

Agent-based simulation to evaluate the impact of seismic retrofit promotion policies

by

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Author's Declaration

This thesis consists of material all of which I authored or co-authored: see Statement of Contributions included in the thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Statement of Contributions

I, Alireza Ahmadi, confirm that I was responsible for reviewing the literature, deriving equations, developing models, computer programming, data processing, conducting analyses, and interpreting the results in this thesis. A manuscript based on this research was drafted by me and finalized in an iterative process with the thesis advisor, Dr. Rodrigo Costa and has been submitted for publication in a peer-reviewed journal as follows:

Ahmadi, A., & Costa, R. (n.d.) *Agent-based simulation of the effectiveness of policies for the adoption of seismic retrofits* (submitted in February 2025). I was the principal investigator, responsible for major areas of concept formation, literature analysis, as well as the majority of manuscript composition. Dr. Rodrigo Costa was the supervisory author on this manuscript and was involved in concept formation and manuscript edits.

Abstract

Seismic risk is a global concern, as buildings around the world are vulnerable to damage or collapse during earthquakes. Recent developments in engineering design have resulted in substantial improvements to the seismic performance of new buildings. However, buildings constructed before recent upgrades to the seismic regulations comprise a large portion of the existing building inventory. Buildings with insufficient seismic capacity are susceptible to extensive damage or collapse during an earthquake, contributing to economic losses and casualties. Effective risk mitigation strategies such as seismic retrofitting could potentially address the vulnerability of the existing building stock to earthquake hazards. Yet, seismic retrofit programs suffer from low take-up rates. Thus, identifying barriers for seismic retrofit adoption and strategies to increase take-up rates can help mitigate losses from future events. This study develops an agent-based model to assess homeowner response to multiple seismic retrofit promotion strategies including running education campaigns or providing retrofit cost subsidies. The simulation framework is applied to a case study of owner-occupied, residential-detached dwellings in Vancouver, British Columbia, Canada, to evaluate the effectiveness of various potential seismic retrofit promotion strategies. These strategies are compared regarding the number of adopters and the reduction in total annual losses to residential building structures and contents in the City of Vancouver.

The results suggest that a combination of educational programs and retrofit cost subsidies for low-income households yield the highest adoption rates and the largest reduction in total annual losses to detached residential dwellings. However, the results show focusing only on an educational campaign can achieve similar results in terms of adopters and loss reduction. The model highlights that risk perception is the main barrier for moderate and high-income groups, while the combination of risk perception, willingness to pay, and perceived benefits (tangible financial returns) are the factors impeding the adoption of retrofit measures among low-income homeowners. The analysis on the effectiveness of retrofit promotion policies in reducing earthquake-induced annual losses suggest that government investment in education or subsidies could be cost-effective provided that the implementation costs remain below the projected savings in avoided losses. The model results could be used to inform local government what would be the viable annual budget to be spent on seismic risk reduction strategies. A more comprehensive cost-benefit analysis is needed, involving collaboration between public agencies, insurers, and the construction industry to quantify implementation costs, co-benefits, and risk-sharing mechanisms. This study contributes both methodologically and quantitatively to the development of effective seismic risk mitigation policies. By modelling policy impacts before implementation, policymakers can better evaluate and refine strategies to minimize damage and losses in future seismic events.

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I would like to thank all the people who made this thesis possible.

Dedication

This is dedicated to the one I love.

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Chapter 1

Introduction

1.1 Research significance

Seismic risk is a global concern, as buildings worldwide are vulnerable to damage or collapse during earthquakes, often resulting in casualties and extensive economic losses [28, 120, 67]. Earthquakes are the deadliest natural hazards, and their impacts are particularly severe in urban regions with high population densities and aging infrastructure. The risk posed by seismic events depends not only on the magnitude and frequency of earthquakes but also on the vulnerability of the built environment and the exposure of populations and assets. Appropriate risk mitigation strategies, such as seismic retrofitting, can minimize social, economic, and socioeconomic consequences of earthquakes. In recent earthquakes in countries with proactive seismic retrofit policies (e.g., Japan, Italy, and New Zealand), the number of collapses and severely damaged buildings was lower than expected [120]. Recent studies by the Geological Survey of Canada suggest that seismic retrofits would have similar benefits in Canada. According to the Canadian National Earthquake Scenario Catalogue, a magnitude 7.0 earthquake beneath the Strait of Georgia in British Columbia could cause \$30.3 CAD billion in total losses, heavy damage to 10,626 buildings and displace 345,774 people. However, across all residential buildings in Vancouver, seismic retrofitting could reduce economic losses by 25% and the number of heavily damaged buildings by 34% [50]. This suggests that improved seismic design, including retrofits, can have a meaningful impact on building performance during an earthquake.

Although seismic retrofitting can help to protect life and property, many homeowners are reluctant to adopt retrofit measures due to various reasons, such as underestimating

the earthquake risk, not believing in retrofitting effectiveness or benefits [29, 26, 28, 62]. At present, only a few countries (e.g., the US and New Zealand) have enacted mandatory retrofit requirements for privately owned residential dwellings. However, implementing mandatory policies is often challenging due to high enforcement costs and potential resistance from property owners. Therefore, most countries rely on voluntary retrofitting programs supported by government-sponsored financial and technical assistance [120]. Well-designed incentive policies can encourage homeowners to undertake seismic adjustments, thereby reducing earthquake-related risks in their communities [29, 26]. This highlights the crucial role of governments in encouraging homeowners to adopt retrofit measures through targeted policy interventions. A review of international practices reveals that common incentive mechanisms include retrofit grants, tax rebates, and government-backed loans [120]. While most retrofit promotion mechanisms focus on financial incentives, the costs of retrofits are small relative to the building’s value. For example, in Canada, seismic retrofitting of a single detached dwelling would cost between CAD 4,000-10,000, while the average price of a detached home in Vancouver is between CAD 1.5-2 million [112]. Thus, it is arguable that other barriers exist that prevent private residential homeowners from adopting seismic retrofit measures. Understanding these differences would enable policy-makers to design targeted interventions that encourage adoption among specific population groups.

