often takes place through news outlets.

Preliminary analysis of official response shows it is reactionary and fails to consider a multifaceted view of heat stress and its consequences on vulnerable groups. Cross-sectional effort to tackle heat as a multidimensional issue is limited, for example from the domains of housing, urban planning, and health.

This poses a challenge, especially as Malaysia faced a period of high temperature in the second quarter of 2023, coinciding with the return of the El Nino conditions after 3 years of absence. At least 3 deaths were attributed to the heat, with schools directed to stop all outdoor activities on the 5th of May 2023 for slightly over a month (Kasinathan, 2023). There is also likely underreporting of heat-health impacts as protocols for diagnosis are not set in place.

On the 12th of May 2023, civil society groups active in climate action pushed for authorities to take measures to increase resilience to heat-related challenges to address vulnerabilities in the population (Gabungan Darurat Iklim Malaysia, 2023).

Public Housing Communities

Almost 2.8 million people live in public and private strata low-cost housing in Malaysia. These communities are characterised by lower educational attainment, lower income generating capabilities, poor health outcomes, unsatisfactory living conditions, likelihood of outdoor work and more. Many public housing complexes are unsuitably located, poorly built, with limited access to services, amenities, or green space. The units are typically small and poorly ventilated, sometimes housing large families within a small space. These factors place public housing communities particularly at risk of heat-related challenges (Dietrich & Ismail, 2022).

1.3 Research Objective

There is a paucity of heat-related research in Malaysia. This study contributes to knowledge by understanding how a specific vulnerable group, public housing communities, experience, understand, and respond to heat in their daily lives.

This will be done through the development of a heat vulnerability assessment tool, incorporating social and economic dimensions tailored to the local context. This study has the support of Think City, a Malaysian organisation active in the urban resilience field, and PERWACOM, a women's residents association active at the chosen site.

Successful completion of the study will produce a heat vulnerability assessment tool that can be used and refined by Think City to conduct further heat vulnerability assessments in other communities. This information can be used to shape policy and action to shape public housing communities resilient to heat.

1.4 Research Question

In this explanatory study, the research question is: What are the factors driving Malaysian public housing communities (PHC)'s Vulnerability to Heat? The following sub-questions are posed:

1. What are the drivers of PHC household *sensitivity* to heat?
2. What are the drivers of PHC household *adaptive capacity* (or lack thereof) to heat?
3. How do *Exposure, Thermal Comfort*, and *Risk Perception* affect vulnerability to heat?
4. What *challenges* and *opportunities* exist within PHC's relationship with heat?

Sub-questions 1 and 2 are important as, by definition, the dependent variable, *Vulnerability to Heat* is formulated through sub-variables *Sensitivity* and *Adaptive Capacity*. Examining the sub-variables provides greater detail on the primary drivers of vulnerability, at the household level.

Sub-question 3 investigates three independent variables, and their links with *Vulnerability to Heat*, based on relationships found in literature. These independent variables are useful to understand as stand-alone variables too.

Sub-question 4 provides insights on *challenges and opportunities* influencing PHC *Vulnerability to Heat*, important considerations for intervention or policy formulation.

1.5 Thesis Structure

The following chapters are structured as follows.

Chapter two contains the literature review, exploring drivers of heat in cities, impacts on health, as well as other social determinants of heat vulnerability. The latter half of the chapter discusses conceptual frameworks commonly used and ends with the selected conceptual framework for the study.

Chapter three discusses the research strategy, site selection, data collection and analysis methodologies, as well as limitations encountered.

Chapter four presents the results through formulation of the independent and dependent variables, statistical analysis, and discussion of findings.

Lastly, chapter five ends with the conclusions of the research, recommendations, and other implications.

Chapter 2: Literature Review

Heat is considered a critical global health hazard, causing high mortality and morbidity across the world (Kenny, Flouris, Yagouti, & Notley, 2019; Leyk, 2019). It is a silent killer, being attributed to about 62000 excess deaths in Europe alone in the summer of 2022 (Ballester et al., 2023). In 2023, as at the time of writing, record-breaking temperatures have been reported from Southeast Asia to Europe, with the first week of July 2023 being the hottest week recorded, globally (Paddison, 2023).

Growing recognition of heat-related challenges saw a corresponding increase in research on the subject, particularly over the last two decades. A review of studies on heat show diversity in topic and climactic zones, ranging from health to agriculture to economic productivity (Campbell, Remenyi, White, & Johnston, 2018; Li, Y., Sun, Kleisner, Mills, & Chen, 2023).

This literature review focuses on population vulnerability resulting from exposure to heat in an urban environment, narrowing the scope to drivers of heat in urban areas, consequences to health, and other social determinant of heat vulnerability. Mapping the cause and effect of heat on urban populations is complex, with climate change, urbanisation, and urban heat islands all acting as key factors. Links with health, productivity, inequalities, and other social determinants are reviewed.

A global perspective is adopted, alongside contextualisation to Malaysia or surrounding regions where possible. Additionally, vulnerability frameworks and definitions commonly used are examined, along with a special focus on adaptive capacity.

2.1 Heat and the Urban Population

2.1.1 A Changing Climate

Human induced global warming has led to increased global surface temperatures of 1.1°C since 1900, with projections to exceed 1.5°C within the 21st century (Calvin et al., 2023). Rising temperatures further disrupt climate systems, resulting in extremes which lead to catastrophic losses (Watts et al., 2015).

Increasing temperatures caused a rise in frequency, intensity, and duration of extreme heat events or heatwaves, globally, as well as regionally in Southeast Asia (Li, X., 2020; Perkins, Alexander, & Nairn, 2012). Heatwaves are on the rise across Peninsula Malaysia, linked in part to changes in humidity levels. In addition, analysis of minimum temperatures during heatwaves in Southeast Asia show higher increases than maximum temperatures, pointing to increasingly warmer nights. This is significant as higher nightly temperatures link to higher mortality during heatwaves (Ho, Lau, Ren, & Ng, 2017).

Humidity also worsens the impact of heat, affecting thermoregulation and disrupting evaporative cooling processes of the human body. The combination of heat and humidity (wet-bulb conditions) can be deadly, and has been linked to high mortality such as in South Asia during the 2015 heatwaves (Li, X., 2020). Worryingly, an estimated 30% of the global population is already exposed to deadly thresholds of average surface air temperatures and relative humidity for at least 20 days in a year (Mora et al., 2017). This is only expected to increase.

Heatwaves in Southeast Asia are also impacted by the natural climate phenomenon El Nino, with high magnitudes of heatwave characteristics coinciding with strong El Nino years (1983,1998, 2010 and 2016) (Li, X., 2020). The 2023 heatwave experienced in Malaysia is also attributed in part to El Nino, returning after 3 years of absence (The Star, 2023).

2.1.2 Urbanisation and Urban Heat Islands

Exacerbating effects from climate change and rising temperatures are Urbanisation and the Urban Heat Island effect.

Over half the world's population is now urbanised, with the trend expected to rise to 68% by 2050 (UN-Habitat, 2022). In developing regions, the pace of urbanisation is far more rapid, placing immense pressures. Malaysia too saw rapid urbanisation, with 75% of the population urbanised now, up from 28.4% in 1970 (Nai & Siow, 2022). Much of this growth is concentrated in the capital, Kuala Lumpur, and the surrounding urban conurbation – Greater Kuala Lumpur, which is home to at least 7.2 million people and considered the country's engine of economic growth (Ramakreshnan et al., 2018).

Higher population densities lead to more urban development, and are linked to the Urban Heat Island (UHI) effect through warmer temperatures (Elsayed, 2012). The UHI effect is linked to increased risk of illness and death across major cities (Tomlinson, Chapman, Thornes, & Baker, 2011).

UHI is a form of urban thermal pollution caused by increases in ambient air temperature in dense, built environments (Ramakreshnan et al., 2018). There are many types of UHIs in cities but overall it is a systemic event with at least nine major contributors, including but not limited to; man-made heat emissions, pollution and energy consumption of cities, low-albedo (*lower light reflectivity*) materials on facades and surfaces, reduced wind speed due to structure of built environment, and intensive land use and building density with large heat retaining properties (Aflaki et al., 2017; Elsayed, 2012; Harlan & Ruddell, 2011; Santamouris, Synnefa, & Karlessi, 2011).

UHI has negative impacts – increasing heat stress and related health conditions of urban dwellers, as explored in section 2.1.4. It is also a massive driver of air conditioning use, perpetuating a vicious cycle of increasing energy consumption, elevating formation of ground level ozone, affecting microclimates within cities and contributing to global warming overall (Aflaki et al., 2017).

In Malaysia, robust and continuous large-scale studies of UHI are lacking. Nonetheless, existing studies of Greater KL using various methodologies show rising temperatures of anywhere from 0.6°C to 3°C (on the conservative end) attributable to land use change due to development, depletion of vegetation, and increase in artificial impervious surfaces amongst other reasons (Ramakreshnan et al., 2018).

2.1.3 Heat Exposure in Daily Urban Life

Uncomfortable levels of heat exposure have been documented in various urban settings globally. For example, urban commuters experience heat stress during travel around the city (especially via public transport) and at work (Arifwidodo & Chandrasiri, 2020; Zander, Botzen, Oppermann, Kjellstrom, & Garnett, 2015). Children also experience heat stress in schools, public space, and commutes (Meng et al., 2023).

While many studies examine outdoor temperatures, indoor temperatures (at work, school, or home) can be as harmful, if not more so. Between 50 - 80% of heat-related mortality occur indoors, especially at home, due to sustained high indoor heat exposure. Those living in poorly built or poorly ventilated conditions, such as slums with exposed tin roofs, are more vulnerable. Those spending substantial periods of time indoors, such as women in caregiving or home-based roles, may also be more at-risk. These vulnerable communities have been documented to have more heat-related medical needs than less vulnerable communities (Arifwidodo & Chandrasiri, 2020; Kenny et al., 2019; Rana et al., 2022; Samuelson et al., 2020; Zander et al., 2015). Indoor thermal conditions, are understudied, but can be measured using instruments or subjective assessments of thermal comfort, such as the ANSI/ ASHRAE Standard 55 (Kenny et al., 2019).

2.1.4 Heat and Health

Heat and Health is well-studied from a public health perspective, though there is a research bias towards higher-income, mid to high latitude countries with lower population densities. There is a predisposition to studying mortality as opposed to morbidity for various reasons including ease of data collection and validation (Campbell et al., 2018). Regardless it is accepted that heat poses danger to human health not just during periods of extreme heat events, but also during periods of moderate warmth (Campbell et al., 2018; Leyk, 2019; Lungman et al., 2023). Individual physiology, and a range of other factors play a role (Campbell et al., 2018).

In addition, while populations in tropical or hotter climates are better physically adapted to hot weather in general, the human body requires time (approximately 7-10 days) for true acclimatisation to occur (Leyk, 2019; Makaremi et al., 2012). Rapid temperature changes happening within a short span are not easy to adapt to. In addition, as covered in section 2.1.1, rising humidity, affects bodily cooling mechanism and increases fatal climactic conditions. Thus, despite the relatively smaller research attention given, consensus of research carried out in the tropics indicate populations there are also susceptible to heat-health challenges (Campbell et al., 2018; Kenny et al., 2019; Kjellstrom et al., 2016). Heat tolerance is affected by the following physiological and non-physiological factors; being overweight, being unfit, infections and illness, dehydration, medication, age, clothing, and physical activity (Campbell et al., 2018; Leyk, 2019; Soomar & Soomar, 2023). The human body is affected by temperature increase externally, but also independently generates heat through physical exertion and activity of the muscles. Thus, even in the absence of extreme heat, physical activity can induce increases in core body temperature. Physiologically, bodily heat loss is facilitated by increased rate of sweating and increased skin surface blood flow, amongst other means (Leyk, 2019). Outdoor work, domestic work, and type of clothing can affect this.

In a study of US Army recruits, being *overweight* and having *low physical fitness* increases heat illness risk by 8 times in a heat related event. *Disease* may impair thermoregulation, as in the case of cardiac patients where increased heat dissipation requiring increased cardiac output places pressure on bodily systems (Leyk, 2019). Respiratory, endocrine, cerebrovascular, mental health and other chronic diseases too are linked to heat-related mortality (Campbell et al., 2018). *Prescription medication* also impairs resilience to heat by affecting five bodily defence mechanisms including the perception for thirst, altered awareness, and central thermoregulation (Leyk, 2019).

Thus, the elderly especially are at risk due to lower age-related physiological adaptability, higher prevalence of chronic disease, and use of prescription medication (Campbell et al., 2018; Leyk, 2019) Age, disease, and medication link to impaired heat perception, lower rates of skin blood flow, lower sweating rate and other factors leading to reduced heat dissipation. Children below 5 are vulnerable as they sweat less relative to their body surface area. While men and women are physically different, studies show a comparable physiological ability to withstand heat stress (Leyk, 2019; Li, F., Yigitcanlar, Nepal, Thanh, & Dur, 2022).

Heat illness manifests variously without sequence and with unclear transition from one form to the other, making it difficult to recognise. It includes heat cramps (painful muscle contractions), heat rash, nausea, heat stroke and death. Delays in treatment of heat illness link to rise in morbidity and mortality making education and awareness all more important for prevention (Kjellstrom et al., 2016; Leyk, 2019).

Even short periods of high-heat exposure are linked with reduced functionality affecting quality of life through sleep disruption and poor thermal comfort (Kenny et al., 2019) Heat stress can also negatively impact mental wellbeing (Li, F. et al., 2022; Zander et al., 2015). In the workplace, heat may increase occupational accidents, disrupt productivity, and increases chance of heat stroke and death (Flouris et al., 2018; Xiang, Bi, Pisaniello, & Hansen, 2014).

2.1.5 Heat and Productivity

Linked to the above, in terms of workplace productivity loss, a systematic review of 111 studies involving 447 million workers across the world found evidence of 1) four times greater likelihood of occupational heat strain after a single work shift under heat stress, 2) reported productivity losses due to heat stress. Projections suggest up to 1 million work life-years lost by 2030 due to occupational heat stroke fatalities, and 70 million work life-years lost due to reduced labour productivity (Flouris et al, 2018).

GDP losses of up to 0.47% in Australia and up to 5.9% in Malaysia have also been estimated due to heat related absenteeism (Kjellstrom et al., 2016; Zander et al., 2015). Costs from labour productivity loss due to heat stress could increase to 27% by 2080 in regions like Asia. At the household level, nearly 10% of annual median income of a Malaysian individual could be lost due to heat related productivity loss (Zander & Mathew, 2019).

2.1.6 Heat and other Social Determinants

Climate inequalities worsen impacts of heat. A study of neighbourhoods in Phoenix, Arizona found positive correlations between heat stress and poor or minority neighbourhoods, likely due to underinvestment, deteriorated physical neighbourhood conditions, and general lack of green space. Underserved neighbourhoods were up to 7°C hotter. Warmer neighbourhoods' vulnerability was also made worse due to inadequate coping resources of residents (Harlan, Brazel, Prashad, Stefanov, & Larsen, 2006; Harlan, Declet-Barreto, Stefanov, & Petitti, 2013; Soomar & Soomar, 2023).

Various socio-economic indicators linked to inequalities or marginalisation such as income, education, and ethnicity, are correlated with higher mortality and morbidity levels due to heat. Large household sizes are also connected to increased risk during high temperatures, as a result of a greater concentration of people in an area (Johnson, Stanforth, Lulla, & Luber, 2012; Kenny et al., 2019; Malik, Awan, & Khan, 2012).

Meanwhile, studies on gender and heat are contradictory, though most studies find women at greater risk of mortality and morbidity due to heat than men, likely due to awareness, exposure, and access to resources (Nayak et al., 2018). In more traditional settings, women are greatly exposed to impacts of heat, as there are confined to indoor domestic spheres, often in dilapidated and poorly ventilated conditions (Rana et al., 2022).

Community ties also have been studied in relation to heat. Strong community networks signal the ability to rely on others during periods of hardship, despite living in poverty or isolation (Guardaro, Hondula, Ortiz, & Redman, 2022; Harlan et al., 2006). During the 1995 Chicago heatwave, neighbourhoods with stronger community ties reported lower death rates and stronger support (Klinenberg, 2002).

2.1.7 Heat, Knowledge, Awareness and Risk Perception

Knowledge, Awareness, and Risk Perception are important factors in successful responses to heat. Increased levels of these factors improve community and individual engagement with risk reduction activities and encourage success of risk-reduction programmes related to heat. Variables such as age, gender, income, and more affect these.

In general, information and knowledge received via peers or media has a positive impact on perception. Perception is also influenced by personal experience and levels of education, the latter with greater education providing greater risk awareness (Rana & Routray, 2016; Rauf et al., 2017).

2.2 A Framework for Heat Vulnerability

Current thinking on vulnerability accepts that it is multidimensional, and its evolution developed via two primary streams which have at times merged; 1) biophysical, risk-hazard focused and 2) a socio-political, contextual focus (Naylor, Ford, Pearce, & Van Alstine, 2020). Below, selected vulnerability frameworks and definitions are explored, contextualised for heat vulnerability.

2.2.1 Overview of the IPCC Frameworks

Heat challenges within climate change scenarios are typically discussed in *vulnerability* or *risk*-related terminology, in line with the language and frameworks used by the Intergovernmental Panel on Climate Change (IPCC).

Within climate vulnerability assessments, the IPCC vulnerability definition from the 2001 Third Assessment Report (TAR) and 2007 Fourth Assessment Report (AR4) is commonly referred to; t*he degree to which a system is susceptible to, or unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate variation to which a system is exposed, its sensitivity, and its adaptive capacity* (UNFCCC, 2007). Therefore, vulnerability is expressed as a function of the three (exposure, sensitivity, and adaptive capacity).

The IPCC subsequently recognised criticism and shortcomings in this definition among which; an underemphasis on the role of social components (O'Brien, Eriksen, Schjolen, & Nygaard, 2004), and the fact that vulnerability needs to be contextualised so that its derivation and subcomponents are better understood (Downing et al., 2005).

Later, in SREX/Fifth Assessment Report (AR5), the IPCC redefined vulnerability to be a component of only sensitivity and adaptive capacity. This risk-focused framework therefore had climate risk as a product of exposure, hazard, and vulnerability. This change reflected the shift towards a risk management perspective, integrating more climate adaptation pathways. The language in the definitions is also more accessible, and people-oriented (Estoque et al., 2023; Li, Y. et al., 2023)

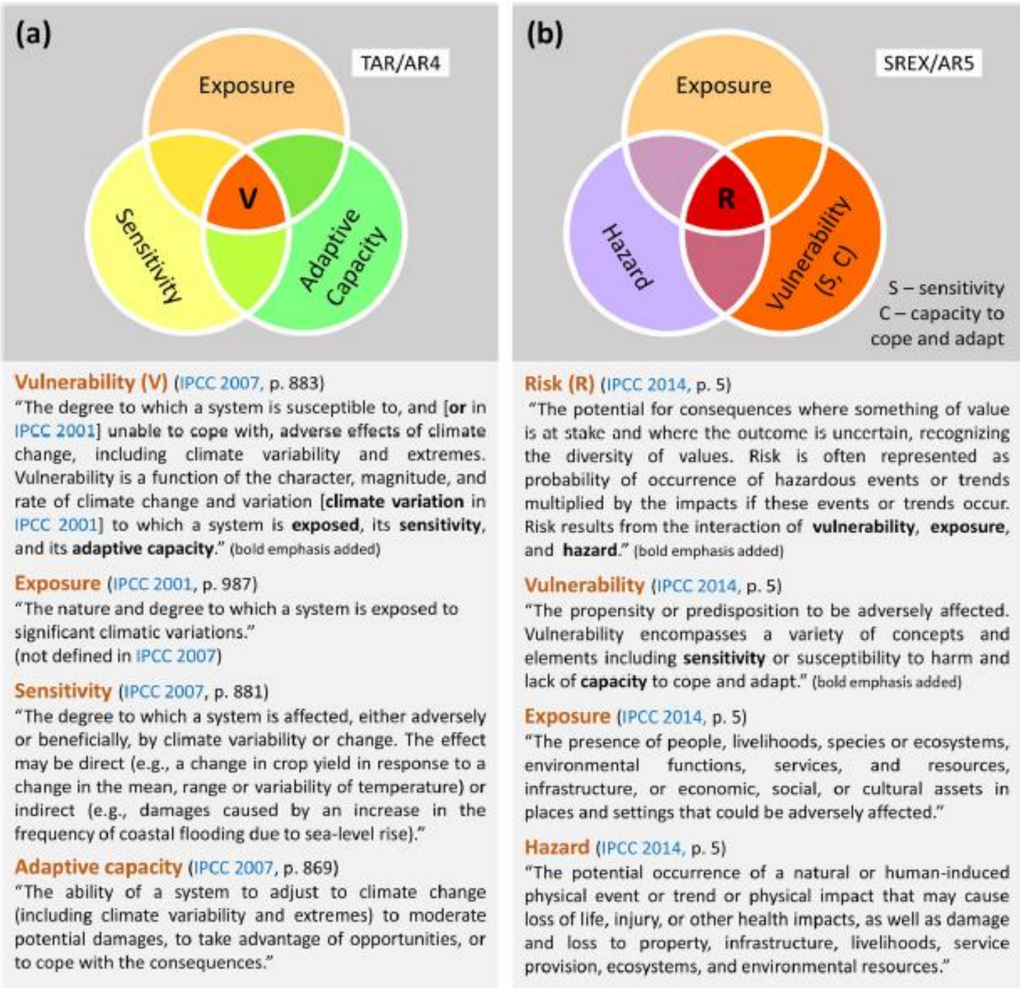

Figure 1: Change in Vulnerability Framework by the IPCC.