1.2 Scope and objectives

This study provides two contributions. First, a computational simulation framework is developed to provide insights into the implementation of seismic retrofit programs. An agent-based approach is developed to simulate the homeowner’s decision processes as they engage with seismic retrofit programs. Homeowners are the primary agents in this model. These agents have attributes (e.g., disposable income, risk perception, education level) and behaviours (e.g., their attitude towards seismic retrofit). Policies are implemented by local authorities to encourage the adoption of seismic retrofit measures (e.g., subsidies or education programs). Homeowner Agents also interact with each other. These interactions might influence their understanding of seismic risks and attitudes towards seismic retrofitting, leading to behavioural changes over time. Second, this framework is applied to a case study of Vancouver, British Columbia, Canada, to compare the effectiveness of different policy interventions in encouraging detached homeowners in Vancouver to retrofit their homes. The suggested seismic retrofit promotion policies are evaluated regarding

the total number of homeowners adopting the retrofit measures and the reduction in total annual losses to residential building structures and contents in the City of Vancouver. The main barriers to adopting seismic adjustment measures among different income groups are identified, and appropriate policy interventions to target those barriers are suggested. Modelling the impact of policies before their application allows policymakers to evaluate their effects. So they can fine-tune the policy interventions before they are implemented. This study provides insight into the efficient design of seismic risk mitigation policies in earthquake-prone communities.

1.3 Thesis organization

The thesis is structured into five chapters. Following the introduction, Chapter 2 presents a literature review that covers seismic risk and mitigation strategies, seismic retrofitting of residential dwellings, modelling seismic retrofit decision-making, agent-based models (ABMs), validation and verification of ABMs, and their applications in various fields. Chapter 3 provides a detailed methodology, description of the agents' attributes and behaviours, the investigated policies, and the ABM development process. Chapter 4 presents the case study, including the study area (Vancouver, British Columbia), the datasets used in the study, model results, sensitivity analysis, and discussions and limitations of the model. The thesis concludes with Chapter 5, offering recommendations for policy-making to promote seismic retrofitting of residential dwellings in earthquake-prone regions and suggesting directions for future research.

Chapter 2

Literature review

2.1 Seismic Risk and Mitigation Strategies

Seismic risk is a global concern due to its overwhelming toll on communities [28, 120]. Seismic risk is critical in tectonically active regions, such as the Pacific Ring of Fire, the Himalayan belt, and parts of the Mediterranean and Middle East. In these areas, seismic activity is frequent and often intense, placing millions of lives and billions of dollars' worth of infrastructure at risk. Over the past few decades, high-impact earthquakes in countries like Chile, Japan, Nepal, and Turkey have highlighted the need for proactive seismic risk mitigation measures, particularly in urban areas with large inventories of non-engineered or poorly constructed buildings [40, 10].

While western Canada, particularly British Columbia, is well known for its seismic hazard due to proximity to the Cascadia Subduction Zone, other regions of Canada also face significant but often underrecognized seismic risks. Central and eastern provinces, such as Ontario and Quebec, experience intraplate seismicity associated with the Western Quebec Seismic Zone and the Charlevoix Seismic Zone. Although earthquakes in these regions tend to be less frequent than those along plate boundaries, they can still produce damaging ground motions due to local soil conditions and the older, more brittle building stock. Crustal earthquakes in these regions may also be shallower and closer to populated areas compared to subduction zone earthquakes. Historic events such as the 1732 Montreal earthquake and the 2010 Central Canada earthquake serve as reminders of the region's vulnerability. Moreover, public awareness and preparedness tend to be lower in these areas,

which can further exacerbate the risk when the earthquake occurs [6, 66].

In the early 20th century, countries such as Italy, Japan, and the United States began developing earthquake-resistant design standards for new construction in response to catastrophic earthquakes [51]. Canada’s building codes were updated in 1973 to include requirements for lateral load-resisting systems in new constructions. These early efforts laid the foundation for modern seismic building codes, incorporating principles of lateral force resistance and ductile design. However, despite advancements in structural engineering and geotechnical analysis, many of the world’s buildings were constructed prior to the enforcement of such codes [59]. These older structures, often made from unreinforced masonry, non-ductile concrete, or lightly framed wood, lack adequate seismic detailing and anchorage, making them particularly susceptible to ground shaking and structural failure.

Seismic risk mitigation strategies have been continuously gaining attention over the years to address the vulnerability of existing building stock [37, 1]. Zhang et al.[120] reviewed seismic risk mitigation policies in some of the most earthquake-prone countries worldwide. In the United States, mitigation policies vary by state and city. California leads with mandatory retrofits for unreinforced masonry, soft-story wood-frame, and non-ductile concrete buildings, supported by grants, low-interest loans, and cost-sharing policies. However, seismic retrofitting remains largely voluntary in other jurisdictions. In New Zealand, a national framework mandates local governments to identify and address earthquake-prone buildings. The Building Act sets retrofit targets (e.g., 34%–67% of the new building standard), with stricter timelines introduced following the Christchurch earthquake. Financial incentives, including grants for heritage buildings, are provided, though support varies by municipality. Japan mandates retrofits for large-scale and critical buildings through national laws. The 1995 Seismic Retrofitting Promotion Law and its amendments introduced public disclosure of seismic diagnostics and aggressive subsidies for residential retrofits, covering up to 100% of diagnostic and 66.7% of retrofit costs during limited-time campaigns. Iran prioritizes retrofitting public and critical infrastructure. The government collaborates with research institutions to develop guidelines, and the Housing Foundation plays a major role in rural seismic rehabilitation. Most retrofits are voluntary and supported through state-led programs.

In China, retrofitting is typically led and fully funded by local governments under national five-year plans, targeting vulnerable public and residential buildings. Though this top-down approach accelerates upgrades, it imposes significant fiscal burdens on municipalities. In Turkey, the Urban Transformation Law mandates retrofits or demolitions

for hazardous buildings following catastrophic earthquakes. Financing is backed by international loans and national insurance programs, though retrofitting remains costly and time-intensive. In Romania, the national programs support seismic assessment, but retrofit implementation is limited due to fragmented ownership and financial barriers. Only a few buildings undergo strengthening despite widespread risk classification. India mandates retrofit for selected public and critical buildings, with voluntary provisions for private buildings. National Disaster Management Authority supports implementation through training, guidelines, and financial assistance for structural retrofitting. In Nepal, the government-led retrofitting efforts focus on schools and critical infrastructure. Residential retrofits remain voluntary, with external financing from the World Bank, Asian Development Bank, and other donors.

Seismic retrofitting is widely recognized as an effective risk mitigation strategy that can significantly reduce the adverse social and economic impacts of earthquakes. Countries with established retrofit programs such as Japan, Italy, and New Zealand have experienced fewer building collapses and severe structural damages in recent seismic events than originally projected [120]. Recent studies by the Geological Survey of Canada suggest that seismic retrofits would have similar benefits. According to the National Earthquake Scenario Catalogue, a magnitude 7.0 earthquake beneath the Strait of Georgia in British Columbia could cause \$30.3 CAD billion in total losses, heavy damage to 10,626 buildings and displace 345,774 people. However, across all residential buildings, seismic retrofitting in Vancouver would reduce the economic losses by 25% and the number of heavily damaged buildings by 34% [50]. This suggests that improved seismic design, including retrofits, can have a meaningful impact on building performance during an earthquake.

2.1.1 Brace and Bolt Method

In the context of wood-frame residential buildings (often one- and two-story homes) constructed prior to modern seismic building codes and municipal by-laws, earthquake-resistant features were rarely included during original construction. These homes often suffer from one or more of the following vulnerabilities: (i) The foundation is not anchored to the house; (ii) the wood-framed basement walls (known as cripple walls) lack adequate lateral support; or (iii) the first-floor framing is not securely connected to the cripple walls [115]. Figure 2.1-a illustrates a typical cripple wall failure in a wood-frame single-family dwelling during a major earthquake. In an attempt to reduce the risk of earthquake damage and loss, and thereby promote post-earthquake recovery, the California Earthquake Authority (CEA) introduced Earthquake Brace and Bolt (EBB) program, to retrofit unbraced cripple

walls in single family dwellings in accordance with the Federal Emergency Management Agency (FEMA) P-1100 guidelines [116]. The seismic retrofitting makes a home safer and more resistant to structural damage by preventing it from shifting from its foundation during an earthquake. The retrofit procedure includes bracing the cripple wall with plywood, bolting the cripple wall to the foundation, and fastening cripple wall to the house frame using shear transfer ties [115]. Figure 2.1-b shows the conditions of a cripple wall before and after retrofit in a single-family dwelling. A recent study by the Pacific Earthquake Engineering Research (PEER) Center estimates that the owners of retrofitted houses can save between \$75,000 and \$150,000 in repair costs resulting from a major earthquake by bracing and bolting their houses [116].

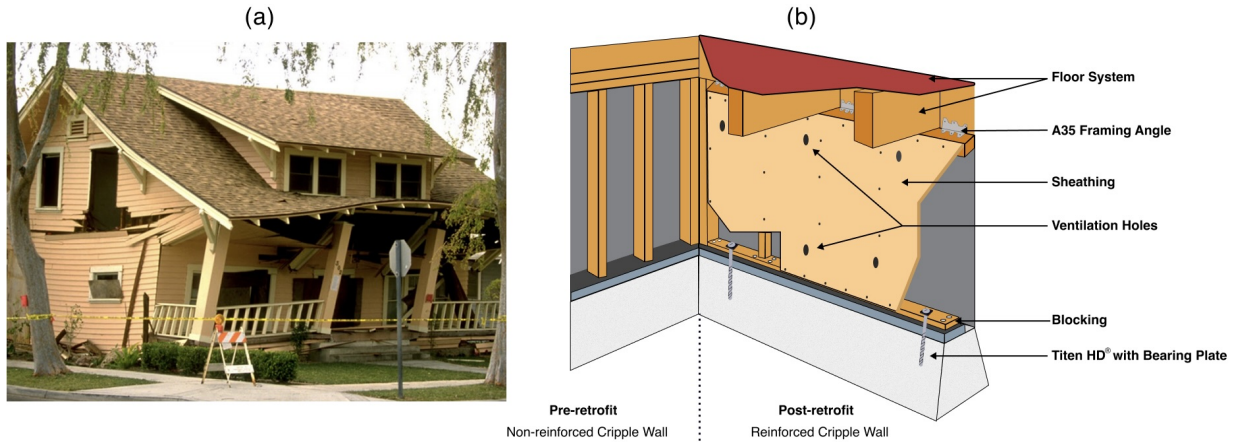


Figure 2.1: Cripple wall collapse and brace and bolt retrofit method: a) A cripple wall collapse in a wood-frame single-family dwelling during a major earthquake [14], b) The conditions of a cripple wall before and after retrofit using brace and bolt method [115].

2.1.2 Implementation of seismic retrofit policies

While seismic retrofitting is an effective method for reducing the risk of injury, loss of life, and property damage during earthquakes, adoption rates among private residential homeowners remain low. This reluctance originates from a variety of factors, including the underestimation of seismic risk, skepticism about the effectiveness or necessity of retrofitting, and limited awareness of the potential long-term benefits [29, 26, 28, 62]. At present, only a few countries (e.g., the US and New Zealand) have enacted mandatory retrofit requirements for privately owned residential dwellings. However, implementing mandatory policies is often challenging due to high enforcement costs and potential resistance from

property owners. As a result, most countries rely on voluntary retrofitting programs supported by government-sponsored financial and technical assistance [120]. Well-designed incentive policies can encourage homeowners to undertake seismic adjustments, thereby reducing earthquake-related risks in their communities [29, 26]. This highlights the crucial role of governments in encouraging homeowners to adopt retrofit measures through targeted policy interventions. A review of international practices reveals that common incentive mechanisms include retrofit grants, tax rebates, and government-backed loans [120]. Despite the focus on financial incentives, retrofit costs are relatively small compared to the market value of most homes. In Canada, seismic retrofitting of a single detached dwelling would cost between CAD 4,000-10,000, while the average price of a detached home in Vancouver is between CAD 1.5-2 million [112]. Thus, it is arguable that other barriers exist that prevent private residential homeowners from adopting seismic retrofit measures. Therefore, a deeper understanding of the behavioral and psychological factors influencing homeowner decision-making is critical. Identifying these drivers can enable policymakers to tailor retrofit promotion strategies to specific demographic or socioeconomic groups. Such targeted interventions may include not only financial mechanisms but also educational programs, community engagement efforts, and trust-building measures that collectively foster a culture of seismic preparedness.

2.2 Modelling Seismic Retrofit Decision Making

The process of individuals’ undertaking protective actions has been studied in psychology, sociology, economics, and health sciences mainly through two theories: (i) attitude-behavioural theories and (ii) social and cognitive processes theories.

The models originated from attitude-behavioural theories focus on the relationship between attitudes, intentions, and behaviours. They explain how people’s attitudes toward risks and mitigation strategies influence their decisions and actions [3, 98]. Within the context of the attitude-behavioural theoretical perspective, the models with application in seismic risk mitigation are the Theory of Reasoned Action (TRA) and the Theory of Planned Behavior (TPB) [3, 26]. TRA assumes that an individual’s intention to perform a behaviour (e.g., seismic retrofitting) is the primary determinant of whether the behaviour will occur. This intention is influenced by two factors: the individual’s attitude toward the behaviour (i.e., whether they view retrofitting positively or negatively) and subjective norms (i.e., perceived social pressure from others to perform or not perform the action). In the seismic context, homeowners may decide to retrofit if they believe it is beneficial and

if they perceive that important others—such as family, neighbours, or authorities—expect them to take such action [3]. The Theory of Planned Behavior extends TRA by incorporating perceived behavioural control - the individual’s perception of their ability to perform the behaviour. This addition accounts for situations in which individuals may intend to act but face barriers, such as financial constraints, a lack of technical knowledge, or insufficient access to contractors. In seismic risk mitigation, TPB suggests that even if a homeowner recognizes the importance of retrofitting and feels social pressure to do so, they may refrain from taking action if they perceive the process as unaffordable or overly complex [3, 70].