Source: Estoque, 2022

Briefly, the TAR/AR4 framework uses the variables *exposure*, *sensitivity*, and *adaptive capacity* to assess vulnerability. In the context of heat challenges, *exposure* refers to direct or indirect exposure from heat such as land surface temperatures, and outdoor work. Exposure alone does not imply a risk (Rana et al., 2022). *Sensitivity* refers to demographic or socioeconomic factors reflecting susceptibility to heat, like age and health conditions. *Adaptive capacity* refers to actions, services, or facilities reducing risk of heat exposure such as air conditioning or medical services (Li, F. et al., 2022).

The SREX/AR5 framework has facets of hazard, exposure, and vulnerability. *Hazard* refers to threats from spatiotemporal distribution of heat waves such as days with extreme temperature readings. In this framework *exposure* refers to land cover and population density, while *vulnerability* covers aspects under the categories sensitivity and adaptive capacity under the previous framework (Li, F. et al., 2022).

2.2.2 Adoption of the IPCC Frameworks and Alignment with Others

To-date, the TAR/AR4 framework is preferred in climate vulnerability assessments. One systematic review of 464 climate vulnerability assessments found that 43% used the TAR/AR4 framework, 52% employed other vulnerability concepts and only 3% used the SREX/AR5 concept (Estoque et al., 2023). Similar observations of preferences were made by other reviews (Borges, Ribeiro, Lopes, & Loyola, 2019; Pinnegar, Engelhard, Norris, Theophille, & Sebastien, 2019). In heat vulnerability assessments, a 2022 review of 76 studies found 25% using TAR/AR4, 20% using SREX/AR5 and 38% using other vulnerability frameworks (Li, F. et al., 2022).

Reasons for the inconsistency or dominance of the TAR/AR4 framework are due to a combination of researcher's preference, misinterpretation or confusion, and lack of awareness. Researcher's preference linked to their desire to use a framework that was more established and well-known, in order to remain consistent and comparable with other studies in the same field (Estoque et al., 2023).

Other heat vulnerability assessments explored biophysical, socio-ecological, and social vulnerability domains among others (Li, F. et al., 2022). The indicators selected also varied, reliant on local context, data constraints, and again, guided by the operational framework identified by the researcher (Soomar & Soomar, 2023). In the development of a heat vulnerability index for New York State, for example, thirteen variables under four components (social/ language, socio-economic, environmental/ urban, and elderly/ social isolation) were used, selected via Principal Components Analysis (Nayak et al., 2018).

Regardless of the framework, indicators broadly fall into the following categories. 1) demographic and socio-economic, 2) health, and 3) environmental (built or natural). Top indicators that appeared consistently were age, economic status, and social isolation. A significant limitation is that to-date there is no standardised system for heat vulnerability assessments, making comparison difficult even within the same framework. Due to subjectivity of interpretation, the same indicator may be categorised differently by different studies. In addition, the selection of indicators must be contextualised to suit the local context (Li, F. et al., 2022; Rana et al., 2022).

2.3 Understanding Adaptive Capacity

Adaptive capacity is important to social resilience, in the context of sustainability and disaster-risk reduction discussions (Waters & Adger, 2017). It refers to the entire potential of individuals or social systems to adapt to climate change, its associated events and resulting consequences (IPCC, 2019). In heat vulnerability assessments, adaptive capacity typically looks at assets (e.g. fan ownership), actions (e.g. migrating), and services or amenities (e.g. medical service, distance to green space).

Some researchers argue that conventional adaptive capacity analysis suffers from the following challenges. First, adaptive capacity is not homogenous across a population. Studies conducted at large city or reginal scales miss out on important distinctions best captured at the household or neighbourhood levels (Guardaro et al., 2022; Laranjeira, Göttsche, Birkmann, & Garschagen, 2021; Waters & Adger, 2017). These limit the possibility of tailored interventions.

Second there should be a distinction between generic adaptive capacity (e.g. income) and specific adaptive capacity (e.g. specific response to heat like air-conditioning use). Guardaro (2022) argues that in some cases, there are trade-offs occurring between the two that need to be examined further, particularly as it relates to poverty and climate inequality. For example, in low-income households, an increase in air-conditioning use might diminish income due to high energy bills. Thus, the household is unable to save and stays in a poverty trap. The same may not be true in high-income households, where savings capacity is not disrupted.

Third, it is useful to distinguish between *adaptive capacity*, which is strategic and involves planning, as opposed to *coping capacity*, which is short-term focused. Lastly, adaptive capacity goes beyond asset ownership or resources. It is also a factor of knowledge, agency, attitudes, practices, motivations, social capital, and perceptions.

Studies have explored relationships between risk perception and willingness to adapt, coping capacity and social ties, and more (Guardaro et al., 2022; Laranjeira et al., 2021; Waters & Adger, 2017). Therefore, adopting a more encompassing definition of adaptive capacity enriches studies, providing useful insights and better solutions.

2.4 Conceptual Framework

Condensing information found through the literature review, about heat, as well as frameworks popularly used, the conceptual framework for the study is created. The framework chosen is the IPCC SREX/AR5 vulnerability framework, as it is the latest used by the trusted body, and as it is aligned with the latest disaster-risk reduction thinking and methods. The study takes place at the household level which would show greater granularity in vulnerability patterns than studies at neighbourhood or city scales (Sorg et al., 2018; Wilhelmi & Hayden, 2010).

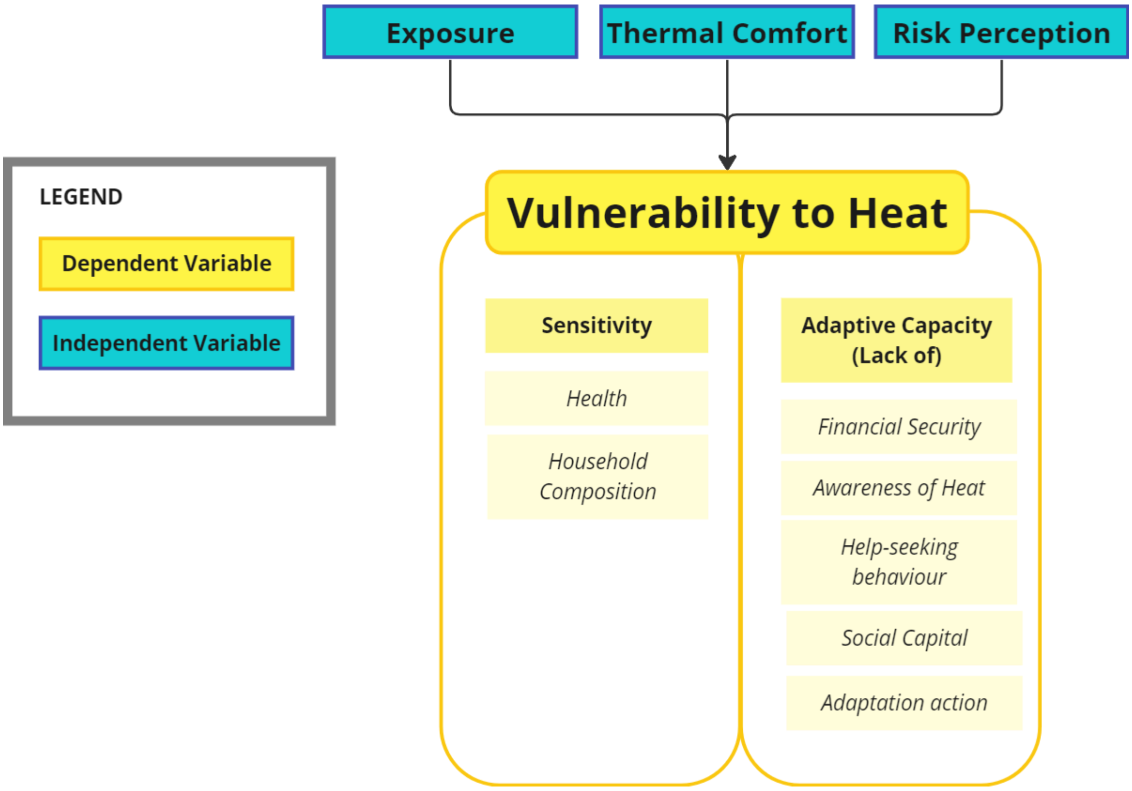

Figure 2: Conceptual Framework

Thus, *Vulnerability to Heat* is created as the Dependent Variable, and derived from sub-variables household *Sensitivity* and *Adaptive Capacity*. The sub-indicators within these have been selected at the discretion of the researcher, alignment with other studies, and contextualisation to local contexts.

Sensitivity, comprises *health* and *household composition*. Meanwhile, *Adaptive Capacity* comprises *financial security*, *awareness of heat*, *help-seeking behaviour*, *social capital*, and *adaptation action*.

Additionally, the independent variables; *Exposure*, *Thermal Comfort*, and *Risk Perception* are examined for links with *Vulnerability to Heat*, as well as with *Sensitivity* and *Adaptive Capacity*. These independent variables were selected due to possible links identified during the literature review. The independent variables also work well standing alone, providing useful information about the households' experience with heat.

Chapter 3: Research design, methodology

This chapter discusses the study's research design which includes strategy and data collection methods, sample size, site selection, operationalisation, and limitations.

3.1 Research Strategy

The primary goal of the study is to understand heat vulnerability, via sensitivity and adaptive capacity. Typically heat vulnerability assessments (HVAs) are developed in a three-step process; 1) indicator selection, 2) modelling or weighting of the indicators, and 3) validation (Li, F. et al., 2022). This study selected indicators consistent with the framework and context, mirroring similar studies (Rana et al., 2022; Soomar & Soomar, 2023).

As for step 2, modelling, or weighting; HVAs have used indexing, GIS techniques, statistical, composite, and survey data analytics. This study will construct an index from the indicators, using an Equal Weights method, as is commonly used in HVAs (Bao, Li, & Yu, 2015; Li, F. et al., 2022) Meanwhile, validation is typically carried out with morbidity, mortality, or other health data. For the purpose of this study, steps 1 and 2 will be completed, but step 3 will not be pursued due to time constraints and lack of data.

With the construction of the Vulnerability to Heat Index, the dependent variable is measured. The independent variables, Exposure, Thermal Comfort, and Risk Perception are similarly constructed as explained in the following sections. Ordinal regressions are then run between the dependent and independent variables on Stata to examine relationships (STATA Corporation, 2000). Lastly, using the information found via these steps and additionally combining several secondary data sources specific to public housing, further analysis on challenges and opportunities is done.

3.2 Site Selection

The study was conducted in PPR Kg Baru Hicom (PPR Hicom), a public housing complex located in Section 26, Shah Alam, in the state of Selangor. The area lies within the Malaysian urban conurbation of Greater Kuala Lumpur. The site was selected due to its representation of an identified vulnerable community, links to the partner organisation (Think City), and pre-existing familiarity with the researcher.

PPR Hicom is one example of Malaysia's public housing programme – Projek Perumahan Rakyat (PPR), which aims to provide housing to the urban poor and simultaneously eradicate slums. Rental per unit is RM250 or approximately €52 monthly. The complex, completed in 2005, comprises 980 units within 3 blocks (A, B, C), 16-17 storeys high. The complex is bordered by the Klang River, a village, and a light industrial area (Figure 3). The unit size is about 600sqft (Pavither, 2018).

As with other public housing, residents of PPR Hicom face myriad conditions that make them susceptible to heat stress. This is linked to deteriorating infrastructure, inadequate management, and a mix of other social, economic, and environmental factors. Accessibility to services and amenities, as well as links to public transit are currently poor. Overall, the complex itself is dominated by impervious surfaces (concrete or tarred) of 12,100 sqm. About 7,500sqm of the compound is characterised as green space though the quality of it is inadequate (e.g., a sparse patch of grass).

Since 2020, Think City has a presence at PPR Hicom, running studies and programmes designed to understand and improve quality of life. Programmes like health and mental health initiatives (K2K Aktif Bersama) and Rights to the City helped build trust and familiarity with residents. The local resident women's organisation, PERWACOM, played a key facilitation role between the organisation and community. Having assisted with multiple surveys and initiatives in the past, PERWACOM members are ideally placed to support the execution of this survey (Dietrich & Ismail, 2022; Krishna Kumar, Tam, & Dietrich, 2022).

Figure 3: PPR Hicom and its surroundings.

Source: Think City

3.3 Sampling and Data Collection

A semi-structured survey was chosen to administer data collection at the household level replicating similar studies (Rana et al., 2022; Soomar & Soomar, 2023; Sorg et al., 2018)The survey contains 24 questions, is translated into Bahasa Malaysia, and uses simple, accessible language. Questions are a mix of binary (yes/no), multiple choice, 4-point Likert scale, and open-ended questions. Open-ended questions were limited and used to capture additional information. It took 15 minutes to complete. The survey was reviewed and tested by 4 members of the Think City team and 3 members of PERWACOM, prior to launch. Appendix 2 contains the English version of the survey form.

Data Collection: The survey was hosted on the Qualtrics platform and designed to be completed individually, online. In addition, three members of PERWACOM were hired and trained to guide residents through the questions, support those who had limited access, and promote completion of the survey. The survey was promoted via community WhatsApp groups, at religious gatherings, and other events held within the complex. Only residents of PPR Hicom, aged 18 and above could participate. Responses were limited to one per household. The survey ran for two weeks from 31/5/2023 – 14/6/2023, coincidentally during periods of high temperatures in Malaysia. Survey respondents were eligible to participate in a lucky draw for small cash vouchers of RM300 in total (RM100 X 1, RM50 X 4). This was to overcome survey fatigue and encourage participation.

Sample Size: Calculations for Sample Size used Yamane's Formula (Yamane, 1967):

$$n = \frac{N}{1 + N(e)^2}$$

Where n is the sample size, N is the total population and e represents the precision value, or margin of error. Based on the population size of 980 households and margin of error of 6%, the sample size is calculated as follows

$n = 980/\ (1+ 980(0.06)^2 \quad = \mathbf{216}$

3.4 Operationalisation

The Table below shows the operationalisation of the indicators. Not all sources of data are included in index construction for Sensitivity and Adaptive Capacity. For Exposure, *frequency of experiencing heat related symptoms in various locations* is used as a proxy variable.

Variable	Sub-Variable	Sub-sub-variable	Indicator
Vulnerability	**Sensitivity**	Household Composition	Number of people in household
			Number of female occupants in household
			Number of elderly occupants (>65) in household
			Number of children aged below 5 in household
			Number of disabled people in household
			Isolated Living
			Number of chronically ill people in household
		Health	Number of heat-health symptoms experienced by household
			Type of heat-health symptoms experienced by household
	Adaptive Capacity	Financial Security	Monthly household income of household
			Number of financial assistance received by household
			Types of financial benefits received by household
		Awareness of Heat	Level of knowledge on heat and health
			Source of knowledge on heat and health
			Highest level of education within household
		Help-seeking behaviour	Number of sources of help for heat stress
			Type of help sought for heat stress
		Social Capital	Level of social cohesion with neighbours
		Adaptation Action	Number of household modifications to adapt to heat
			Type of household modifications to adapt to heat
			Number of behavioural modifications to adapt to heat
			Type of behavioural modifications to adapt to heat
			Number of challenges faced for adaptation action
			Types of challenges faced for adaptation action
			Access to cool space outside home
			Availability of first aid kit at home
Variable	**Sub-Variable**		**Indicator**
Exposure	Experiencing Heat Symptoms in Urban Life		Frequency of experiencing heat related symptoms at work
			Frequency of experiencing heat related symptoms on commute
			Frequency of experiencing heat related symptoms at school
			Frequency of experiencing heat related symptoms at home
			Frequency of experiencing heat related symptoms in public space
			Primary mode of travel
Thermal Comfort	Thermal Comfort at Home		Level of self-reported thermal comfort -air temperature
			Level of self-reported thermal comfort - humidity
			Level of self-reported thermal comfort - ventilation
Risk Perception	Risk Perception Towards Heatwaves		Level of risk perception towards heatwaves for self
			Level of risk perception towards heatwaves for household
			Level of risk perception towards heatwaves for community

Table 1: Operationalisation of Indicators

3.5 Data Analysis

3.5.1 Overview

The data comprised continuous, binary, and ordinal data. Following data collection, the data was cleaned. Incomplete surveys and duplicates were discarded. In addition, household composition answers were examined for inconsistencies by comparing sub-group composition to total household size. If the former exceeded the latter, the survey was flagged and discarded.

An analysis of summary statistics of all indicators was done, looking at frequencies, standard deviations, mean, and other descriptors appropriate to the type of data.

Next the Composite Vulnerability Index was constructed using the sub-variables Sensitivity and Adaptive Capacity. Then, Compound Variables for Exposure, Thermal Comfort, and Risk Perception were constructed. Later, correlations were examined between the constructed variables, and between variables at the indicator level based on possible links from literature. Lastly ordinal regression analysis was done.

3.5.2 Construction of Composite Vulnerability Index (CVI)

Step 1: Normalisation of Sensitivity and Adaptive Capacity Data

The Sensitivity and Adaptive Capacity Index were constructed as follows. The different types of data were normalised on a scale of 0 to 1. 0 indicates no vulnerability, and 1 indicates high vulnerability. With little precedent for the creation of this index at the public housing household level, the normalisation method is subjective and based on an analysis of summary statistics, contextualisation, and reference to other heat vulnerability studies (Bao et al., 2015; Rana et al., 2022; Soomar & Soomar, 2023). Given that the studied population is highly vulnerable, lower vulnerability thresholds were set. These can be adjusted with future iterations and validation. Min-max normalisation and other normalisation methods were considered and discarded due to the variability of data types.

Sensitivity Index (SI)

Below are the variables for sensitivity, and the corresponding scores.