Theories that incorporate social and cognitive processes focus on understanding how individuals evaluate risks, resources, and social influences to make decisions about disaster preparedness and mitigation [81]. These theories incorporate cognitive appraisal, social interaction, and behavioural intention to explain preparedness behaviours. Some of the key theories in this category include the Protection Motivation Theory (PMT) [96], Person-Relative-to-Event Theory (PrE) [80], Protective Action Decision Model (PADAM) [73], and Social Cognitive Preparation Model [87]. PMT explains how individuals assess threats and coping mechanisms through four key cognitive processes: perceived severity of the threat, vulnerability, response efficacy, and self-efficacy [11]. These processes generate protection motivation, which drives intentions to adopt protective behaviours [81]. While effective in predicting intentions for earthquake preparedness, the theory struggles to fully explain how these intentions translate into actual behaviours [81, 26]. The PrE theory emphasizes the relationship between the perceived level of threat and the individual’s available resources to mitigate it [80]. It suggests that preparedness increases when personal resources are appraised as sufficient to cope with the threat, but decreases when resources are perceived as insufficient. The theory highlights the importance of both primary threat appraisals and secondary resource appraisals in motivating protective action [25]. The application of the PrE model to earthquake preparedness emphasizes that the perception of the earthquake hazard and one’s own ability to respond to the reduction of the hazard impacts are significant parameters for preparedness against earthquake disasters [82]. PADAM integrates social, behavioural, and cognitive processes to explain how people identify risks, evaluate responses, and decide on protective actions [73]. Threat perception arises from environmental cues and trusted communications, followed by the evaluation of response efficacy, cost, and feasibility. The model emphasizes the interaction of hazard attributes, personal beliefs, and social influences in shaping decisions for seismic mitigation [73]. The Social Cognitive Preparation Model developed by Paton [87] combines elements of Social Cognitive Theory and Stress and Coping Theory [26], outlining three phases: motivators (e.g., risk perception, critical awareness), intention formation (e.g., self-

efficacy, response efficacy), and linking intentions to behavior (e.g., sense of community, perceived responsibility). Models based on social and cognitive process theories recognize that problem-focused coping motivates action but also accounts for barriers, such as perceived lack of resources, that may inhibit preparedness. These models have been used to study the impact of proposed variables within the context of several natural hazards such as earthquakes, volcanic eruptions, and tsunamis [89, 88].

Building upon factors identified by these theoretical models, which influence the adoption of precautionary action, Egbelakin [26] developed a conceptual framework to describe homeowners' seismic retrofit decision-making. Similar variations of this model have been used by other scholars to study the seismic risk mitigation behaviour of homeowners (e.g., [109, 62]). According to this model, the process of adopting and implementing the seismic adjustment measures comprises three sequential phases: (i) intention formation, (ii) decision formation, and (iii) adoption and implementation of seismic adjustment. These phases are described below.

2.2.1 Decision Making Phases

Intention Formation Phase

The intention formation phase describes an individual's process of developing the intention to adopt seismic mitigation measures. Intention, as a behavioural attribute, is driven by intrinsic factors or external stimuli [87]. Behavioural intention is a critical precursor to protective actions, although it does not translate directly into decisions or behaviours. Several factors have been identified in the earthquake risk management literature to predict behavioral intention [4, 26, 90]: self-efficacy, defined as the belief in a personal capacity to succeed in a task or achieve a goal; outcome expectancy, which anticipates whether personal actions lead to a desirable outcome [87]; perceived responsibility, which reflects the individual's sense of responsibility for personal and close family safety against earthquake potential impacts (or a potential threat)[80]; and risk perception, which refers to the individual's subjective judgment of the likelihood and consequences of a future adverse event [103]. Risk perception is shaped by how individuals interpret and personalize a hazard and its potential impacts, with those who perceive themselves as vulnerable and at risk being more likely to seek actions to mitigate the consequences of a potential disaster [21]. Risk perception has been long established as a valid precursor for intention formation in disaster preparedness [106].

Decision Formation Phase

During the decision formation phase, an individual intending to reduce their seismic risk evaluates the mitigation actions and decides whether to adopt the adjustment measures. The decision is influenced by individual attributes such as the perceived benefit of retrofitting, trust in the stakeholders' relationship, seismic adjustment efficacy, and resource requirements. Perceived benefit refers to an individual's judgment of the advantages of adopting seismic adjustments, such as ensuring safety, reducing repair costs, avoiding relocation expenses, and potentially increasing property value or reducing insurance premiums [26]. Individuals who recognize that the benefits of retrofitting outweigh the costs are more likely to form positive attitudes and make informed decisions about implementing mitigation measures. However, a lack of understanding of these tangible benefits can deter owners from proceeding with retrofits. Trust in stakeholder relationships influences their acceptance or rejection of information about seismic risk and mitigation measures [26]. The credibility and perceived trustworthiness of information sources, such as government organizations, affect homeowners' confidence in the information provided, ultimately shaping their decision to adopt seismic mitigation measures [73, 89]. Seismic adjustment efficacy refers to an individual's perception of how effective seismic mitigation measures are in protecting people and property during an earthquake [80, 73]. Seismic adjustment efficacy is measured by the mitigation actions that reduce vulnerability to hazard impacts. Both theoretical models and empirical studies in earthquake risk management suggest that seismic adjustment efficacy significantly influences an individual's decision to adopt hazard mitigation measures [80, 73]. Resource requirements refer to an individual's belief about having sufficient knowledge, skills, and resources (e.g., funding, materials, and equipment) necessary to implement seismic mitigation measures [87, 73]. Studies have shown that adequate resources are positively correlated with the decision to adopt hazard mitigation and the actual implementation of these measures. In contrast, a lack of resources often hinders action [26].

Adoption and Implementation Phase

The final phase involves the adoption and implementation of seismic adjustments. This occurs when factors influencing intention and decision formation in earlier stages are sufficiently high. At this point, individuals who have decided to take a risk reduction action do so by utilizing available resources to implement the necessary adjustments.

2.2.2 External Motivators

This section examines external factors that influence different phases of seismic retrofit decision-making. These factors include policies implemented by local governments, such as financial incentives and educational campaigns, which aim to encourage homeowners to adopt retrofit measures. Moreover, social interactions among homeowners can shape opinions about earthquake risk and seismic retrofitting, potentially leading to changes in their decisions.