	Sensitivity Index		
	Indicator	**Code**	**Score for Index**
1	Number of people in household	Total Household Size	1-3 members = 0 4-6 members = 0.5 >6 members = 1
2	Number of children aged below 5 in household	Children <5 y/o	If present = 1
3	Number of elderly occupants (>65 y/o) in household	Elderly 65 y/o and >	If present = 1
4	Number of chronically ill people in household	Chronically Ill	If present = 1
5	Number of disabled people in household	Disabled	If present = 1
6	Female/ Male ratio (derived from total female occupants)	Gender Ratio	0 women = 0 Ratio <1 = 0.25 Ratio 1 = 0.5 Ratio >1 or if only women = 1
7	Isolated Living	Isolated Living	If isolated = 1
8	Number of heat-health symptoms experienced by household	Number of Health Symptoms	0 symptoms = 0 1-2 symptoms = 0.5 >2 symptoms = 1

Table 2: Creation of Sensitivity Index

Adaptive Capacity Index (ACI)

Below are the variables for Adaptive Capacity, and the corresponding scores. *Score of 1 indicates highest vulnerability, and the lack of adaptive capacity.*

	Adaptive Capacity Index		
	Indicator	**Code**	**Score for Index**
1	Monthly household income of household	Income	>RM3000 = 0.25 RM2001-3000 = 0.5 <RM2000 = 1
2	Number of financial assistance received by household	Financial Assistance	>1 benefits = 0 1 benefit = 0.5 0 benefits = 1
3	Highest level of education within household	Education	If higher than SPM = 0 If completed formal schooling (up to SPM) = 0.5 If did not complete formal schooling = 1
4	Level of knowledge on heat and health	Knowledge	A lot of knowlegde = 0 Some knowledge = 0.33 A little knowledge = 0.66 No knowledge = 1
5	Number of sources of help for heat stress	Help Sought	2 and more sources of help = 0 1 source of help = 0.5 No help = 1
6	Number of household modifications to adapt to heat	Home Adaptation	>4 adaptations = 0 4 adaptations = 0.2 3 adaptations = 0.4 2 adaptations = 0.6 1 adaptation = 0.8 0 adaptation = 1
7	Number of behavioural modifications to adapt to heat	Behavioural Adaptation	>6 adaptations = 0 5-6 adapations = 0.25 3-4 adaptations = 0.5 1-2 adaptations = 0.75 0 adaptation = 1
8	Number of challenges faced for adaptation action	Challenges	0 challenges = 0 1 challenge = 0.5 >1 challenge = 1
9	Level of social cohesion with neighbours	Social Cohesion	(Know) Very well = 0 Fairly well = 0.33 Not very well = 0.66 Not at all = 1
10	Access to cool spaces outside home	Access to Cool Spaces	If access available = 0 If access unavailable = 1

Table 3: Creation of Adaptive Capacity Index

Step 2: Equal Weights Index Construction

Finally, the normalised data is assigned Equal Weights. Once completed, the scores for each are calculated according to the following formula (Rana et al., 2022).

$$CI = (W_1 + W_2 + \ldots + W_n) / n$$

CI = respective index.
W = the normalised values
n = number of indicators in the index

$$SI = \sum_{i=1}^{8} SW_i \,/\, n \quad (n = 8)$$

$$ACI = \sum_{i=1}^{10} ACW_i \,/\, n \quad (n = 10)$$

The Composite Vulnerability Index is measured using an additive aggregate method, combining the Sensitivity and Adaptive Capacity values (OECD, 2008).

$$CVI = \sum_{i=1}^{18} CVW_i \,/\, n \quad (n = 18)$$

Step 3: Stratification of Vulnerability Levels

Two methods are compared for stratification of the vulnerability scores into four vulnerability classes as below. Method A sets the range based on mean and standard deviation scores (Rana, 2022). Method B uses pre-set thresholds from 0 to 1.

Vulnerability Level	Method A	Method B
High	>Mean+SD	0.76-1
Moderate	Mean to Mean+SD	0.51-0.75
Low	(Mean-SD) < Mean	0.26-0.50
Very Low	<Mean-SD	0-0.25

Table 4: Vulnerability Classification

3.5.3 Creation of Compound Independent Variables

First, multivariate analysis using Cronbach's Coefficient Alpha (C-alpha) was carried out to understand the structure of the data and assess the appropriate treatment (OECD, 2008).

Next, like the Composite Vulnerability Index, the data was normalised and Equal Weights method applied to the Exposure Variable (E), Thermal Comfort Variable (TC), and Risk Perception Variable (RP). Like the CVI, TC and E are scored with 0 indicating no vulnerability and 1, high vulnerability. Risk perception follows the same scale. Low-risk perception is scored 0 and High-risk perception is scored 1. The table below contains the details of normalisation.

Exposure: Experience of Heat Symptoms in Different Locations		
Indicator	**Code**	**Normalisation Score**
Frequency of experiencing heat related symptoms at work	Heat at Work	Never =0 Rarely = 0.33 Occassionally = 0.66 Often = 1
Frequency of experiencing heat related symptoms on commute	Heat on Commute	
Frequency of experiencing heat related symptoms at school	Heat at School	
Frequency of experiencing heat related symptoms at home	Heat at Home	
Frequency of experiencing heat related symptoms in public space	Heat in Public Space	
Thermal Comfort: Thermal Comfort at Home		
Indicator	**Code**	**Normalisation Score**
Level of self-reported thermal comfort -air temperature	Air Temperature	Comfortable = 0 Acceptable = 0.33 Uncomforable = 0.66 Very Uncomfortable = 1
Level of self-reported thermal comfort - humidity	Humidity	
Level of self-reported thermal comfort - ventilation	Ventilation	
Risk Perception: Risk Perception towards Heatwave		
Indicator	**Code**	**Normalisation Score**
Level of risk perception towards heatwaves for self	Risk for Individual	Would Cause No Harm at all = 0 A little Harm = 0.33 Moderate Harm = 0.66 Extreme Harm = 1
Level of risk perception towards heatwaves for household	Risk for Household	
Level of risk perception towards heatwaves for community	Risk for Community	

Table 5: Normalisation Scores for Compound Independent Variables

The calculation of the compound variables are as follows:

$$E = \sum_{i=1}^{5} EW_i \,/\, n \quad (n= 5)$$

$$TC = \sum_{i=1}^{3} TCW_i \,/\, n \quad (n= 3)$$

$$RP = \sum_{i=1}^{3} RW_i \,/\, n \quad (n= 3)$$

3.5.4 Correlations

Correlations were run using Spearman's rank coefficient to investigate relationships between the Index and Compound Variables. Correlations were also run between sub-indicators, between indices, and between compound variables. Values significant at the 1% level are reported. Survey data analytics was conducted using Microsoft Excel and STATA.

3.5.5 Regressions

Regressions as in Table 5 were run using STATA using the Ordinal Regression method (STATA Corporation, 2000). The indices (SI, ACI, and CVI), and the 'Number of Health Symptoms', are treated as ordinal dependent variables. Regressions 1-3 use the indices' vulnerability levels (Very Low, Low, Moderate, High) as dependent variables. For Regression 4, the regression is run using the reported number of symptoms as dependent variable (9 categories). Prior to running the regression, necessary assumptions were checked (UCLA: Statistical Consulting Group, 2012).

	Dependent (Y)	**Independent (X_1 - X_n)**	**Regression Model**
1	Sensitivity	Exposure	Ordinal Regression
		Thermal Comfort	
		Risk Perception	
2	(Lack of) Adaptive Capacity	Exposure	
		Thermal Comfort	
		Risk Perception	
3	Composite Vulnerability	Exposure	
		Thermal Comfort	
		Risk Perception	
4	Number of Health Symptoms	Exposure	
		Thermal Comfort	
		Risk Perception	

Table 6: Regression Variables

3.5.6 Secondary Data Sources

Two documents from Think City are used as sources for secondary data, as they contain information specific to PPR Hicom, including spatial mapping. These documents are included in the bibliography.

3.6 Validity and Reliability

Validity refers to the extent to which the concept is accurately measured in a study (Heale & Twycross, 2015).
Two main factors affecting the validity are

1. The study is an explanatory study conducted at the household level, for a specific sub-group within the city. Few similar studies exist in the Malaysian context.
2. Resource constraints. The survey was designed to be completed with limited manpower, availability of data, and time.

Nonetheless, the selection of indicators was based on extensive literature reviews of heat vulnerability assessments both regionally and globally. The indicators were adapted and localised as appropriate.

The contents of the survey were reviewed by the partner organisation and piloted with residents. With this feedback, modifications were made to the number and type of questions asked, translation choices, and feedback to capture the most accurate data.

The survey captured many respondents from one housing complex, pointing to high internal validity. However, while the complex is typical of other public housing communities, differences in demographic makeup and other site-specific characteristics may skew results, rendering external validity moderate. It is expected that further refinements will be needed in future iterations of the survey.

Reliability of the survey indicates it can be replicated with similar results (Heale & Twycross, 2015). This survey is based on a clear operationalisation table, sufficiently defined and quantified. The survey tool was translated to Bahasa Malaysia by a professional translator, and made available to the partner organisation for future use. The sample was randomly selected, and all respondents are above 18-years of age.

The survey was carried out during periods of high temperatures in Malaysia, which may have induced those more affected to participate. However, the incentive to participate in a lucky draw (which was offered to overcome survey fatigue) may have countered the bias and encouraged broader participation.

3.7 Limitations

The survey faced the following limitations.

1. Cronbach's Alpha test (Alpha) was not run for the creation of the Composite Vulnerability Index. Alpha is commonly used to test the internal consistency of a set of indicators in relation to how it describes a uni-dimensional construct. Many studies commonly select scores of 0.7 and higher to be acceptable. However there remains debate on the accurate use and interpretation of these scores, with high scores not necessarily reflecting a better tool construct (OECD, 2008; Taber, 2018). In this study, the dimensions Sensitivity and Adaptive Capacity respectively comprise different subsets of information that are not uni-dimensional, and therefore would individually result in a low score. For example, Adaptive Capacity measures the factors 'Knowledge', 'Income', and 'Behavioural Adaptation'. The Alpha test is run for creating the compound variables Risk Perception, Thermal Comfort, and Exposure as they measure very similar variables.

2. The collection of various types of data at the household level provided rich information of a specific community, but constrained the methodology selected. Exploratory Factor Analysis and Principal Components Analysis could be run with different data collected at a larger scale.

3. The use of a 4-point Likert scale limited midpoint bias, limited scale abuse, and increased measurement consistency, but also limited the size of correlations found. Future iterations of the survey could adopt the 5 or 6-point Likert scale to better represent correlations between variables (Chang, 1994; Chyung, Roberts, Swanson, & Hankinson, 2017).

4. Indices are subjective, and accurate representations of the construct it measures depends on iterative processes, validation, and appropriate contextualisation (Bao et al., 2015; Li, F. et al., 2022).

5. Some information collected is self-reported, and is subject to bias.

6. One member of the household answered the survey, representing the entire household.

7. The survey did not capture data on pregnant women, a recognised vulnerable group.

Chapter 4: Results, analysis, and discussion

4.1 Descriptive Data

A summary of the descriptive data, containing selected information on respondent and household profile is included below. Other survey data is contained in Appendix 3. 233 surveys were completed, exceeding the targeted 216 surveys, and representing 24% of households at the site.

4.1.1 Respondent Profile

The average respondent is likely female, a household head, and between 34 to 43 years old:

76% of respondents are self-reported household heads. Of these, 48.1% are female. Household heads may be best placed to represent the collective experience of the household, being the ones with greater decision-making and financial power.

72% of the respondents were female. This predominance of female respondents could be due to the strong network of women present through PERWACOM (women's resident association), choice of survey distribution channels, or due to availability of women present at home through the day.

The average age of respondents was 41 years old. The 34–43-year-old group is pre-dominantly represented. 96% of respondents fall within the official Malaysian working age population group of 15 to 64 years old (Department of Statistics Malaysia, 2022).

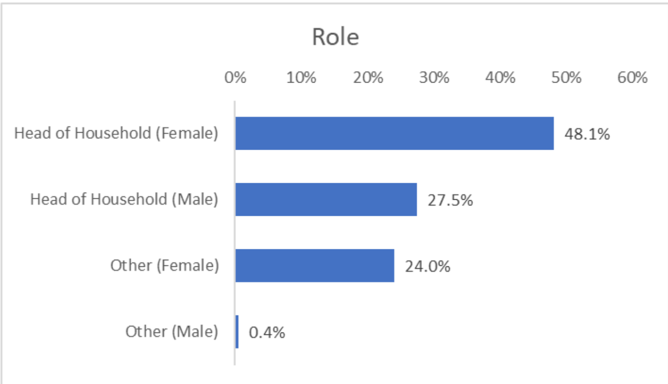

Figure 4: Role of Respondent in Household

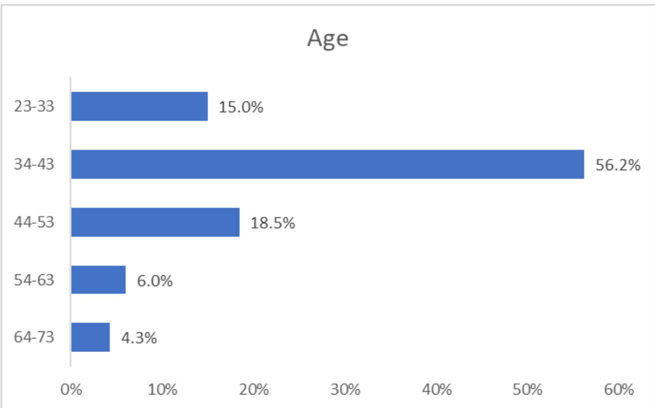

Figure 5: Age of Respondent

4.1.2 Household Profile: Sensitivity Summary

This section examines health and household composition determining sensitivity to heat.

Household Composition:

The average household size is 4.8 people, with minimum size of 1 and maximum size of 11 people.

The composition of vulnerable groups in households is as in Figures 6 and 7. Women are present in almost all households. Around half of households surveyed have young children and around a quarter have chronically ill household members. Meanwhile, only 2% of households are living in isolation.

Health: Heat- health symptoms reported are discussed in-depth in section 4.2.

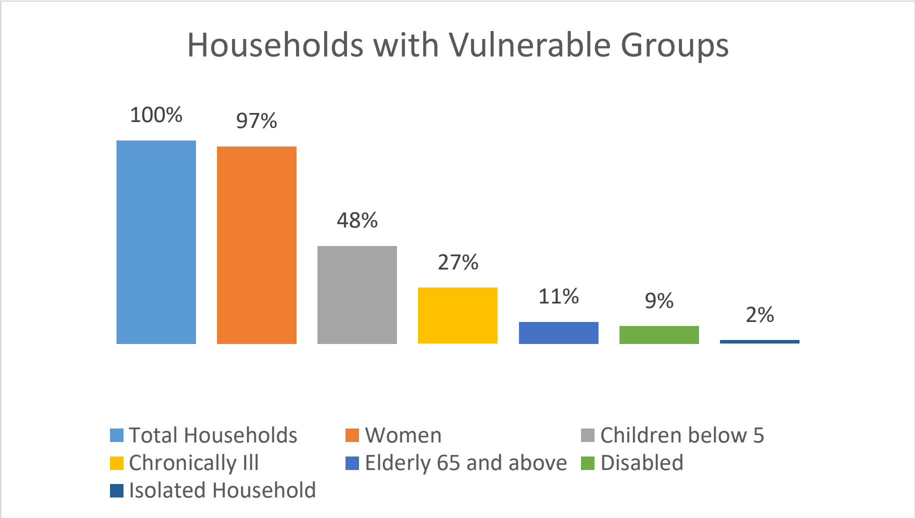

Figure 6: Percentage of Households with Vulnerable Groups

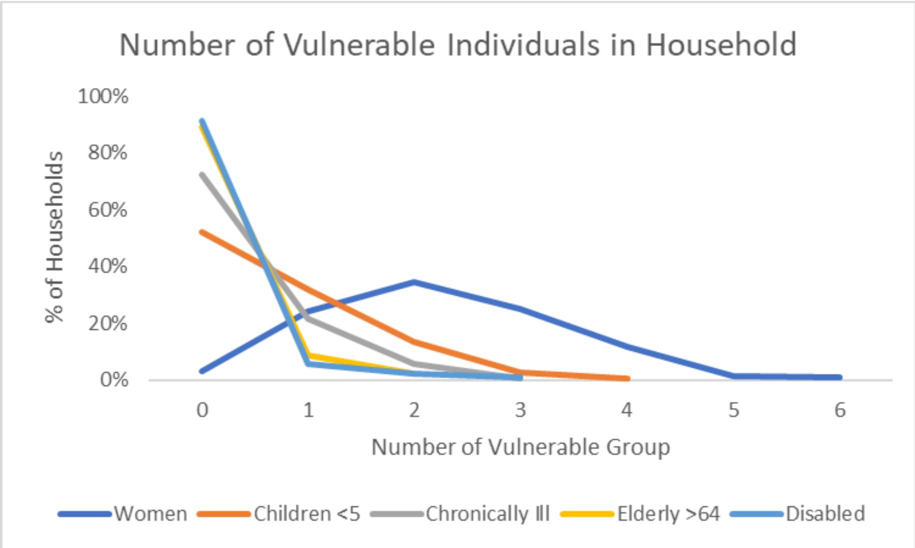

Figure 7: Number of Vulnerable Individuals in Household

4.1.3 Household Profile: Adaptive Capacity Summary

This dimension measures the household's capacity to overcome heat-related challenges and has both general and specific adaptive capacity factors.

Financial Security: Households surveyed have low income and receive at least one form of financial support (most commonly BPR, a government cash aid programme). This is further discussed in section 4.2.

Awareness of Heat: Education levels are taken as proxy for awareness and better decision-making in the household. 64% of households have a member who had completed formal schooling (up till SPM, 17 years old) and 25% had members with some form of tertiary education. Nonetheless, over 90% of respondents surveyed knew little about heat and health, as discussed in 4.2.

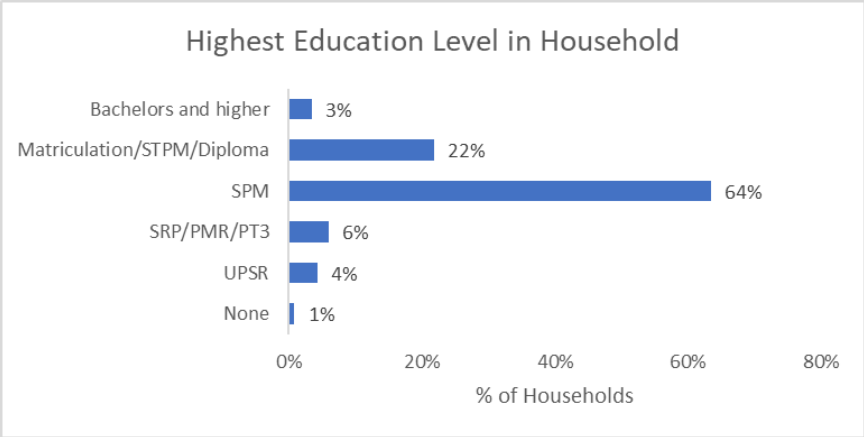

Figure 8: Highest Level of Education in Household

Social Capital: Social cohesion in the community is high, with over 70% of households reporting knowing neighbours well or very well.

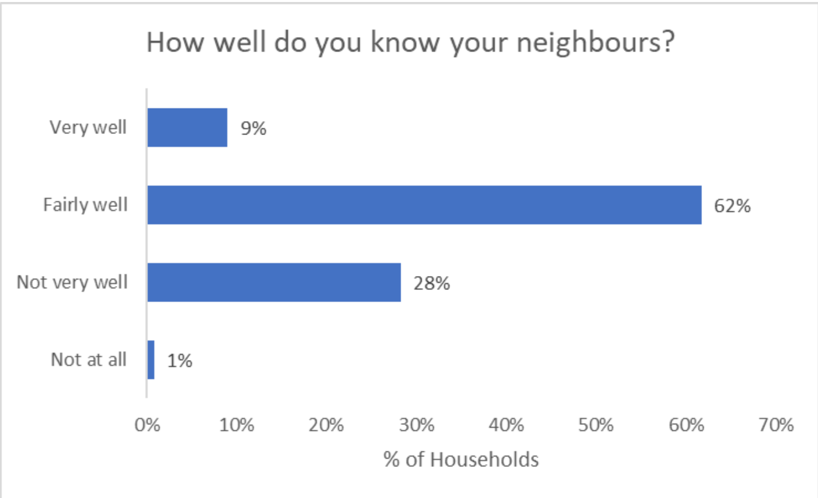

Figure 9: Relationship with neighbours

Help-Seeking Behaviour: Despite the high social capital, only 8% seek help from neighbours. Most households (62%) sought help for heat symptoms in the government health clinic, though this is not easily accessible, being between 5-10 minutes away by car (Dietrich & Ismail, 2022).