Financial Incentives

The availability of financial incentives can motivate homeowners to adopt and implement seismic adjustments [29]. Financial incentives can be grants, low-interest loans, or tax deductions distributed to eligible homeowners. Financial incentives can enhance households' willingness to pay and perceived benefit attributes. One well-documented seismic risk financial incentive program is the Earthquake Brace and Bolt (EBB) retrofit in California [17]. The cost of retrofitting a single detached house through the EBB program ranges from USD\$3,000 to USD\$7,000, depending on location and retrofit type. The EBB retrofit program offers \$3,000 grants to all detached homeowners [15]. Moreover, supplemental grants are available for households with less than 80% of the median household income in California to cover up to 100% of the retrofit costs [16].

Educational Campaigns

Educational measures highlight the potentially devastating consequences of earthquakes and the effectiveness of seismic adjustment measures in protecting life and property. Education campaigns can include videos on television or social media that showcase the potential damage of a severe earthquake and recommend seismic retrofitting as an effective risk mitigation strategy. Education can enhance homeowners' perception of risk and the efficacy of mitigation measures. They can also disseminate the earthquake awareness and preparedness message in a community through social interactions. A survey by Egbelakin et al. [29] showed that 88% of the homeowner participants stated that mass media would largely influence their willingness to prepare for disasters and that repeated exposure to information can strengthen homeowners' intentions to adopt retrofit measures.

Social Influence

Social influence is a fundamental aspect of human interaction that may cause individuals to adapt their opinions or behaviours to align more closely with those of the people they interact with. This adaptation can occur due to persuasive arguments, a desire for similarity, uncertainty leading to reliance on others, or social pressure to conform to norms [39]. However, individuals may reject the attitudes or behaviours of others and even strive to further differentiate themselves. There is also considerable uncertainty about the mechanisms that lead to assimilation or differentiation, as well as how these processes contribute to shaping opinion dynamics in societies. This makes social interaction a complex phenomenon. According to Flache et al. [39], a large part of the studies on social influence in the literature could be categorized into three classes of models: models of assimilative social influence, models with similarity-biased influence, and models with repulsive influence.

The assimilative social influence models propose that when two individuals are connected through an influence relationship, they consistently influence each other to minimize their opinion differences. This framework suggests that societal interactions ultimately lead to consensus, but struggles to explain how diversity might increase over time or how opinion clustering can endure in densely connected networks without individuals' fixation on their initial opinions [39].

Models with similarity bias abandon the assumption that there is always influence if there is a structural connection between agents [39]. Instead, these models propose that social influence depends on the similarity between individuals, with greater similarity leading to stronger influence. If opinions differ too greatly, influence may cease altogether, as agents lose "confidence" in the source of influence [7, 24, 93]. This similarity-based dynamic creates a feedback loop where agreement reinforces influence, and influence further strengthens agreement among like-minded individuals. As a result, these models can explain the persistence of distinct opinion clusters within a society rather than convergence toward a consensus [7, 24, 93].

Models with repulsive influence recognize that interactions can sometimes lead individuals to adjust their opinions to become more dissimilar from those with whom they disagree [39]. As dissimilarity between two agents increases, they may evaluate each other more negatively, resulting in a widening of their opinion differences [97]. These dynamics prevent consensus and instead lead to the formation of distinct clusters, which may even adopt maximally opposing views, resulting in bi-polarization [39].

2.3 Agent-based models

Agent-Based Modelling (ABM) is a computational approach used to simulate the behaviour of individual entities, or agents, and their interactions within a defined environment. ABMs are particularly effective for modelling complex systems where macro-level phenomena emerge from the bottom-up, driven by the localized behaviour and decision-making of heterogeneous agents [12, 75]. Each agent is defined by a set of attributes (e.g., preferences, beliefs, resources) and behavioural rules that dictate how it perceives the environment, interacts with other agents, and makes decisions over time.

Agents in an ABM are autonomous, meaning they operate independently without central control. They are typically situated within a spatial or networked environment and may have capabilities such as adaptation, learning, or evolution in response to internal goals or external stimuli. Interactions among agents—whether cooperative, competitive, or neutral—are central to the dynamics of an ABM and can lead to emergent system-level outcomes that are often nonlinear, path-dependent, and counterintuitive [30, 79].

The modelling process in ABM generally involves: (i) defining agent types and their attributes, (ii) specifying rules of behaviour and interaction, (iii) constructing the environment (spatial, temporal, or network-based), and (iv) simulating system evolution over time steps. This bottom-up framework enables researchers to analyze "what-if" scenarios by altering parameters, decision rules, or policy inputs, offering insights into the robustness and sensitivity of system behaviours [75].

ABMs offer several distinct advantages compared to traditional top-down modelling approaches. First, they can accommodate heterogeneity in agent characteristics, such as differences in risk perception, economic status, or access to information, crucial in domains like natural hazard preparedness or technology adoption. Second, ABMs are well-suited for representing agents with bounded rationality—where agents make satisficing rather than optimizing decisions—and social influence, such as peer effects and information diffusion [41]. Third, ABMs can incorporate adaptive behaviours and feedback mechanisms, capturing how agents modify their actions over time in response to environmental changes or interactions.

2.3.1 Validation and verification of agent-based models

Verification and validation (V&V) are essential for establishing the credibility of any agent-based model before it is used for policy analysis or scientific inference. Verification asks: "*Are we building the model right?*"—that is, does the coded implementation faithfully reflect the conceptual design? Validation asks: "*Are we building the right model?*"—does the model (and its underlying assumptions) provide an adequate representation of the real-world system for its intended purpose [102]?

Verification focuses on detecting programming errors, logical inconsistencies, and numerical inaccuracies that can arise when translating the model specification into computer code. Common practices include: (i) Code walkthroughs and peer review to ensure the implemented rules match the pseudo-code or UML sequence diagrams [84]. (ii) Unit and regression tests that exercise agent behaviors, scheduler routines, and random number streams to guard against unintended changes between model versions. (iii) Structured debugging aids, such as event logs, state monitors, and invariant checks that assert domain constraints at run time. (iv) Extreme-condition testing, where parameters are pushed to limits to verify the model's numerical stability and logical consistency.