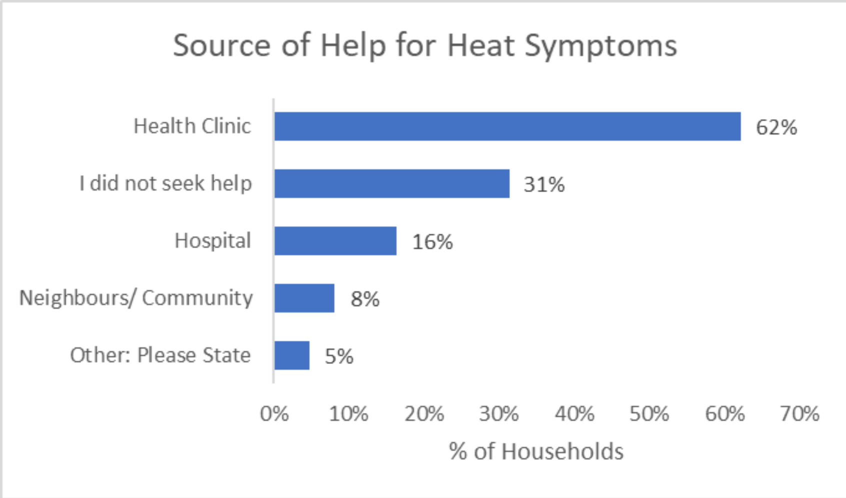

Figure 10: Source of Help for Heat Symptoms

Adaptation Action: Common home adaptations (Figure 11**)** are the use of fans (99%) and opening doors or windows to enable ventilation (77%). At least 79% of households use 2 or more adaptation methods. Air conditioning use (3%) and shading use (14%) is low, linked to restrictions by housing management.

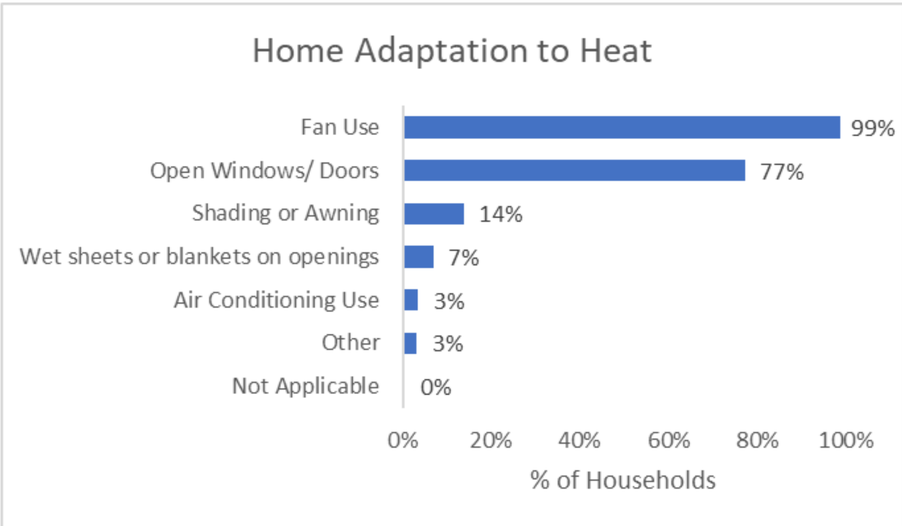

Figure 11: Home Adaptation to Heat

91% of households report using 2 or more methods for behavioural adaptation (Figure 12). Drinking more fluids (95%), taking frequent showers (85%) and opting for lighter/ cooler clothing (59%) are popular behavioural adaptations used during periods of high temperatures. Few households check in on family or friends during periods of high temperature. Challenges to adaptation are discussed in section 4.2 and 4.4.

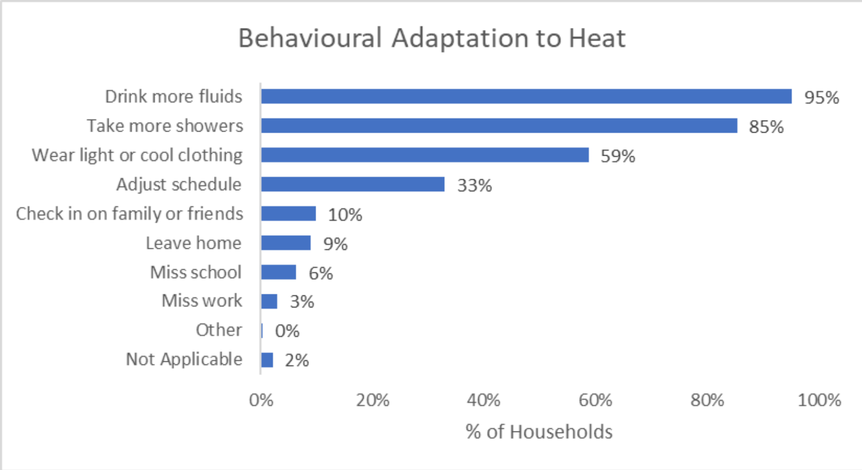

Figure 12: Behavioural Adaptation to Heat

4.2 Drivers of Vulnerability to Heat

This section discusses the dependent variable, Vulnerability to Heat. This variable is constructed as the Composite Vulnerability Index, outlined in Section 3, and is comprised of two sub-indices – Sensitivity and Adaptive Capacity. Here, analysis answers the first two sub-questions – 1*) what are the drivers of PHC household sensitivity to heat, and 2) what are the drivers of PHC household adaptive capacity to heat?*

Table 7 contains statistical summaries of the Sensitivity, Adaptive Capacity and Composite Vulnerability Index scores. The scores range from 1 to 0, with 1 signifying highest vulnerability and 0, lowest vulnerability. The Sensitivity Index contains the lowest score and the Adaptive Capacity Index contains the highest score. Average scores for the sub-indices range from 0.33 to 0.60.

Variable	Observations	Mean	Std. deviation	Min	Max
Sensitivity Index (SI)	233	0.33	0.13	0.03	0.75
Adaptive Capacity Index (ACI)	233	0.60	0.08	0.39	0.79
Composite Vulnerability Index (CVI)	233	0.48	0.08	0.27	0.67

Table 7: Summary Statistics of all Indices

Figure 13 shows the distribution of the index scores, in a boxplot. Comparison of *ACI* and *SI* shows households in PPR Hicom are more vulnerable in terms of adaptive capacity (or lack thereof) as the scores are higher than SI. Additionally, in ACI, a smaller dispersion of scores is observed, seen through a narrower interquartile-range. Meanwhile, vulnerability due to household sensitivity (SI) is on average lower than adaptive capacity, though it has a larger spread of values, seen through the larger interquartile range and standard deviation scores. Outlier scores are observed for SI.

The resulting Composite Vulnerability Score which is formed through the aggregation of the two sub-indices lies in the middle. By this metric, the average household surveyed is moderately vulnerable.

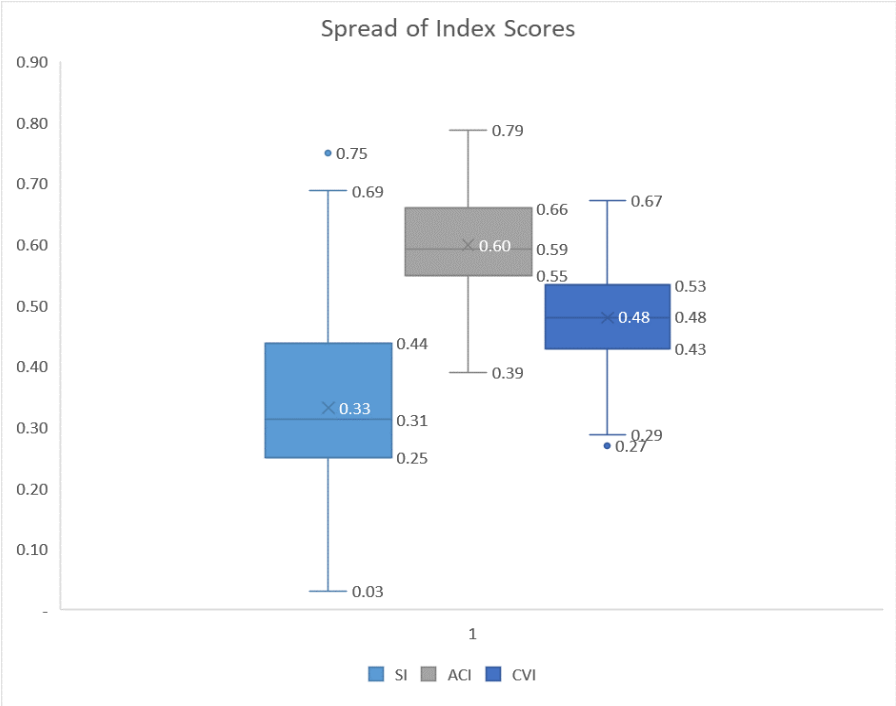

Figure 13: Distribution of Index Scores

4.2.1 Drivers of PHC Household Sensitivity to Heat

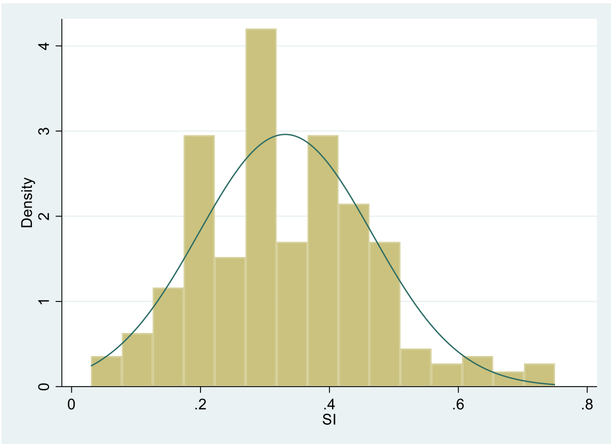

Figure 14: Sensitivity Index Histogram

The Sensitivity Index has a mean of 0.33 and a standard deviation of 0.13. This implies that, on average, respondents in PPR HICOM are *less vulnerable* to heat due to household composition or health symptoms experienced. However, the larger spread of values, with a minimum score of 0.03 and maximum score of 0.75 shows there is substantial diversity in sensitivity indicators between households. For example, some households may have no vulnerable groups represented, while some households may have multiple vulnerable groups represented within one or many household members.

Table 8 shows the summary statistics of the normalised scores for all indicators within the Sensitivity Index. Indicator mean scores above 0.33 are bolded. The mean scores provide a rough guide on which indicators contributed to increased vulnerability, based on the adjusted vulnerability thresholds (see Section 3.5). Drivers with scores above the mean, 0.33, include 'Number of Health Symptoms, Gender Ratio, Total Household Size, and presence of Children Under 5 Years-Old. The mean scores are also visualised in the spider diagram, Figure 15 below.

Indicator	Observations	Mean	Std. deviation	Min	Max
Disabled	233	0.09	0.28	0	1
Elderly 65 y/o and >	233	0.11	0.31	0	1
Isolated Living	233	0.12	0.13	0	1
Chronically Ill	233	0.27	0.45	0	1
Children <5 y/o	233	**0.48**	0.50	0	1
Total Household Size	233	**0.48**	0.28	0	1
Gender Ratio	233	**0.55**	0.33	0	1
Number of Health Symptoms	233	**0.66**	0.37	0	1
Sensitivity Index	**233**	**0.33**	**0.13**	**0.03**	**0.75**

Table 8: Summary Statistics for Sensitivity Index

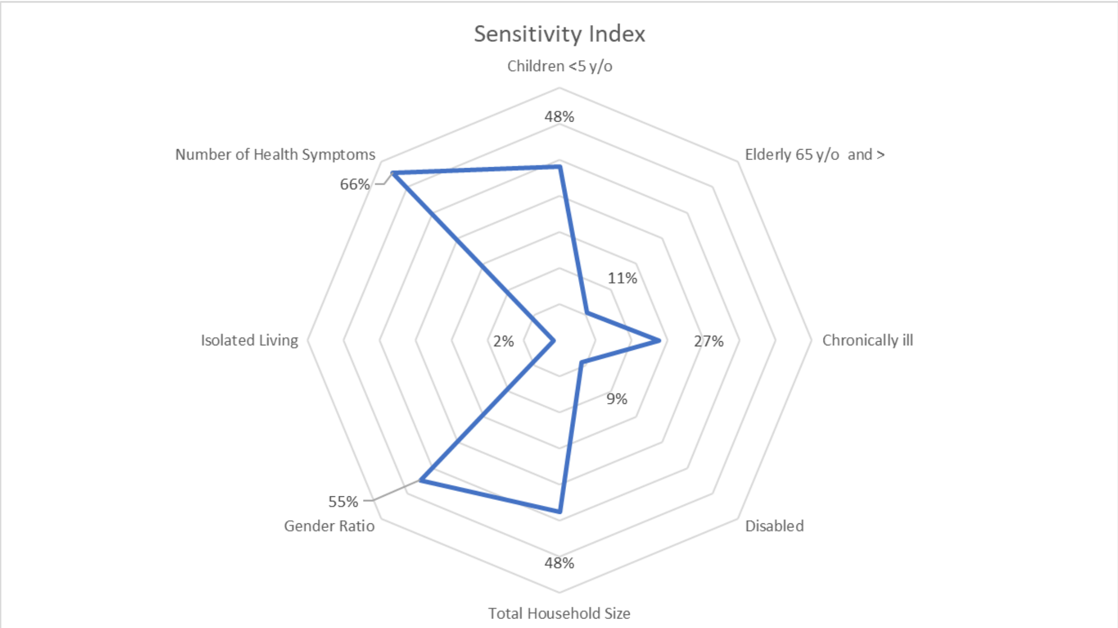

Figure 15: Drivers of Sensitivity Index

4 sensitivity drivers with average scores above the Sensitivity Index mean score are examined.

Sensitivity Driver 1: Heat-Health Symptoms

The average number of symptoms reported by households was 2.6, with 47.6% of households experiencing 3 or more heat related symptoms in the past year. The most frequently reported symptoms were trouble sleeping (60%) and headaches (57%).

Trouble sleeping points to hot and uncomfortable nights. Hotter nights are linked with increased deaths during heatwaves (Li, F. et al., 2022). Sleep disruption links with reduction in capacity to concentrate, affecting performance at work, school, and disrupting quality of life in general Headaches, dizziness, and lethargy/ exhaustion also affect quality of life. Combined with other vulnerabilities such as age or chronic illness, heat-health symptoms could be life threatening (Kenny et al., 2019). Underreporting of symptoms overall is possible due to lack of awareness.

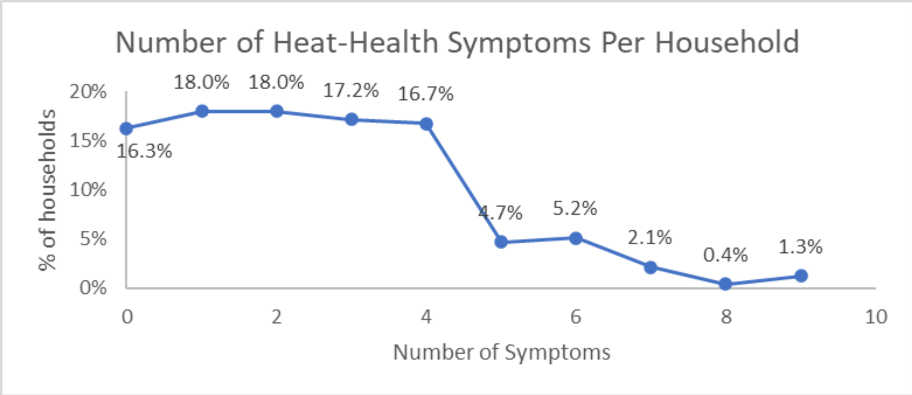

Figure 16: Number of Heat-Health Symptoms per Household

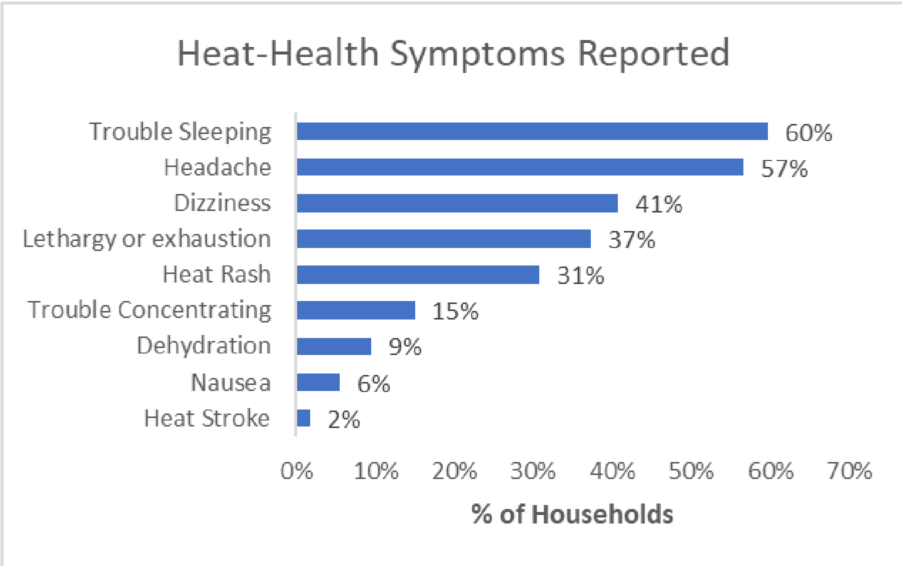

Figure 17: Heat-Health Symptoms Reported

Sensitivity Driver 2: Gender Ratio

Females are present in 97% of households, with an average of 2.3 females per household. The average female-male household gender ratio is 1.20, indicating a marginally larger female composition in households. For comparison, the Malaysian citizen female to male population ratio is 0.97 (Department of Statistics Malaysia, 2022). Studies show women, especially within vulnerable populations, are at higher risk from heat due to spending more time indoors, limited access to resources, and lower overall capacity (Kenny et al., 2019; Rana et al., 2022).

Sensitivity Driver 3: Total Household Size

The average household size at PPR Hicom is 4.8, which is larger than the Malaysian national average household size at 3.8 people per household (Nik Anis & Carvalho, 2022). 59% of households have 5 or more people living in the same unit. Given the small sizes of the housing units (roughly 600sqft), the high density of people living in the same household could pose a problem during periods of high temperatures (Rana et al., 2022).

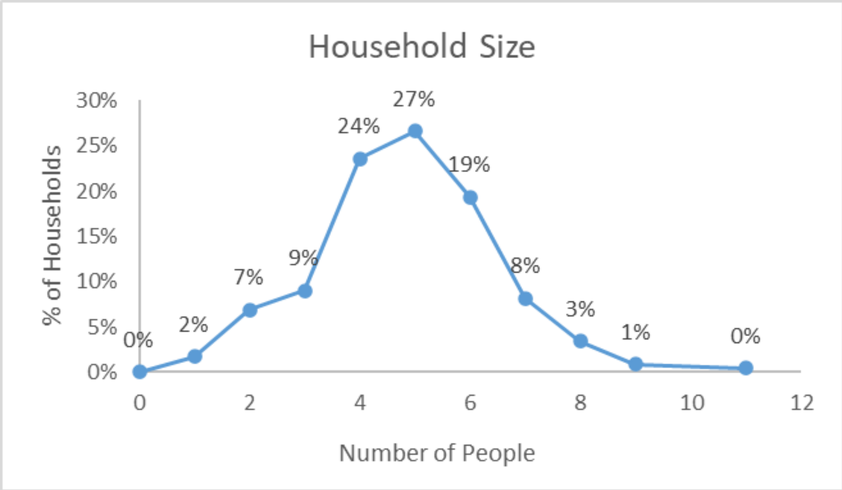

Figure 18: Household Size

Sensitivity Driver 4: Presence of Children under 5 Years Old

48% of households surveyed have at least one child under 5 years old living with them. This age group is at risk of heat stress due to lower sweating capacity relative to their body surface area compared to adults (Leyk, 2019). Additionally, young children are less likely to have the capacity, knowledge, or self-awareness to take appropriate action to report or mitigate heat stress appropriately. Households with presence of this group are more at risk.

Therefore, the top four drivers for PPR HICOM community sensitivity to heat are high Number of Health Symptoms, high Gender Ratio, large Total Household Size, and presence of Children under 5 years old.

4.2.2 Drivers of PHC Household Adaptive Capacity to Heat

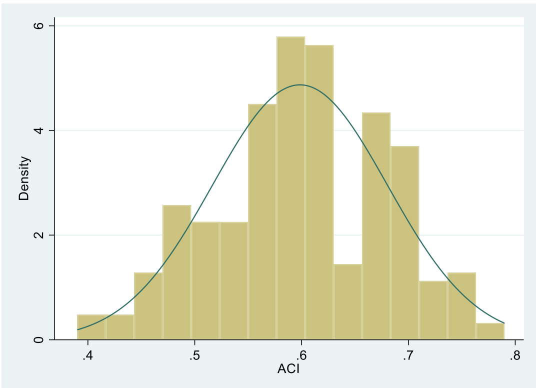

Figure 19: Adaptive Capacity Index Histogram

The Adaptive Capacity Index has a mean score of 0.60 with a standard deviation of 0.08. This indicates that the average household *lacks* adaptive capacity, and is therefore more vulnerable. ACI score differences between households are also less spread out than SI, with a minimum score of 0.39 and a maximum of 0.79. This points to greater similarities between households in terms of adaptive capacity, or lack thereof.

Table 9 shows summary statistics for this index's ten individual indicators, ranked from lowest mean to highest mean score. Scores above the mean, 0.60, are bolded. Like the SI, this provides a rough guide on primary contributors to the index, visualised in Figure 20. Drivers with scores above the mean, 0.60 are Access to Cool Spaces, Income, Knowledge of Heat and Health, and Challenges to Adaptation.

Indicator	Observations	Mean	Std. deviation	Min	Max
Social Cohesion	233	0.40	0.20	0	1
Education	233	0.43	0.29	0	1
Financial Assistance	233	0.44	0.30	0	1
Behavioural Adaptation	233	0.55	0.17	0	1
Help Sought	233	0.57	0.34	0	1
Home Adaptation	233	0.59	0.15	0	1
Challenges	233	**0.61**	0.37	0	1
Knowledge	233	**0.64**	0.13	0	1
Income	233	**0.81**	0.26	0.25	1
Access to Cool Spaces	233	**0.94**	0.25	0	1
Adaptive Capacity Index	**233**	**0.60**	**0.08**	**0.39**	**0.79**

Table 9: Summary Statistics for Adaptive Capacity Index

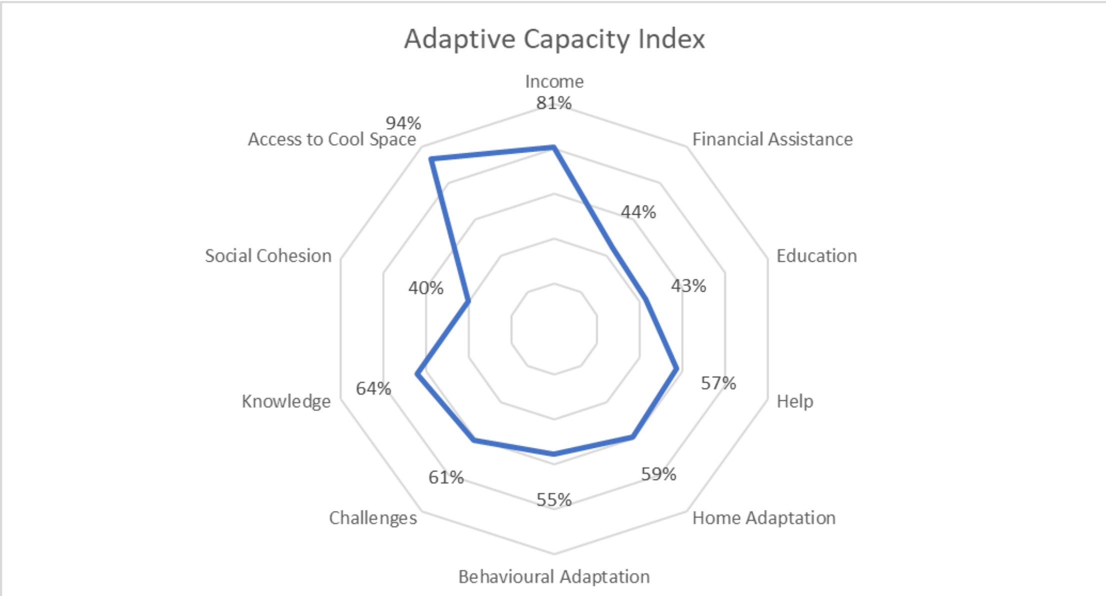

Figure 20: Drivers of Adaptive Capacity Index

For this discussion, the 4 drivers with average scores above the Adaptive Capacity Index mean score of 0.60 are discussed. Nonetheless, the other drivers in this index, though below the mean are relatively close in score, warranting further investigation.

Adaptive Capacity Driver 1: Access to Cool Spaces

94% of households do not have access to cool spaces outside the home to escape the heat. Frequency analysis of the 15 households that have access to cool spaces show that residents seek respite in air-conditioned areas such as their private vehicles, PERWACOM activities room, Islamic prayer hall (surau) and externally in a shopping mall. In addition, the corridors of the housing complex and shaded or green spaces are also mentioned as cool spaces. The small number of responses received highlights issues of accessibility or practicality linked to available cool spaces.

Adaptive Capacity Driver 2: Income

64% of households surveyed report earning RM2000 or less, as seen in Figure 21. Malaysia's national household poverty line is RM2208 per month, which means these households earn below this threshold. For comparison with the wider population, in 2020 (during the Covid pandemic), the average Malaysian monthly household income stood at RM7089 (Department of Statistics Malaysia, 2021).

As discussed in Chapter 2, low income and related financial factors limit short and long-term ability to cope with heat. Householders' choices are limited, due to trade-offs that may occur, such as foregoing fan ownership for more pressing commitments like groceries (Guardaro et al., 2022; Harlan et al., 2013).

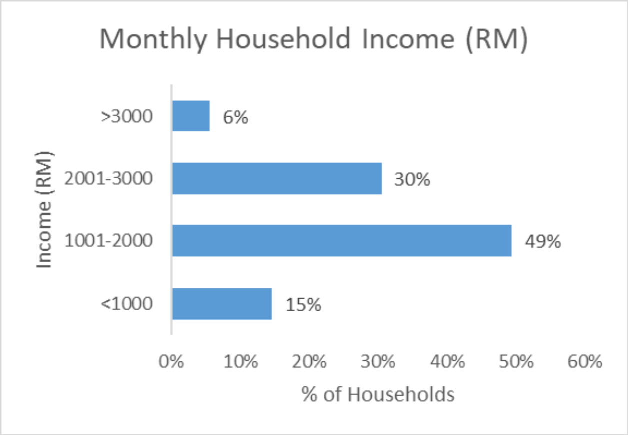

Figure 21: Monthly Household Income

Adaptive Capacity Driver 3: Knowledge of Heat and Health

90% of households know little or nothing about heat and how it affects health. The significant gap in knowledge affects adaptive capacity in terms of risk perception and general ability to adapt or respond to periods of high temperatures (Guardaro et al., 2022). Knowledge received by the respondents comes primarily via social media, the surrounding community, and mass media (Figure 23).

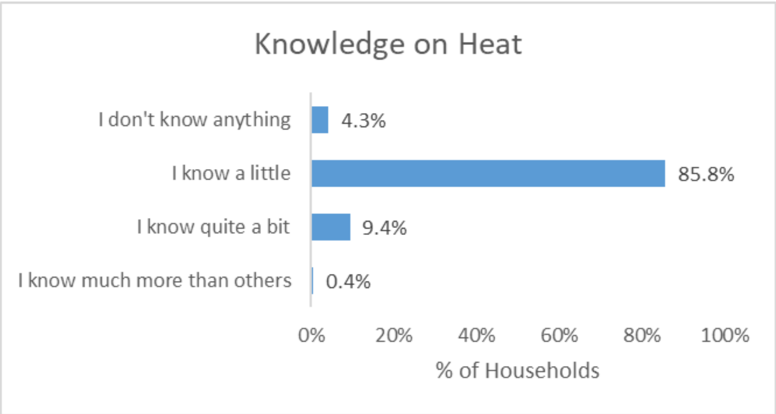

Figure 22: Knowledge of Heat and Health

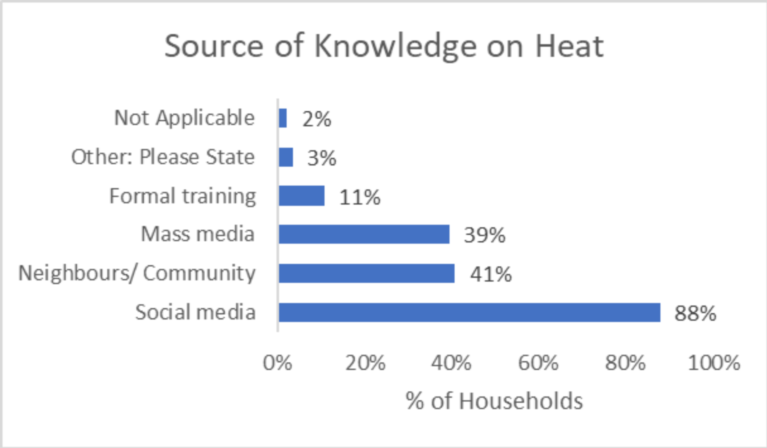

Figure 23: Source of Knowledge on Heat

Adaptive Capacity Driver 4: Challenges to Adaptation

The most common challenge faced by households in relation to heat adaptation is financial (58%), followed by lack of skills or knowledge (30%) and regulations/ rules (28%). 41% of households report facing two or more hurdles to adaptation to heat. The financial and knowledge limitation is in accordance with drivers 2 and 3 above. Meanwhile, rules and regulations can hinder adaptation efforts due to inflexibility and bureaucracy. Suggestions provided by respondents request to allow air-conditioning installation or shading installation, showing there are management rules against modification to the building facade.

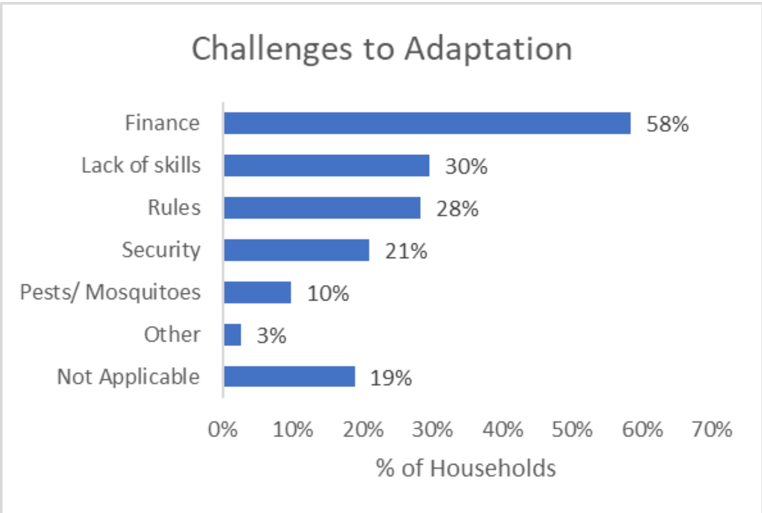

Figure 24: Challenges to Adaptation

Therefore, the top 4 drivers of lack of adaptive capacity to heat are poor Access to Cool Spaces, low household Income, low Knowledge of heat and health, and increased Challenges to adaptation.

4.2.3 Stratified Household Vulnerability Levels

Once indicators are collected, and weighted, the next step is to stratify households by level of vulnerability. Two methods of classification, Method A and Method B, discussed in Section 3.5 are used. Method A, using the respective mean and standard deviation scores of each index to determine vulnerability thresholds returns similar distribution of scores. Method B, using pre-set vulnerability thresholds between 0 to 1 show a different distribution of vulnerability, allowing comparison between indices on the same scale.

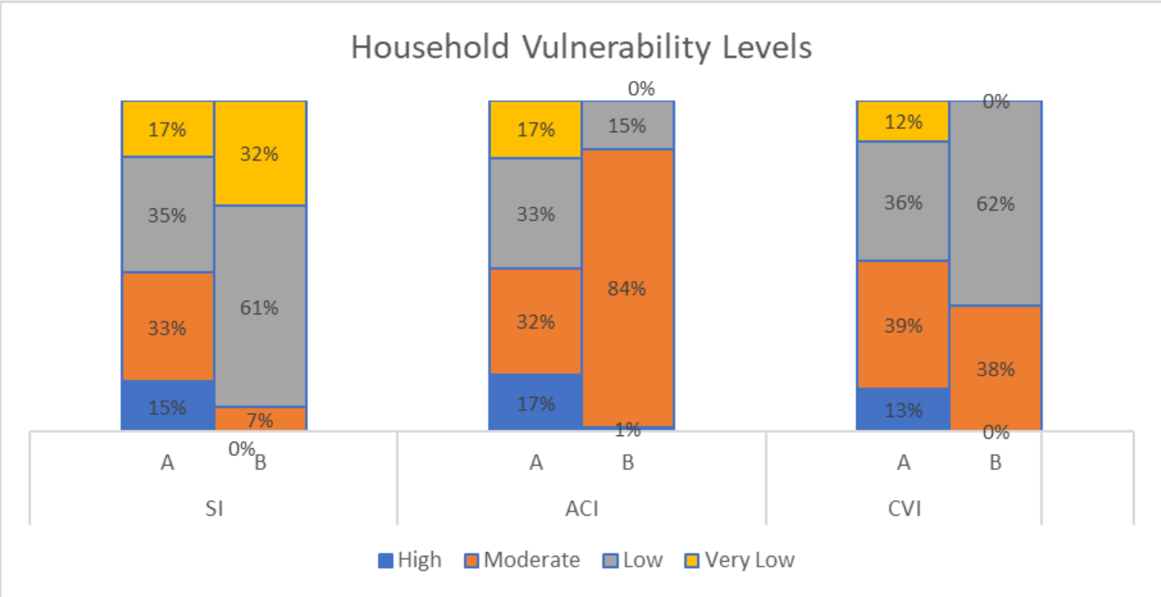

Figure 25: Vulnerability Levels, Method A and Method B

In Method A, examining Composite Vulnerability Index (CVI), 52% of households fall into the high or moderately vulnerable categories. In Method B, this is lower at 38%. The comprehensive table with percentage of households within each category, along with vulnerability thresholds are in Appendix 4.

The difference between the methods highlights the subjectivity of vulnerability scores and scales. Nonetheless, vulnerability classifications help provide narrative, prioritise interventions and are a useful anchor for further analysis (Bao et al., 2015). In this case, all households are within an identified vulnerable segment of society, which are public housing communities. Thus, regardless of the classification method, households at risk should be given urgent attention in preparation for or during periods of high temperatures to minimise damage or negative implications arising from heat stress.

For this study, Method A is selected to create the vulnerability index stratification, as it provides four clear categories. The vulnerability categories are used as the dependent variable for further analysis with ordinal regressions.

4.3 Effect of Exposure, Thermal Comfort, and Risk Perception

This section explores the relationship between the independent variables Exposure, Thermal Comfort, and Risk Perception with the dependent variable, answering sub-question 3.

4.3.1 Compound Independent Variables

Compound variables were created for Exposure, Thermal Comfort, and Risk Perception, following the method outlined in Section 3.5 (normalisation and assignment of equal weights). Cronbach's Alpha was measured, with all three scoring highly, showing the indicators are appropriate for the construction of the compound variable.

Variable	Observations	Mean	Std. deviation	Min	Max	Cronbach's Alpha
Exposure	233	0.49	0.26	0	1	0.8669
Risk Perception	233	0.64	0.29	0	1	0.9339
Thermal Comfort	233	0.57	0.26	0	1	0.8031

Table 10: Summary Statistics for Compound Variables

Independent Variable 1: Exposure

Measurement of Exposure used proxy indicators; respondents were asked how frequently they experienced heat-related symptoms in 5 locations. Over 70% of households experienced heat-related health symptoms in the workplace, school, home, public space, or on the daily commute, as seen in Figure 26. *Home* registers the highest score, with 84% of households having experienced heat-related symptoms there. This is consistent with findings from the literature review, showing urban dwellers experience heat in many areas of urban life (Arifwidodo & Chandrasiri, 2020; Zander et al., 2015).

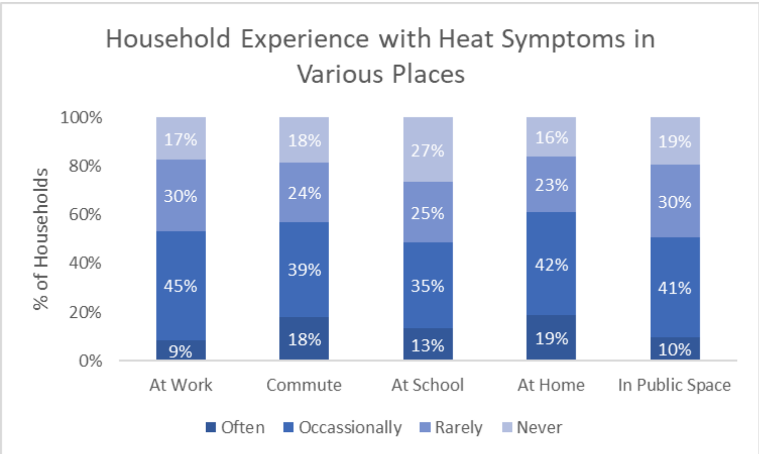

Figure 26: Frequency Analysis of Exposure Indicators

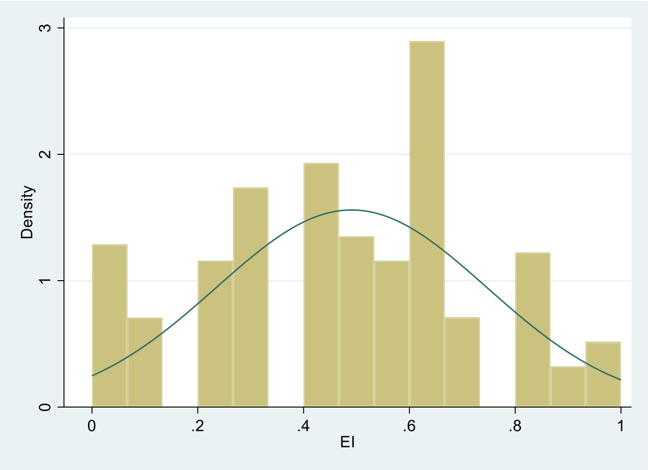

Figure 27: Exposure Compound Variable Histogram

The combined variable score averages at 0.49, shown in Table 10, indicating households are moderately exposed to heat in various locations from work, school, daily commute, home, and public spaces. In the histogram, Figure 27, a peak is observed at 0.6, aligned with the normalisation score for 'occasionally'.