Validation establishes confidence that the model's mechanisms and outputs are meaningful for the target system and research questions. Because ABMs often incorporate heterogeneous agents, non-linear interactions, and emergent patterns, validation typically proceeds at multiple levels [45]: (i) Structural (micro-level) validation: confirming that each agent's rules and decision heuristics are grounded in empirical or theoretical evidence—through expert interviews, laboratory experiments, or survey data. (ii) Pattern-oriented (macro-level) validation: comparing emergent outputs (e.g., adoption curves, spatial clustering, aggregate rates) against observed stylized facts or time-series data. Statistical measures such as K-S tests, Theil's inequality coefficient, or root-mean-square error quantify goodness-of-fit. (iii) Cross-model validation: demonstrating that qualitatively similar results arise when the ABM is rebuilt with alternative platforms (e.g. NetLogo vs. Repast) or when its outcomes are compared to analytical benchmarks and system-dynamics models [117]. A transparent documentation framework such as the ODD (Overview–Design concepts–Details) or the ODD+D (extension for human Decision making) protocols facilitates replication and external validation [44].

When empirical data are available, parameter values can be calibrated using heuristic search methods (such as genetic algorithms and particle swarm optimization), Bayesian

inference, or history-matching approaches [64]. Sequential data assimilation (e.g. particle filters) further refines state estimates by periodically conditioning the simulation on new observations, thereby improving predictive skill in real time.

2.3.2 Sensitivity analysis

Global sensitivity analysis seeks to divide and allocate the uncertainty of a model output $Y = f(\boldsymbol{\theta})$ to the uncertainty in each input factor $\boldsymbol{\theta} = (\theta_1, \dots, \theta_k)$ over their entire admissible domain. Among the many Global sensitivity analysis techniques, the variance-based method introduced by Sobol [105] and refined by Saltelli et al. [99, 100] is widely regarded as the standard because it is (i) model-free, (ii) able to capture non-linear and non-additive effects, and (iii) provides quantitative, easily interpretable indices. It is therefore suited for agent-based models, whose emergent behaviours often arise from complex interactions and feedbacks.

Let $V = \text{Var}[Y]$ denote the total output variance. Under the assumption that the k inputs are statistically independent, the law of total variance permits an orthogonal expansion in which V is expressed as the sum of partial variances that reflect successively higher-order interaction terms [101]:

$$V = \sum_{i=1}^k V_i + \sum_{i < j} V_{ij} + \dots + V_{12\dots k}$$

Each component is defined as $V_i = \text{Var}_{\theta_i}[\mathbb{E}[Y \mid \theta_i]]$, the variance that remains when all inputs except θ_i are integrated out. Similarly, V_{ij} captures the extra variance that appears only when θ_i and θ_j vary together, and so forth [100]. Because the components arise from an orthogonal ANOVA-like expansion, they sum exactly to V .

Normalising by the total variance produces dimensionless indices in $[0, 1]$:

$$S_i = \frac{V_i}{V}, \quad S_{T_i} = 1 - \frac{V_{\sim i}}{V}, \quad (2.1)$$

where S_i is the first-order (main-effect) index and S_{T_i} is the total-order index. Here $V_{\sim i} = \text{Var}_{\boldsymbol{\theta}_{\sim i}}[\mathbb{E}[Y \mid \boldsymbol{\theta}_{\sim i}]]$ is the variance attributable to all inputs except θ_i . These indices are useful for identifying not only the relative influence of each input, but also their interaction effects [101]. Intuitively,

- S_i answers the question: “If θ_i alone were allowed to vary within its range while all other inputs were fixed, what fraction of the output variance would we see?”
- S_{T_i} answers: “If θ_i were *frozen* at a single value, how much of the total variance would disappear—including the variance arising from interactions with other factors?”

Because $\sum_{i=1}^k S_i \leq 1$, the gap $S_{T_i} - S_i$ quantifies the strength of interaction effects involving θ_i [100].

Sobol indices are commonly estimated via numerical integration over the input space. A popular and efficient estimator, proposed by Saltelli [99], uses two sample matrices $\mathbf{A}$ and $\mathbf{B}$ of size $N \times k$, often generated using quasi-Monte Carlo methods such as Sobol low-discrepancy sequences [105]. For each input θ_i , a hybrid matrix $\mathbf{A}_B^{(i)}$ is constructed by replacing the i -th column of $\mathbf{A}$ with the corresponding column of $\mathbf{B}$. The model is then evaluated at

$$\{\mathbf{A}, \mathbf{B}, \mathbf{A}_B^{(1)}, \dots, \mathbf{A}_B^{(k)}\},$$

resulting in $(k + 2)N$ simulations. Estimator variance decreases with $1/\sqrt{N}$, and improved convergence is achieved using Latin hypercube sampling or Owen-scrambled sequences [101]. A practical rule is to use $N \gtrsim 500$ –1000 per input factor for reliable estimates.

Because ABMs are typically stochastic, each parameter setting $\mathbf{x}$ is simulated R times, and the mean output $\bar{Y}(\mathbf{x})$ is used in place of a single run. At each design point, the standard error $\text{SE}[\bar{Y}]$ quantifies the variability due to the model’s internal randomness and is computed as the sample standard deviation of the R replications divided by $\sqrt{R}$. To ensure that this stochastic noise does not dominate the sensitivity analysis, one can select R such that [48]

$$\frac{\text{SE}[\bar{Y}]}{\sqrt{V}} \leq \varepsilon,$$

where V is the total variance of the model output across the global parameter space, and $\varepsilon \approx 0.05$ is commonly used in practice. When computational resources are limited, prioritizing a larger outer sample size N over a large number of replications R (e.g., using $R = 10$) often yields better overall precision [68].

Practical workflow for ABMs includes: (i) Define the quantity of interest: For policy-oriented ABMs, this might be the number of adopters at after 5 years running the policy.

(ii) Screen inputs: Apply expert elicitation or a Morris screening method [18] to reduce dimensionality to $k \lesssim 20$. (iii) Generate Sobol design: Use Saltelli’s extension of the Sobol sampling scheme with appropriate marginal distributions (uniform, log-normal, triangular, etc.). If empirical evidence suggests correlated parameters, techniques like Iman–Conover sampling can be used [42]. (iv) Run the ABM: Automate batch runs via HPC clusters or cloud platforms, and store outputs to enable reproducibility. (vi) Compute indices & confidence intervals: Apply bootstrap or jackknife resampling to obtain uncertainty estimates for S_i and S_{T_i} [101]. (vii): Interpret results: Rank parameters by total-order indices; inputs with $S_{T_i} \ll 0.05$ can often be fixed at nominal values. When $S_{T_i} - S_i$ is large, this indicates strong interaction effects requiring further investigation [100].

Sobol analysis offers a rigorous, model-agnostic lens for unravelling complex, non-linear parameter influences in agent-based simulations. When integrated early in the modelling cycle, it sharpens calibration efforts, informs data-collection priorities, and ultimately strengthens the credibility of policy insights drawn from ABMs [68].