Independent Variable 2: Thermal Comfort

For Thermal Comfort, respondents were required to select levels of comfort in relation to air temperature, humidity, and ventilation levels within the home. Over a quarter of respondents find the air temperature, humidity, and ventilation levels very uncomfortable in their homes. The *air temperature* category registers the highest levels of responses in '*uncomfortable* and '*very uncomfortable'*. The average Thermal Comfort score, combining the respondent's perception of all three levels in the home is 0.57.

This study did not collect data on indoor temperature readings, but this variable provides a proxy for indoor temperatures. Studies show indoor temperature extremes can be harmful, with homes cooling much slower than the outdoors and having implications for morbidity, mortality, and general quality of life (Kenny et al., 2019; Samuelson et al., 2020). The high number of households reporting thermal discomfort indoors needs to be further investigated. The histogram of the combined variable shows a peak at around 0.3.

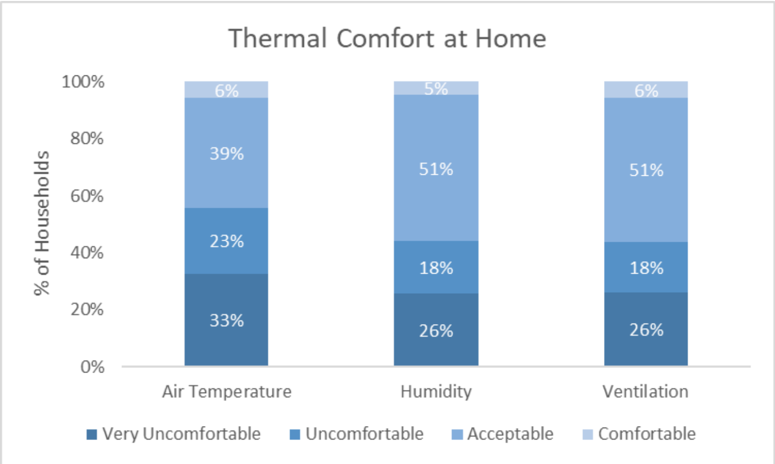

Figure 28: Thermal Comfort at Home

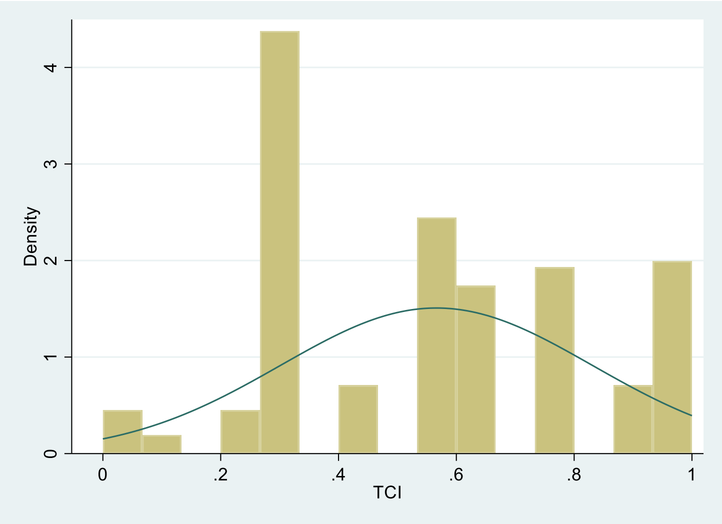

Figure 29: Thermal Comfort Compound Variable Histogram

Independent Variable 3: Risk Perception

In terms of **risk perception**, ~60% of respondents believe that a heat wave is of moderate harm or very harmful to themselves, their household, and their community. The average compound variable score is 0.64, indicating households tend to perceive heat waves as events posing greater risk to themselves, their household and community. This shows a gap, on the one hand risk perception is generally high, but knowledge of heat is low.

Thus, residents may feel helpless or lack capacity to act or respond appropriately during heat waves. There is great opportunity for community education programmes to increase levels of awareness on heat. Analysing the distribution of results in more detail, there are two peaks, one around 0.3 and the second around 1, perhaps showing clusters dividing low and high-risk perception.

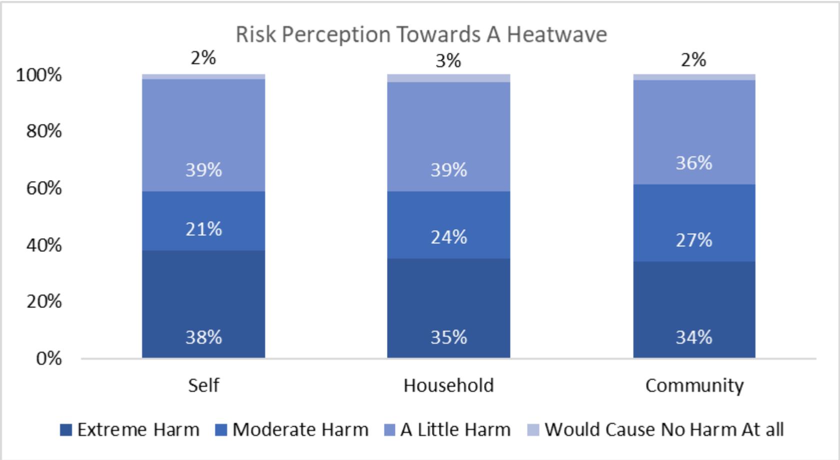

Figure 30: Risk Perception Towards a Heatwave

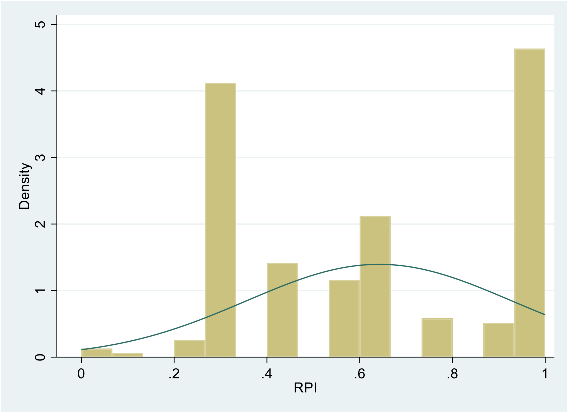

Figure 31: Risk Perception Compound Variable Histogram

4.3.2 Correlations

Spearman's Correlation was run between the independent variables, dependent variable, sub-variables (*Indices*), and all indicators. Generally, correlations are low, showing weak positive or weak negative relationships, with one exception (highlighted in red).

Only results significant at the 1% level are shown in the tables below, with the p-value contained in brackets. Positive correlations range from 0.24 to 0.53, while negative correlations range from -0.26 to -0.32. The choice of 4-point scale for many of the survey questions may have limited correlation scores.

To recap, variables and indicator scoring are calibrated towards levels of vulnerability, with 0 being low vulnerability and 1 high vulnerability. For example, a negative correlation between Behavioural Adaptation and Exposure indicates that greater vulnerability due to household exposure to heat is correlated with lower vulnerability due to more behavioural adaptations.

1. **Correlations between Independent Variables and Dependent Variables (CVI, SI, ACI).** Correlations significant at the 1% level exists between Exposure and Sensitivity (SI), Thermal Comfort and Sensitivity (SI), as well as between Thermal Comfort and Exposure.

	Sensitivity	**Exposure**
Exposure	0.2666 (0.0006)	
Thermal Comfort	0.2737 (0.0003)	0.2459 (0.0022)

Table 11: Correlations between Independent Variables and Dependent Variables

2. **Correlation between Independent Variables and All Indicators.** Weak positive correlation is observed between Challenges to Adaptation and Exposure, Challenges to Adaptation and Risk Perception, and Health Symptoms and Thermal Comfort. Moderate positive correlation is observed between Number of Health Symptoms Experienced and Exposure. Weak negative correlation is seen between Behavioural Adaptation and Exposure, and Risk Perception and Behavioural Adaptation.

	Exposure	Risk Perception	Thermal Comfort
Behavioural Adaptation	-0.2973 (0.0003)	-0.2554 (0.0063)	
Challenges to Adaptation	0.3556 (0.00001)	0.2621 (0.0040)	
Health Symptoms	0.5283 (0.00001)		0.3294 (0.00001)

Table 12:Correlation between Independent Variables and All Indicators

3. **Correlations between a) Sensitivity Index score and the Adaptive Capacity Index indicators, as well as b) between the Adaptive Capacity indicators.** At the 1% significance level, weak positive relationship is seen between Challenges to Adaptation and **Sensitivity**, Education, and Income, Help Sought and Behavioural adaptation, Home Adaptation and Behavioural Adaptation. Weak negative correlation exists between Income and Financial Assistance, Challenges to Adaptation and Financial Assistance, and Behavioural Adaptation and Challenges to Adaptation.

	Sensitivity	Income	Financial Assistance	Behavioural Adaptation
Financial Assistance		-0.3202 (0.00001)		
Challenges to Adaptation	0.2765 (0.0010)		-0.2630 (0.0026)	-0.3553 (0.00001)
Education		0.2586 (0.0036)		
Help Sought				0.2474 (0.0075)
Home Adaptation				0.3461 (0.00001)

Table 13: Correlations between a) SI and ACI indicators, and b) between all ACI indicators

4. **Correlation between a) Adaptive Capacity Index score and Sensitivity Index indicators, as well as b) between Sensitivity indicators**. No significant correlation was found with Adaptive Capacity. Between sub-indicators, weak positive relationship, significant at the 1% level was found between Total Household Size and Presence of Children under 5, Elderly and Isolated living, Elderly and Chronically ill.

	Children <5	Elderly (65 and>)
Total Household Size	0.3652 (0.00001)	
Chronically Ill		0.3148 (0.00001)
Isolated Living		0.2745 (0.0008)

Table 14: Correlation between a) ACI and SI indicators, and b) between all SI indicators

4.3.3 Regression

The following regressions are investigated. The remaining relationships could be explored with further studies.

	Dependent (Y)	Independent (X_1 - X_n)	H_0	H_1	Regression Model
1	Sensitivity	Exposure	No significant relationship between SI and E, TC, and RP	Significant relationship between SI and E, TC, and RP	Ordinal Regression
		Thermal Comfort			
		Risk Perception			
2	Lack of) Adaptive Capacit	Exposure	No significant relationship between ACII and E, TC, and RP	Significant relationship between ACI and E, TC, and RP	
		Thermal Comfort			
		Risk Perception			
3	Composite Vulnerability	Exposure	No significant relationship between CVI and E, TC, and RP	Significant relationship between CVI and E, TC, and RP	
		Thermal Comfort			
		Risk Perception			
4	Health Symptoms	Exposure	No significant relationship between Health Symptoms and E, TC, and RP	Significant relationship between Health Symptoms and E, TC, and RP	
		Thermal Comfort			
		Risk Perception			

Table 15: Regressions

The four assumptions for Ordinal Regression are met for all 4 regressions, as follows (Laerd Statistics, 2018):

1. The dependent variable is at the ordinal level.
2. One or more independent variables are continuous, ordinal, or categorical. In this case, the Compound Independent Variables are treated as continuous data.
3. There is no multicollinearity between independent variables. All correlations remain low.
4. The proportional odds assumption is met, using the Brant test, showing non-significant results. Results of the STATA Brant test are in Appendix 5.

Regression equation:

The regression equation is defined as follows (UCLA: Statistical Consulting Group, 2021):

$$\text{logit}\,(P\,(Y \leq j)) = \beta_{j0} + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3$$

- Y = ordinal outcome (vulnerability categories)
- P $(Y \leq j)$ = cumulative probability of Y less than or equal to a specific category j=1,…J-1
- j = four vulnerability categories (1- very low, 2 – low, 3 – moderate, 4 – high)
- $x_1 – x_3$ = the independent variables, x_1 = Exposure, x_2 = Thermal Comfort, x_3= Risk Perception

The equation is parameterized differently in STATA (as below), but the interpretation in the sections below hold.

$$\text{logit}\,(P\,(Y \leq j)) = \beta_{j0} - \eta_1 x_1 - \eta_2 x_2 - \eta_3 x_3$$

$$\eta_i = -\beta_i$$

Regression #1

Ordinal Regression		
	1	**2**
Exposure	1.7127	1.7666
	(3.41)***	(3.55)***
Thermal Comfort	1.1325	1.1820
	(2.4)**	(2.52)**
Risk Perception	0.8100	
	(0.415)	
N	233	233
Log Likelihood	-295.3234	-295.6556
LR chi2(x)	24.7900	24.1300
Prob>chi2	0.0000	0.0000
Pseudo R^2	0.0403	0.0392
t-statistics/ z-statistics in parentheses *p<0.1, **p<0.05, ***p<0.01		

Table 16: Regression 1

Regression 1 is run between the **dependent variable Sensitivity** and the **Independent variables Exposure, Thermal Comfort, and Risk Perception**.

The Ordinal Regression Models 1-2 are similar, with **Model 1** chosen as it has the higher Likelihood Ratio (LR) Chi-Square and Log Likelihood. For every one unit increase in Exposure, the ordered log-odds of being in a higher vulnerability category increase by 1.7, while other variables are held constant, significant at the 1% level. Similarly, for one unit increase in Thermal Comfort, the ordered log-odds of being in a higher vulnerability category increase by 1.1, while other variables are held constant, significant at the 5% level. For a one unit increase in Risk Perception, the ordered log-odds of being in a higher vulnerability category increase by 0.81, while other variables are held constant, though it is not significant. Thus, we **reject the null hypothesis** and conclude that **there is a relationship between *sensitivity* and the *exposure* and *thermal comfort* compound variables.**

Regression #2

Ordinal Regression	
	1
Exposure	-.6333851
	(-1.31)
Thermal Comfort	0.4611
	(1.00)
Risk Perception	-2.755757
	(-0.65)
N	233
Log Likelihood	-309.9338
LR chi2(x)	2.8300
Prob>chi2	0.4193
Pseudo R^2	0.0045
t-statistics/ z-statistics in parentheses	
*p<0.1, **p<0.05, ***p<0.01	

Table 17: Regression 2

Regression 2 is run between the dependent variable **Adaptive Capacity** and the **Independent variables Exposure, Thermal Comfort, and Risk Perception**. The Ordinal Regression Model 2 has low Likelihood Ratio (LR) Chi-Square and none of the coefficients are significant at the 1%, 5% or 10% levels. Thus, we **fail to reject the null hypothesis**.

Regression #3

Ordinal Regression		
	1	2
Exposure	0.8729	0.8873
	(1.77)*	(1.81)*
Thermal Comfort	1.3449	1.3611
	(2.78)***	(2.84)***
Risk Perception	0.1120	
	-0.2600	
N	233	233
Log Likelihood	-286.0261	-286.0605
LR chi2(x)	14.4100	14.3500
Prob>chi2	0.0024	0.0008
Pseudo R^2	0.0246	0.0245
t-statistics/ z-statistics in parentheses *p<0.1, **p<0.05, ***p<0.01		

Table 18: Regression 3

Regression 3 is run between the dependent variable **Composite Vulnerability** and the **Independent variables Exposure, Thermal Comfort, and Risk Perception**.

The Ordinal Regression Models 1-2 are similar, with **Model 1** chosen as it has the marginally higher Likelihood Ratio (LR) Chi-Square and Log Likelihood. For every one unit increase in Exposure, the ordered log-odds of being in a higher vulnerability category increase by 0.87, while other variables are held constant, significant at the 10% level. Similarly, for one unit increase in Thermal Comfort, the ordered log-odds of being in a higher vulnerability category increase by 1.3, while other variables are held constant, significant at the 1% level. For a one unit increase in Risk Perception, the ordered log-odds of being in a higher vulnerability category increase by 0.1, while other variables are held constant, though it is not significant. Thus, we **reject the null hypothesis** and conclude that **there is a relationship between *adaptive capacity* and the *exposure* and *thermal comfort* compound variables**.

Regression #4

Ordinal Regression		
	1	2
Exposure	4.7116	4.8097
	(7.21)***	(7.39)***
Thermal Comfort	1.8394	1.9771
	(3.42)***	(3.7)***
Risk Perception	0.9680	
	(1.98)*	
N	233	233
Log Likelihood	-189.1773	-191.1640
LR chi2(x)	95.4800	91.5100
Prob>chi2	0.0000	0.0000
Pseudo R^2	0.2015	0.1931

Table 19: Regression 4

Regression 4 is run between the dependent variable **Health Symptoms (number of)** and the independent variables **Exposure, Thermal Comfort, and Risk Perception**.

The Ordinal Regression Models 1-2 are similar, with **Model 1** chosen as it has the higher Likelihood Ratio (LR) Chi-Square and Log Likelihood. For every one unit increase in Exposure, the ordered log-odds of being in a higher vulnerability category increase by 4.7, while other variables are held constant, significant at the 1% level. Similarly, for one unit increase in Thermal Comfort, the ordered log-odds of being in a higher vulnerability category increase by 1.8, while other variables are held constant, significant at the 1% level. For a one unit increase in Risk Perception, the ordered log-odds of being in a higher vulnerability category increase by 1.0, while other variables are held constant, significant at the 10% level. Thus, we **reject the null hypothesis** and conclude that **there is a relationship between *number of health symptoms* reported by the household and the *exposure, thermal comfort, and risk perception* compound variables.**

4.4 Discussion

This section synthesises results from previous sections, collectively discussing findings and simultaneously answering sub-question 4 which is *'What Challenges and Opportunities exist within PHC's relationship with heat?'*

1. PHCs are exposed to heat and its associated stressors in daily life, with implications for health and quality of life.

While the study did not measure indoor or outdoor temperatures, questions gauging Exposure, Thermal Comfort, and Risk Perception establish that the community at PPR Hicom does experience heat, and the associated discomfort or stressors linked with it. This happens both within the domain of the home, as well as externally at work, school, public space, and during commutes around the city. Indoor thermal discomfort, linked with air temperature and humidity, is concerning. Coupled with reported health symptoms such as trouble sleeping, as well as chronic illness or age, indoor thermal discomfort could be life-threatening, or at least reduce quality of life. These experiences likely play a role in raising the community's Risk Perception towards Heat Waves, though further studies are needed.

The regressions show relationships between the Independent Compound Variables (*Exposure, Thermal Comfort, Risk Perception*) and Dependent Variables, Sub-variables, and Indicators (*Composite Vulnerability Index, Sensitivity Index, Number of Heat Health Symptoms*). Ultimately this is probably driven by *Number of Heat-Health Symptoms* reported, which is a subset of the *Sensitivity Index*, and therefore of the *Composite Vulnerability Index*. Under Regression 4, with *Number of Heat-Health symptoms* as the dependent variable, the regression shows that the 1) households exposed to more heat, 2) households experiencing worse thermal comfort, and 3) households with greater risk perception; are likely to report more heat-health symptoms.

2. PHC Sensitivity to Heat shows lower vulnerability, but with significant diversity.

The study shows a community that appears to be less sensitive to heat on average, but displays significant diversity in the composition of at-risk groups within households, justifying the household level focus (Sorg et al., 2018). Data shows there may exist large intergenerational households, and there may be isolated, individual households. There may be households with several at-risk members, and households with few at-risk members. In this specific community, sensitivity to heat stress is primarily driven by the *gender ratio*, *presence of children under 5 years old*, *total household size* and the *heat-health symptoms* experienced.

Most importantly this shows that Malaysian public housing communities should not be treated as a homogenous vulnerable group, with blanket, one-size fits all solutions applied. Unfortunately, this is frequently the case, resulting in less effective interventions (Dietrich & Ismail, 2022).

Recognising the nuances of vulnerability, within an already vulnerable population provides the granularity required for tailored, targeted and successful interventions.