2.3.3 Agent-based models of decentralized decision-making

Agent-Based Models (ABMs) have been applied across different domains due to their ability to simulate decentralized decision-making, heterogeneity, and complex interactions among autonomous agents. In epidemiology, ABMs have modelled the transmission dynamics of infectious diseases by simulating individual movements and contact networks [34].

In economics and finance, ABMs are used to model market dynamics emerging from the behaviour of interacting agents such as consumers, firms, and investors. These models enable researchers to investigate how heterogeneity in preferences, learning mechanisms, and bounded rationality affects market outcomes. For instance, ABMs have provided insights into the formation of asset price bubbles, volatility clustering, and the role of institutional structures in systemic risk [111]. They also enable the analysis of policy impacts under non-equilibrium conditions, such as the effects of monetary policy, tax reforms, or financial regulations in adaptive, evolving economic systems. Importantly, ABMs can capture micro-level shocks propagating through interdependent sectors, making them valuable tools in macro-financial stability assessments and crisis forecasting [19, 32].

In urban studies and planning, ABMs have proven effective in modelling spatially distributed populations and their interactions with the built environment. They have been

used to simulate residential segregation dynamics based on income or ethnicity, and household mobility in response to local amenities and perceived environmental risks [52, 36]. They also support analysis of the emergence of land-use patterns under zoning regulations, economic incentives, and environmental change, often incorporating realistic land market mechanisms and heterogeneous agent behaviours [86, 85, 49]. Transportation behaviour has also been extensively modelled, where agents make daily commuting decisions based on time, cost, or congestion levels, facilitating assessments of infrastructure investments or traffic policies. Moreover, ABMs have been used to understand the co-evolution of housing markets and neighbourhood composition, especially under scenarios of climate risk or gentrification [9].

ABMs have also gained attention in domains related to environmental sustainability, infrastructure resilience, and disaster risk mitigation. For example, agent-based frameworks have been used to model the adoption of energy-efficient technologies, where household decisions depend on economic incentives, peer influence, and behavioural biases [92]. Similarly, in the context of electric vehicle diffusion, ABMs help capture the interplay between infrastructure availability, consumer preference heterogeneity, and social networks [118].

In the field of disaster risk mitigation, ABMs are effective for simulating how individuals or organizations make protective decisions in response to policy incentives, social influence, and perceived hazard. Haer et al. [47] developed an agent-based flood damage model that integrates adaptation behaviours such as property-level flood protection measures and insurance uptake, revealing how individual choices under uncertainty influence community-level flood resilience outcomes. Similarly, Husby and Koks [57] argue that traditional macroeconomic disaster models (e.g., Computable General Equilibrium or Input-Output) often fail to capture behavioural responses such as household migration. They advocate for coupling ABMs with macroeconomic frameworks to incorporate adaptive responses to flood risk and analyze their implications for housing and labour markets. In the context of seismic risk, agent-based models have been employed to evaluate household retrofit decisions in response to government policies in Iran. For example, the model developed by Kashani et al. [62] simulates how homeowners decide whether to undertake seismic retrofitting based on individual’s understanding of earthquake risk and benefits of retrofitting, social influence, and financial constraints, allowing policymakers to test the effectiveness of retrofit promotion policies such as subsidies and education campaigns.

In broader terms, ABMs provide a platform for investigating adaptive capacity under climatic and disaster-related risks, where outcomes emerge from agent learning, memory, and network effects. For instance, Husby [58] models flood risk perception, housing decisions, and migration patterns at the micro level and scales them to estimate economy-wide

impacts, revealing feedback loops between behavioural adjustments and regional economic outcomes. These applications collectively demonstrate the flexibility of ABMs in representing dynamic and decentralized processes in hazard-prone systems. Whether modelling the individual-level decisions to retrofit buildings or simulating market-level responses to risk communication and insurance policies, ABMs serve as tools for exploring complex, uncertain, and spatially heterogeneous problems in environmental and infrastructure policy.

Chapter 3

Methodology: Agent-based model for retrofit decision making

As discussed in the literature review chapter, the adoption of seismic risk mitigation is a complex process influenced by multiple intertwined factors. This thesis develops an agent-based model to investigate the impact of potential policy interventions to encourage homeowners to adopt seismic retrofit measures. Agent-based models simulate complex processes as a product of multiple interactions between heterogeneous agents. These agents have attributes that define their characteristics and behaviours and determine how they interact with each other. Agents exist in an environment which can impose pressure or constrain the agents' actions. In this model, households are the primary agents; their attributes represent their demographics, and the main behaviour modelled is their attitude toward seismic retrofit (e.g., adopt or not adopt). The environmental pressures represent policies deployed by local authorities that facilitate the adoption of seismic retrofit measures. These retrofit promotion policies may include running educational campaigns to enhance knowledge about earthquake risks and consequences, creating value for seismic retrofitting, improving people's perceptions of seismic retrofit efficacy, or providing financial incentives to encourage homeowners to retrofit their dwellings. A scenario-based approach is employed to investigate how implementing seismic retrofit promotion policies would compare to a baseline scenario in terms of the total number of agents adopting seismic retrofit measures and the corresponding reduction in total annual losses to residential dwellings. In the following subsections, the decision-making process for seismic retrofitting, attributes of Homeowner Agents, the influence mechanisms of government policy interventions, and the dynamic interactions among agents are discussed. [Figure 3.1](#) illustrates the steps involved in evaluating the agent-based model.