3. PHCs lack Adaptive Capacity, limited by reactionary tendencies arising from low financial capacity, lack of knowledge, and strict rules or regulations.

Analysis of the home and behavioural adaptation actions show that the most popular actions are those easiest to implement. For example, the use of fans; ceiling fans are already installed in most Malaysian households and ventilation stand fans are easily available. Opening windows and doors to encourage cross-ventilation are quick and simple measures. However, adaptation requiring intentional modifications, such as shading installation are less implemented.

Challenges highlighted to adaptation actions include *financial* constraints. With low incomes and limited financial security, households may engage in trade-offs between investing in cooling measures and other, more pressing priorities such as food.

In addition, households list a *lack of knowledge or skill* on how to best adapt as a hurdle faced. Education, upskilling, and awareness raising on practical heat management solutions could be encouraged.

Challenges are also attributed to *rules and regulations* that are in place by management, limiting alterations to the façade or unit. There is little participation from residents in public housing, as decisions are usually implemented from a top-down approach resulting in voices not being heard and needs going unmet (Dietrich & Ismail, 2022). Adopting more flexible management policies, and working with the community to ascertain needs and solutions is a step in the right direction.

Popular suggestions from respondents were to allow the installation of air-conditioning units (59% of all suggestions). Some of these suggestions were accompanied by requests for subsidies or mentions of the high-cost associated with air-conditioning use, again, acknowledging the trade-offs between thermal comfort and disposable income. In addition, air-conditioning use, while effective in the short-run, is not sustainable in the long-run. Other passive, low-cost cooling measures should be explored.

4. PHCs rate well for social cohesion, with opportunities to leverage it further to support one another when faced with Heat related stress.

Many households report knowing neighbours well or very well, reflecting good social ties between neighbours. Households also list neighbours/ community as the second largest source of *knowledge on heat*, highlighting the potential and importance of these networks for effective information dissemination.

However, neighbours rank low on the list of *sources for help*, indicating that households may not turn to neighbours when faced with heat-related health challenges. As the closest source for help, neighbours can be an important asset to mitigate heat-related stressors, particularly in cases of emergencies.

Many opportunities lie in leveraging these strong community networks, and encouraging households to actively use them to collectively overcome heat-related challenges in the community. This begins with empowering the community with information and awareness, as a first step.

5. PHCs face issues of access and spatial marginalisation, resulting in greater heat related vulnerabilities.

The *limited access to cool spaces* highlighted by households prompts a deeper examination of access and spatial marginalisation faced by the communities. The housing complex lies in an area that is underserved and less accessible, and faces myriad challenges increasing vulnerability to heat. This includes access to healthcare (Figure 32), which shows there are no government clinics under a 5-minute drive nor government hospitals under a 10-minute drive from the housing complex (Krishna Kumar et al., 2022).

In addition, the closest walkable public transit option is a bus route, with bus stops between 10 to 15 minutes away (Figure 33). Walkability to the bus stop is poor, the path is unshaded, and lies along roads frequented by heavy-duty vehicles accessing the surrounding factories. Train stations are at least a 10-minute drive away (Figure 33). Meanwhile, green spaces are limited, with the closest park located across the highway. The quality and access to vacant land or other open spaces is questionable (Krishna Kumar et al., 2022). Collectively, this paints a picture of a community that is constrained by spatial challenges that increase heat exposure and limit coping capacity.

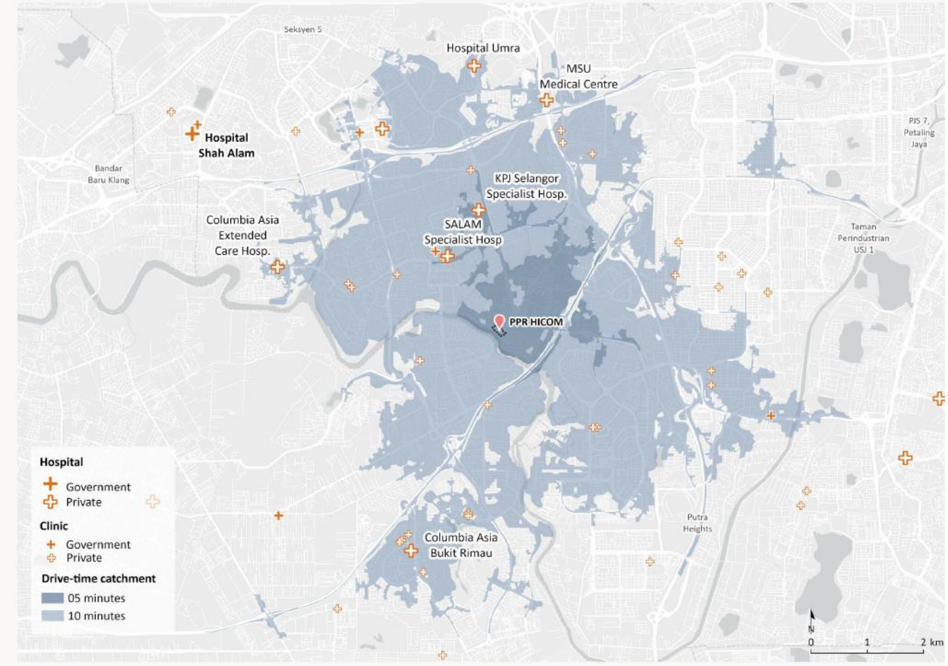

Figure 32: Healthcare Facilities in Surrounding Area

Source: Think City

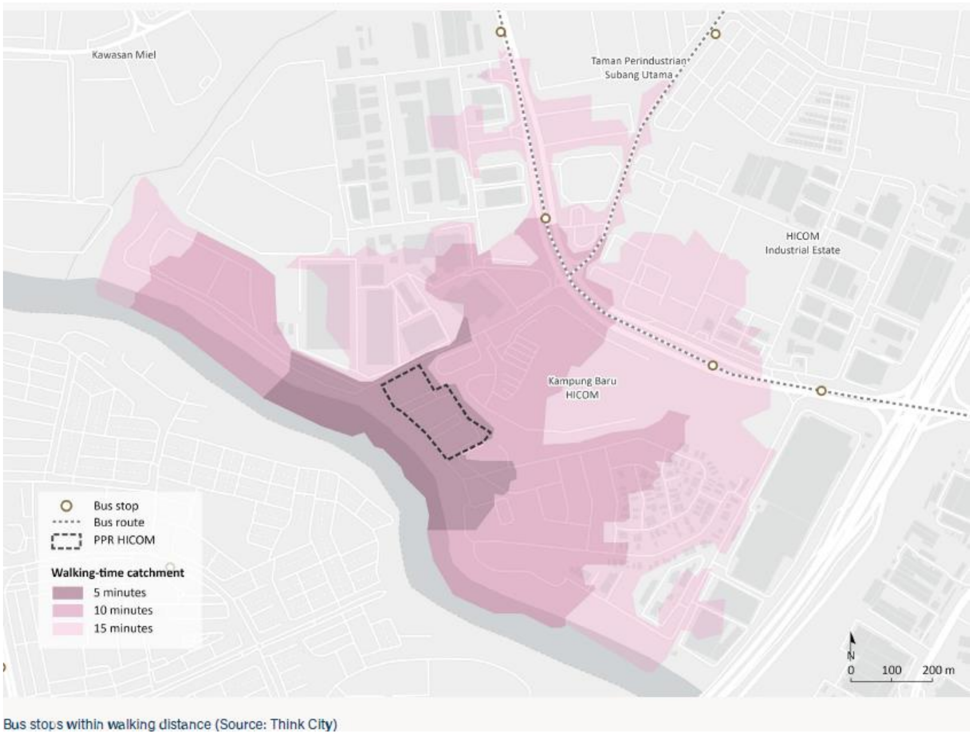

Figure 33: Bus Stops within walking distance

Source: Think City

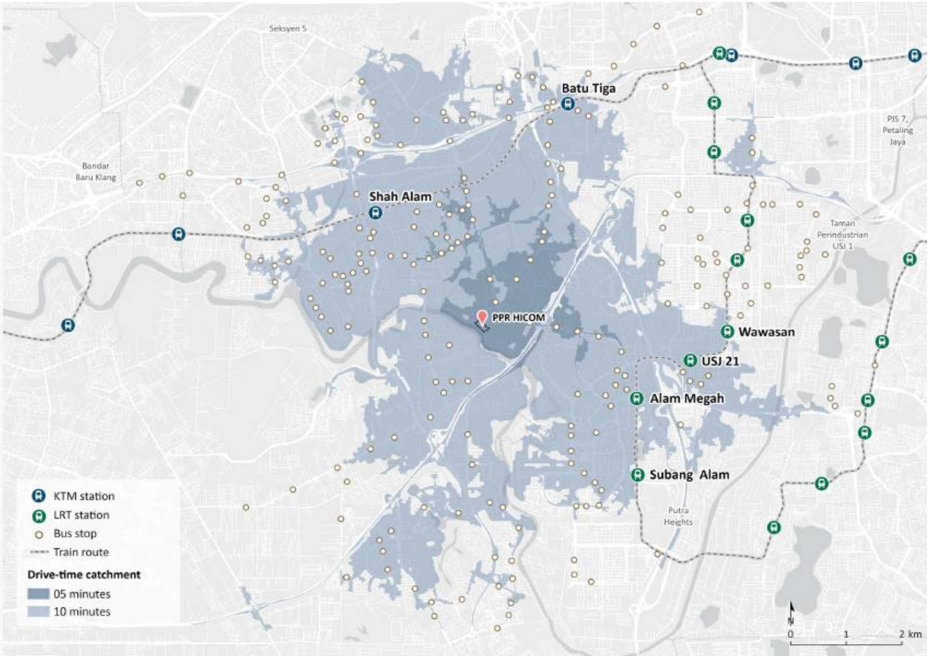

Figure 34: Public Transit stops within driving distance

Source: Think City

Figure 35: Open space and recreational land within walking distance

Source: Think City

Chapter 5: Conclusions & Policy Recommendations

5.1 Conclusions

The study shows that the community at PPR Hicom faces challenges related to heat in their daily lives, with consequences for health and liveability.

A brief summary of the community's Vulnerability to Heat, assessed through Household Sensitivity and Adaptive Capacity, provides the following results. Average scores for the Sensitivity Index show lower vulnerability scores. However, there remains great diversity in score distribution, showing that no one household is the same in composition of vulnerable group or health experience. This shows there is value in collecting data at the household level (Sorg et al., 2018). The primary drivers of household Sensitivity to heat in this specific PHC are high *Number of Health Symptoms*, high *Gender Ratio*, large *Total Household Size*, and presence of *Children under 5 years old*. These are key risk factors identified from other studies; women are likely more at risk due to greater heat exposure and having fewer resources and assets, large household sizes link with higher density of people and greater heat stress, and children under 5 are more susceptible to heat due to their physiology (Leyk, 2019; Rana et al., 2022; Soomar & Soomar, 2023).

Meanwhile, Adaptive Capacity is generally lacking in PHC households, with the average Adaptive Capacity Index score being higher than the Sensitivity Index average score. The lack of adaptive capacity in the community is primarily driven by poor *Access to Cool Spaces*, low household *Income*, low *Knowledge of heat and health*, and increased *Challenges* to adaptation. These factors are linked with inequality, marginalisation, and other determinants associated with lower socio-economic communities. Patterns of spatial exclusion, lack of participation, limited resources and amenities reported by other studies are displayed in this community (Dietrich & Ismail, 2022; Guardaro et al., 2022; Harlan et al., 2006).

The resulting Composite Vulnerability Index provides scores that have been stratified, dividing the community into four vulnerability categories from low to high vulnerability. Despite the subjectivity of scoring, the index provides an important storytelling and prioritisation tool for further interventions (Bao et al., 2015; Li, F. et al., 2022).

Analysis of the independent variables *Exposure*, *Thermal Comfort*, and *Risk Perception* show the following results. PPR Hicom households are exposed to heat in various urban settings, including work, school, the daily commute, public spaces, and at home, consistent with findings of other studies (Arifwidodo & Chandrasiri, 2020; Meng et al., 2023; Zander et al., 2015). Heat exposure at home is reflected in the high levels of thermal discomfort reported by respondents as well as reported symptoms of trouble sleeping. Indoor heat exposure at home can be particularly harmful, with links to higher morbidity and mortality (Kenny et al., 2019; Samuelson et al., 2020). Importantly, even short durations of high heat exposure in any setting have consequences for productivity, mental health, and overall functionality (Flouris et al., 2018; Kenny et al., 2019). These experiences faced by households may reflect in the higher *Risk Perception towards Heat Waves* exhibited in the survey, with personal experience being a critical driver of risk perception (Rana & Routray, 2016).

In addition, regression of the *Exposure*, *Thermal Comfort*, and *Risk Perception* variables against the *Number of Heat-health* symptoms show that the 1) households exposed to more heat, 2) households experiencing worse thermal comfort, and 3) households with greater risk perception; are likely to report more heat-health symptoms. At the Composite Vulnerability level, regression shows 1) households exposed to more heat and 2) households experiencing worse thermal comfort, are likely be in higher vulnerability categories.

Lastly, the study examined challenges and opportunities within PHC's relationship with heat. The key impacts for PHC relating to heat relate to poor health outcomes and disrupted quality of life. Challenges faced include financial constraints, lack of skills or knowledge, hurdles related to rules and regulations, issues of accessibility to cool spaces and healthcare. Within financial constraints, respondents displayed considerations for 'trade-offs' between paying for cooling solutions and preserving funding for other pressing needs (Guardaro et al., 2022).

Opportunities, meanwhile lie in recognising the diversity of household composition in PHC, leveraging the high social cohesion between neighbours which can mitigate impacts of heat (Klinenberg, 2002), utilising social media as an effective tool for spreading information and awareness, and working with the community to explore creative or low-cost ways to mitigate heat stress.

Overall Heat Vulnerability Assessments are useful tools to identify priorities and needs for interventions. They can and should be incorporated into the narratives presented by communities and those working to support them in dealing with heat-related challenges.

This study is one of the first to explore the heat-related experiences and perspectives in a Malaysian Public Housing Community. It is not a study without flaws. Nonetheless, the methodology and approach chosen, like other heat vulnerability assessments, must go through a process of trial and error, requiring contextualisation, reiteration, and validation, to ensure reliability and validity for the chosen local population. At greater scale, and the incorporation of larger sets of data with a more heterogenous group of respondents, the study methodology could be revised, using Principal Component Analysis, Factor Analysis or other robust methodologies to select vulnerability indicators from a larger set of information. Additionally, in-depth interviews with residents and experts, document analysis, and spatial analysis would add to the research findings.

5.2 Policy Recommendations

Heat must be recognised more seriously as a public health hazard, and provided the attention, effort, and resources befitting its severity. This entails acknowledgement that heat stress may occur outside of certain temperature thresholds. Urban Heat Island Effect, spatial disparity, built environment conditions and other factors also contribute to heat stress.

The various public and private players must coordinate and collaborate to ensure the Malaysian population, particularly those most vulnerable, are not negatively impacted by heat stress. Actions that can be taken could be organised as follows:

High-level policy priorities, applicable to all citizens:

- Development of Heat Action Plans with comprehensive needs assessment and prioritisation
- Collection of comprehensive primary and secondary data on heat and its consequences on human health, activity, and productivity
- Cross-functional collaboration between various sectors (e.g. housing, public transit, health)
- Public health campaigns to improve education and awareness. These should leverage community networks, and key communication channels like social media
- Co-creation of solutions with citizens, leveraging on citizen science

At the level of the Public Housing Community, interventions can be divided into two, short-term and long-term solutions.

Short-term solutions:

- Development of local community Vulnerability Registry to identify and monitor highly vulnerable households during periods of heat stress. For example, isolated, elderly households.
- First-Responder training for community members with critical emergency preparedness skills for heat related illnesses.
- Identification and provision of emergency cool spaces outside the home, to provide relief during hot periods or nights. For example, community halls, mosques, and other community spaces.
- Promotion of passive cooling measures within the home, supported by subsidies where available.

Long-Term Measures

- Design Interventions and Measures in the Built Environment
  - Cool roofs
  - Changing of regulations to allow installation of air conditioning (with caveats), shading and awning, exhaust fans, greening
  - Shaded Pathways
  - Urban Greening

The above are compiled from conversations, observations, as well as global case studies (The Nature Conservancy et al, 2017; WSROC, 2018).

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Appendix 2: Survey Form (English)

PPR HICOM HEAT STRESS SURVEY (2023)
Aishwariya Krishna Kumar

Section 1: Consent Form

We are inviting you to participate in our study on heat stress. This is a collaboration between PERWACOM, Think City and an independent researcher. You can stop the survey at any point if you change your mind. You can also choose to remove your data from our study by informing us. For further questions, you can contact Aish Kumar (+60123041992).

Purpose: We want to understand your experience and perspective of heat stress in your daily lives. This survey will ask questions linked to your work, family, home, and activities.
The survey has 24 questions and will take approximately 10 minutes.

Lucky Draw: All participants that complete the survey will be eligible for a lucky draw to win 5 cash vouchers (1 X RM100, 4 X RM50).

Data Use and Confidentiality

- Best practices in data storage will be used.
- Confidentiality: Personal information will be kept private and will be anonymised for analysis purposes.
- Future research: De-identified data (all identifying information removed) may be shared with other researchers. You will not be told about these future research studies.

Agreement to Participate:
To take this survey, you must be:

- A current resident of PPR Hicom and
- The only person from your unit participating in the survey and
- At least 18 years old

If you meet these criteria and would like to take the survey, please consent below

Participation Statement: I have read this informed consent document and the material contained in it has been explained to me verbally. I understand each part of the document, all my questions have been answered, and I freely and voluntarily choose to participate in this study.

- Consent
- Do not consent

PPR HICOM HEAT STRESS SURVEY (2023)
Aishwariya Krishna Kumar

Section 2: Questionnaire

Household Information:

1. Unit
2. Who are you in the household?
    a. Female Head of Household
    b. Male Head of Household
    c. Other Male
    d. Other Female

3. Age (Enter number only, without a space, e.g. '33')
4. Household Composition (Enter number only, without space, e.g. '2')
    a. Number of children aged below 5
    b. Number of elderly people aged 65 and above
    c. Number of chronically ill individuals (e.g. diabetes, hypertension, mental disorders)
    d. Number of women
    e. Number of disabled people
    f. Total number of people living in this unit (including sub-tenants, if any)

5. What is your average monthly household income?
    a. <1000
    b. 1001-2000
    c. 2001-3000
    d. >3000

6. Do you or members of your household receive the following benefits? (Select all that applies).
    a. Bantuan Sara Hidup (BSH)
    b. Zakat
    c. OKU Allowance
    d. Government pension
    e. Financial assistance from family
    f. Elderly support
    g. Others: Please state
    h. Not applicable

7. What is the highest level of education of anyone in your household? (Pick one)
    a. None
    b. UPSR
    c. SRP/PMR/PT3
    d. SPM
    e. Matriculation/STPM/ Diploma
    f. Bachelors and Higher

8. What is the primary mode of transportation for your household (Pick one).
    a. Car
    b. Motorcycle
    c. Public Transport
    d. Foot
    e. Other: Please state

Experience with Heat:

9. Have you or members of your household experienced the following due to heat stress within the past year? Select all that applies.
    a. Dehydration
    b. Dizziness
    c. Headache
    d. Heat rash
    e. Heat stroke
    f. Lethargy or exhaustion
    g. Nausea
    h. Trouble concentrating

10. Where did you or the affected member of the household seek help for your heat issues? Select all that applies.
    a. I did not seek help
    b. Klinik Kesihatan
    c. Hospital
    d. Neighbors
    e. Other: Please State

11. How often have you or members of your household experienced symptoms related to heat in the following areas within the past year?

	Often	Occassionally	Rarely	Never
Workplace	○	○	○	○
Daily commute	○	○	○	○
School	○	○	○	○
Own House	○	○	○	○
Public Spaces	○	○	○	○

12. Have you or members of your household used the following to help cool your home? Please select all that apply.
    a. Add Shading or Awning (e.g. extra curtains)
    b. Add cool or wet sheets to windows and doors
    c. Use of AC
    d. Use of Fans
    e. Open Windows or Doors
    f. Other: Please State
    g. Not applicable

13. Have you or members of the household done the following during periods of heat stress? Please select all that apply.
    a. Drink more fluids
    b. Take more showers
    c. Wear light or cool clothing
    d. Adjust daily schedule to avoid the heat
    e. Leave home to get cooler
    f. Miss work
    g. Miss school
    h. Check in on family or friends or neighbors
    i. Other: Please State
    j. Not applicable

14. What challenges do you face in modifying your home or taking actions to cool down? Please select all that apply.
    a. Lack of skills or knowledge
    b. Rules or regulatory restrictions
    c. Security
    d. Pests or mosquitoes
    e. Finance
    f. Other: please state
    g. Not applicable

15. In general, how do you feel about the following in your home?

	Very Uncomfortable	Uncomfortable	Acceptable	Comfortable
Air Temperature	○	○	○	○
Humidity	○	○	○	○
Ventilation	○	○	○	○

PPR HICOM HEAT STRESS SURVEY (2023)
Aishwariya Krishna Kumar

Knowledge and Preparedness

16. How would you rate your knowledge on heat and how it affects your health?
    a. I don't know anything
    b. I know a little
    c. I know quite a bit
    d. I know much more than others

17. Where did you get the knowledge on heat and how it affects your health?
    a. Formal training
    b. Mass media
    c. Social media
    d. Neighbors/ Community
    e. Other: Please State
    f. Not applicable

18. Statement: A heat wave is a period of hot weather. If it were to occur in your area, how much do you think it would harm the following:

	Would cause no harm at all	A little harm	Moderate harm	Extreme harm
Your heath	○	○	○	○
The health of your household members	○	○	○	○
The health of your community	○	○	○	○

19. How well do you feel you know your neighbors?
    a. Very well
    b. Fairly well
    c. Not very well
    d. Not at all

20. Do you have a first aid kit in the house?
    a. Yes
    b. No

21. Do you or members of your household have access to cool spaces outside your home to escape the heat when you feel too hot?
    a. No
    b. Yes. Please state location

22. Do you have suggestions on how to improve the thermal comfort in your household or community?

Appendix 3: Other Survey Data

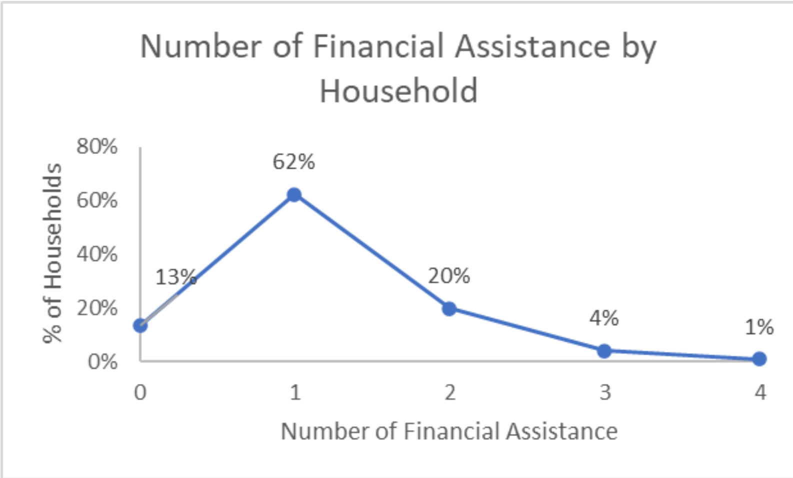

Figure 36: Number of Financial Assistance by Household

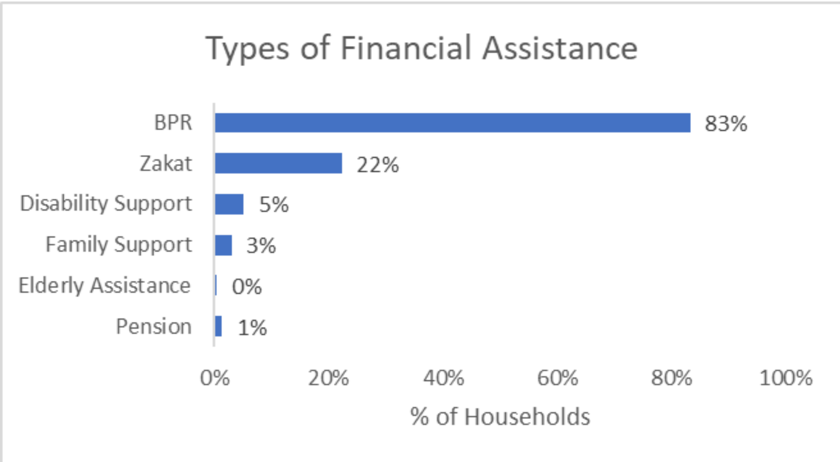

Figure 37: Types of Financial Assistance Received by Household

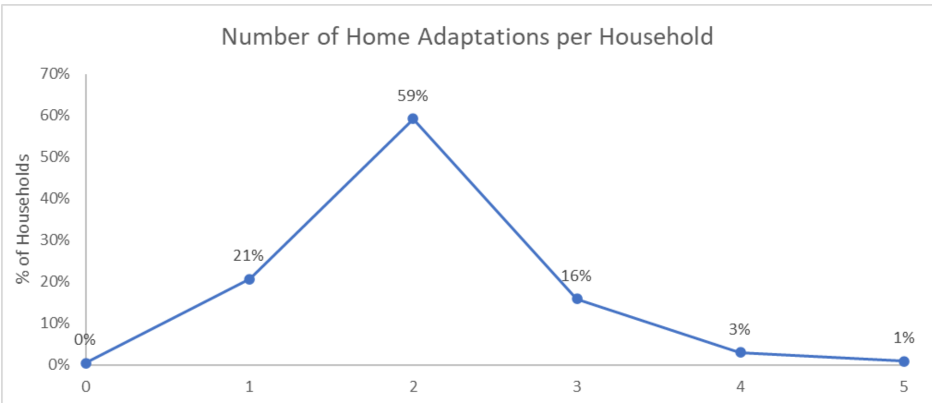

Figure 38: Number of Home Adaptations per Household

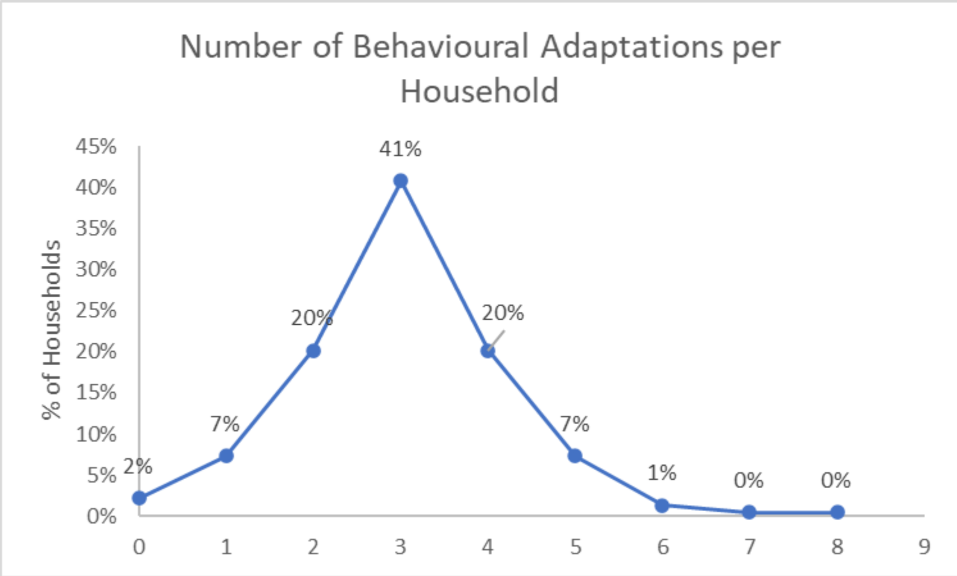

Figure 39: Number of Behavioural Adaptations per Household

Appendix 4: Vulnerability Levels by Index

	Method	High	Moderate	Low	Very Low
SI	A	15%	33%	35%	17%
	B	0%	7%	61%	32%
ACI	A	17%	32%	33%	17%
	B	1%	84%	15%	0%
CVI	A	13%	39%	36%	12%
	B	0%	38%	62%	0%

Table 20: Vulnerability Methods A and B

Appendix 5: Ordinal Regression STATA Outputs

STATA Outputs

Regression 1:

```
. ologit si3 ei tci

Iteration 0:   log likelihood = -307.71966
Iteration 1:   log likelihood =  -295.7517
Iteration 2:   log likelihood = -295.65568
Iteration 3:   log likelihood = -295.65559
Iteration 4:   log likelihood = -295.65559

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(2)    =  24.13
                                                        Prob > chi2   = 0.0000
Log likelihood = -295.65559                             Pseudo R2     = 0.0392

------------------------------------------------------------------------------
         si3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |    1.76662    .497873     3.55   0.000     .7908072    2.742434
         tci |    1.18202   .4689975     2.52   0.012     .2628016    2.101238
-------------+----------------------------------------------------------------
       /cut1 |   -.176638   .3444106                     -.8516704    .4983944
       /cut2 |   1.638129   .3588316                      .9348318    2.341426
       /cut3 |   3.351009   .4031397                       2.56087    4.141148
------------------------------------------------------------------------------
```

```
. ologit si3 ei tci ri

Iteration 0:   log likelihood = -307.71966
Iteration 1:   log likelihood = -295.42457
Iteration 2:   log likelihood =  -295.3235
Iteration 3:   log likelihood =  -295.3234
Iteration 4:   log likelihood =  -295.3234

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(3)    =  24.79
                                                        Prob > chi2   = 0.0000
Log likelihood = -295.3234                              Pseudo R2     = 0.0403

------------------------------------------------------------------------------
         si3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |   1.712671   .5015453     3.41   0.001     .7296603    2.695682
         tci |   1.132518    .472535     2.40   0.017     .2063668     2.05867
          ri |   .3488386   .4281336     0.81   0.415    -.4902879    1.187965
-------------+----------------------------------------------------------------
       /cut1 |  -.0070526   .4023966                     -.7957354    .7816303
       /cut2 |    1.81184   .4184079                      .9917758    2.631905
       /cut3 |   3.526401   .4588065                      2.627157    4.425645
------------------------------------------------------------------------------
```

Figure 40: Regression 1 Outputs

```
. omodel logit si3 ei tci ri

Iteration 0:   log likelihood = -307.71966
Iteration 1:   log likelihood = -295.42457
Iteration 2:   log likelihood =  -295.3235
Iteration 3:   log likelihood =  -295.3234

Ordered logit estimates                           Number of obs   =        233
                                                  LR chi2(3)      =      24.79
                                                  Prob > chi2     =     0.0000
Log likelihood =  -295.3234                       Pseudo R2       =     0.0403

------------------------------------------------------------------------------
         si3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |   1.712671   .5015451     3.41   0.001     .7296606    2.695681
         tci |   1.132518   .4725348     2.40   0.017      .206367     2.05867
          ri |   .3488386   .4281335     0.81   0.415    -.4902877    1.187965
-------------+----------------------------------------------------------------
       _cut1 |  -.0070526   .4023965          (Ancillary parameters)
       _cut2 |    1.81184   .4184077
       _cut3 |   3.526401   .4588063
------------------------------------------------------------------------------

Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(6) =      7.95
       Prob > chi2 =    0.2421
```

Figure 41: Brant Test Regression 1

Regression 2:

```
. ologit aci3 ei tci ri

Iteration 0:   log likelihood = -311.34671
Iteration 1:   log likelihood = -309.93481
Iteration 2:   log likelihood = -309.93375
Iteration 3:   log likelihood = -309.93375

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(3)    =   2.83
                                                        Prob > chi2   = 0.4193
Log likelihood = -309.93375                             Pseudo R2     = 0.0045

------------------------------------------------------------------------------
        aci3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |  -.6333851   .4844384    -1.31   0.191    -1.582867    .3160968
         tci |   .4611055   .4631884     1.00   0.319    -.4467271    1.368938
          ri |  -.2755757   .4266636    -0.65   0.518    -1.111821    .5606696
-------------+----------------------------------------------------------------
       /cut1 |    -1.8157   .4155314                     -2.630126   -1.001273
       /cut2 |  -.2027997   .3981685                     -.9831956    .5775962
       /cut3 |   1.361107   .4103872                      .5567625    2.165451
------------------------------------------------------------------------------
```

Figure 42: Regression 2 Output

```
. omodel logit aci3 ei tci ri

Iteration 0:   log likelihood = -311.34671
Iteration 1:   log likelihood = -309.93481
Iteration 2:   log likelihood = -309.93375

Ordered logit estimates                           Number of obs   =        233
                                                  LR chi2(3)      =       2.83
                                                  Prob > chi2     =     0.4193
Log likelihood = -309.93375                       Pseudo R2       =     0.0045

------------------------------------------------------------------------------
        aci3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |  -.6333851   .4844373    -1.31   0.191    -1.582865    .3160945
         tci |   .4611055   .4631873     1.00   0.319     -.446725    1.368936
          ri |  -.2755757   .4266626    -0.65   0.518    -1.111819    .5606677
-------------+----------------------------------------------------------------
       _cut1 |    -1.8157   .4155302          (Ancillary parameters)
       _cut2 |  -.2027997   .3981675
       _cut3 |   1.361107   .4103859
------------------------------------------------------------------------------

Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(6) =      4.84
       Prob > chi2 =    0.5643

.
```

Figure 43: Brant Test, Regression 2

Regression 3:

```
. ologit cvi3 ei tci

Iteration 0:   log likelihood = -293.23298
Iteration 1:   log likelihood =  -286.0965
Iteration 2:   log likelihood = -286.06048
Iteration 3:   log likelihood = -286.06046

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(2)    =  14.35
                                                        Prob > chi2   = 0.0008
Log likelihood = -286.06046                             Pseudo R2     = 0.0245

------------------------------------------------------------------------------
        cvi3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |   .8873077   .4896848     1.81   0.070    -.0724567    1.847072
         tci |   1.361116   .4798499     2.84   0.005     .4206273    2.301604
-------------+----------------------------------------------------------------
       /cut1 |  -.8048018    .360698                     -1.511757   -.0978467
       /cut2 |   1.168334   .3577196                      .4672167    1.869452
       /cut3 |   3.203679   .4084388                      2.403153    4.004204
------------------------------------------------------------------------------
```

```
. ologit cvi3 ei tci ri

Iteration 0:   log likelihood = -293.23298
Iteration 1:   log likelihood = -286.06279
Iteration 2:   log likelihood = -286.02609
Iteration 3:   log likelihood = -286.02607

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(3)    =  14.41
                                                        Prob > chi2   = 0.0024
Log likelihood = -286.02607                             Pseudo R2     = 0.0246

------------------------------------------------------------------------------
        cvi3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |   .8728633   .4928375     1.77   0.077    -.0930805    1.838807
         tci |   1.344855   .4835415     2.78   0.005     .3971314    2.292579
          ri |   .1120246   .4271713     0.26   0.793    -.7252158     .949265
-------------+----------------------------------------------------------------
       /cut1 |  -.7498783   .4169139                     -1.567014    .0672578
       /cut2 |   1.224372   .4169077                      .4072476    2.041496
       /cut3 |   3.259839   .4616608                      2.355001    4.164678
------------------------------------------------------------------------------
```

Figure 44: Regression 3 Outputs

```
. omodel logit cvi3 ei tci ri

Iteration 0:   log likelihood = -293.23298
Iteration 1:   log likelihood = -286.06279
Iteration 2:   log likelihood = -286.02609
Iteration 3:   log likelihood = -286.02607

Ordered logit estimates                           Number of obs   =        233
                                                  LR chi2(3)      =      14.41
                                                  Prob > chi2     =     0.0024
Log likelihood = -286.02607                       Pseudo R2       =     0.0246

------------------------------------------------------------------------------
        cvi3 | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
-------------+----------------------------------------------------------------
          ei |   .8728634   .4928375     1.77   0.077    -.0930804    1.838807
         tci |   1.344856   .4835415     2.78   0.005     .3971315     2.29258
          ri |   .1120246   .4271713     0.26   0.793    -.7252158    .9492651
-------------+----------------------------------------------------------------
       _cut1 |  -.7498784   .4169139          (Ancillary parameters)
       _cut2 |   1.224372   .4169077
       _cut3 |    3.25984   .4616608
------------------------------------------------------------------------------

Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(6) =       6.49
       Prob > chi2 =     0.3708

.
```

Figure 45: Brant Test, Regression 3

Regression 4:

```
. ologit healthsymptoms ei tci

Iteration 0:   log likelihood = -236.91722
Iteration 1:   log likelihood =   -192.761
Iteration 2:   log likelihood = -191.17039
Iteration 3:   log likelihood = -191.16403
Iteration 4:   log likelihood = -191.16403

Ordered logistic regression                             Number of obs =    233
                                                        LR chi2(2)    =  91.51
                                                        Prob > chi2   = 0.0000
Log likelihood = -191.16403                             Pseudo R2     = 0.1931

------------------------------------------------------------------------------
healthsymptoms | Coefficient  Std. err.      z    P>|z|     [95% conf. interval]
---------------+--------------------------------------------------------------
            ei |   4.809686   .6504396     7.39   0.000     3.534848    6.084524
           tci |   1.977057   .5342009     3.70   0.000     .9300425    3.024072
---------------+--------------------------------------------------------------
         /cut1 |   1.277141   .3982175                      .4966492    2.057633
         /cut2 |   3.668959   .4713348                       2.74516    4.592759
------------------------------------------------------------------------------

.
```

```
. ologit healthsymptoms ei tci ri

Iteration 0:   log likelihood = -236.91722
Iteration 1:   log likelihood =  -190.8686
Iteration 2:   log likelihood = -189.18423
Iteration 3:   log likelihood = -189.17735
Iteration 4:   log likelihood = -189.17734

Ordered logistic regression                     Number of obs =    233
                                                LR chi2(3)    =  95.48
                                                Prob > chi2   = 0.0000
Log likelihood = -189.17734                     Pseudo R2     = 0.2015
```

healthsymptoms	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ei	4.711647	.6536832	7.21	0.000	3.430451	5.992842
tci	1.839414	.5376796	3.42	0.001	.7855818	2.893247
ri	.9680362	.488017	1.98	0.047	.0115404	1.924532
/cut1	1.744829	.4680628			.8274424	2.662215
/cut2	4.165295	.5429687			3.101096	5.229494

Figure 46: Regression 4 Outputs

```
. omodel logit healthsymptoms ei tci ri

Iteration 0:   log likelihood = -236.91722
Iteration 1:   log likelihood = -191.08498
Iteration 2:   log likelihood =  -189.2161
Iteration 3:   log likelihood = -189.17737
Iteration 4:   log likelihood = -189.17734

Ordered logit estimates                         Number of obs   =        233
                                                LR chi2(3)      =      95.48
                                                Prob > chi2     =     0.0000
Log likelihood = -189.17734                     Pseudo R2       =     0.2015
```

healthsymp~s	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
ei	4.711647	.653683	7.21	0.000	3.430452	5.992842
tci	1.839414	.5376795	3.42	0.001	.7855819	2.893247
ri	.9680362	.488017	1.98	0.047	.0115405	1.924532
_cut1	1.744829	.4680628	(Ancillary parameters)			
_cut2	4.165295	.5429686				

```
Approximate likelihood-ratio test of proportionality of odds
across response categories:
         chi2(3) =       2.42
       Prob > chi2 =     0.4896

.
```

Figure 47: Brant Test, Regression 4

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