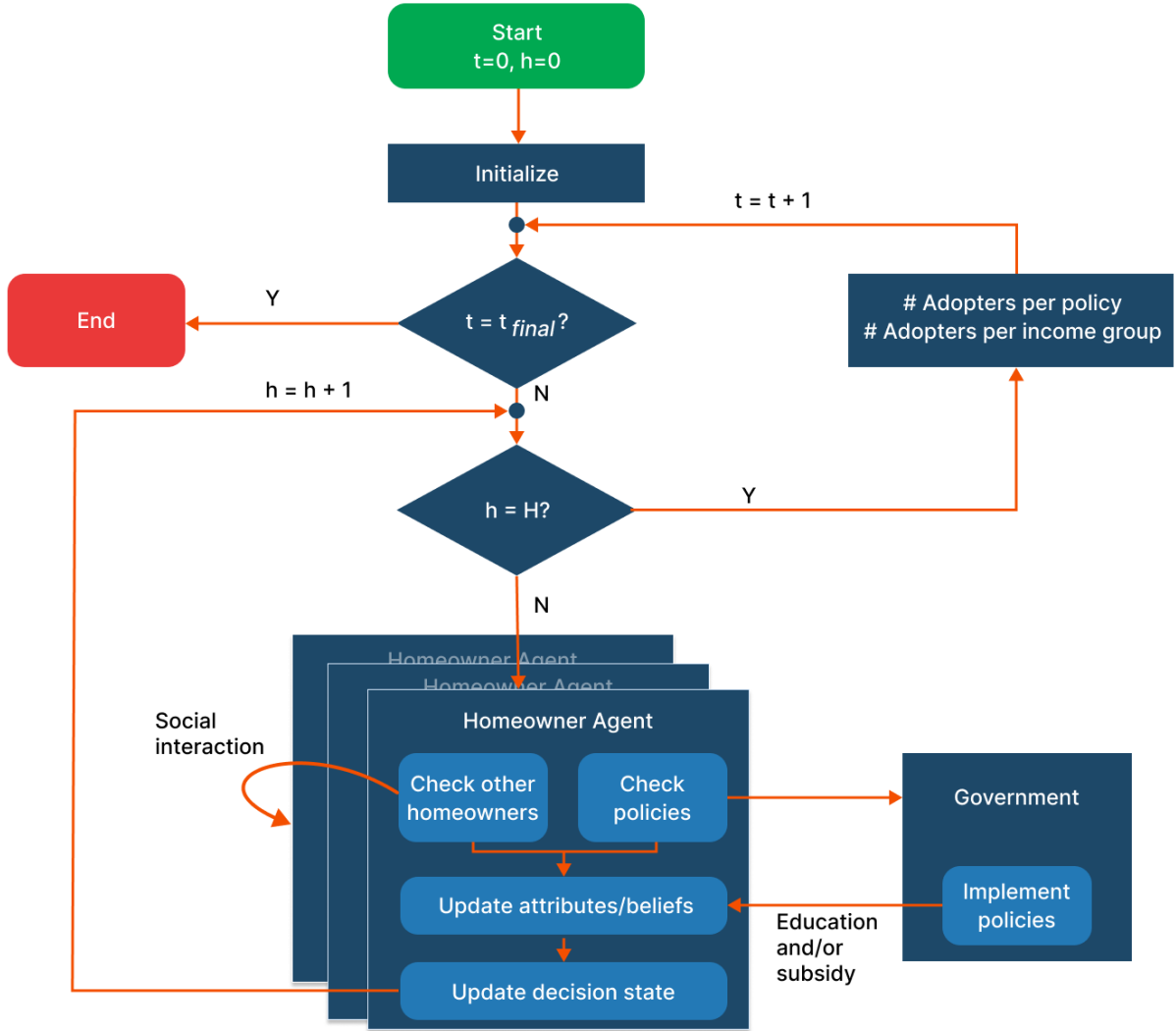


Figure 3.1: Agent-based simulation model flowchart (H = number of homeowners, t_{final} = last time step)

3.1 Homeowner agent's decision state

Each Homeowner Agent follows a decision-making process influenced by their attributes and external motivators. Depending on the final levels of these attributes, each agent

falls into one of four possible states: (i) *Not Intended*, (ii) *Intended*, (iii) *Decided*, or (iv) *Adopter*. Agents in *Not Intended* state are not willing to consider the seismic retrofit measures due to low-risk perception. These agents do not recognize earthquakes as a serious threat to their lives and property. *Intended* agents have a sufficiently high-risk perception but choose not to retrofit due to low perceived benefit and seismic adjustment efficacy attributes. While they understand earthquake risks and potential consequences, they do not believe that seismic retrofitting effectively protects life and property or provides tangible benefits. Agents in *Decided* state have sufficiently high levels of risk perception to understand the earthquake threat and a high level of either perceived benefit or seismic adjustment efficacy. However, the lack of financial resources prevents them from adopting seismic retrofitting. Finally, *Adopter* agents have an adequate understanding of seismic risk, recognize its effectiveness and benefits, and possess sufficient financial resources to implement the retrofit measures. An overview of the decision process for a Homeowner Agent is presented in Figure 3.2, which explains the details of the steps inside the Homeowner Agent box in Figure 3.1.

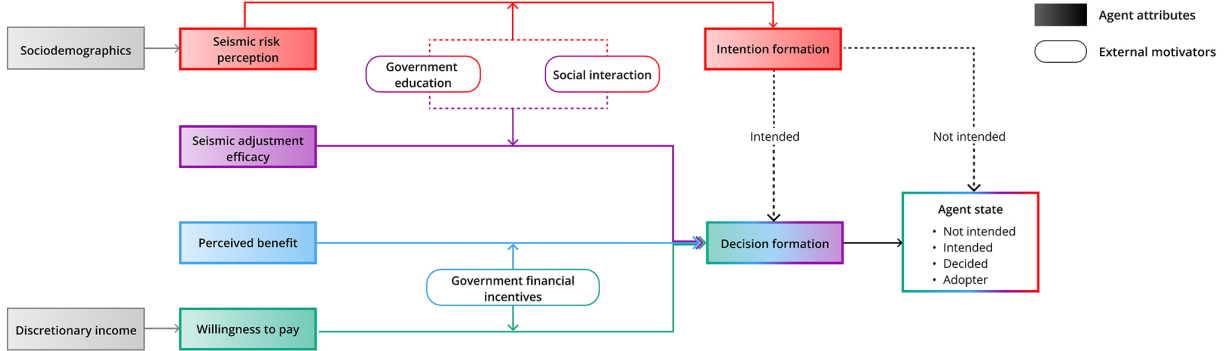


Figure 3.2: Workflow of seismic retrofit decision process for Homeowner Agents.

3.2 Agent's attributes

The attributes defined for Homeowner Agents include (i) seismic risk perception, which is the driving factor in the intention formation phase, (ii) perceived benefit, (iii) seismic adjustment efficacy, and (iv) willingness to pay, which are the governing factors in the decision formation phase. The modelling and initiation of each attribute for agents are explained in this section.

3.2.1 Seismic risk perception model

Seismic risk perception is an indicator of community awareness and preparedness. Fischhoff et al. [38] and Slovic [104] introduced the psychometric paradigm in risk perception research, which uses survey questionnaires to quantify individuals' risk perception. In the questionnaires, respondents rate various aspects of risk, including characteristics such as severity and long-term consequences, their ability to manage the risk (e.g., controllability, knowledge), emotional responses (e.g., dread), and their trust in risk management strategies. These quantitative measures enable comparisons across different types of risks (e.g., natural versus technological hazards), societal groups (e.g., ethnic demographics), and countries [63].

Numerous studies have investigated the impact of socioeconomic factors on risk perception. According to these studies, the key determinants of risk perception include age, gender, education, employment status, income levels, household structure and building quality (e.g., construction period, land ownership patterns) [72, 5, 69, 65, 35, 91, 71, 119, 78]. Other influential factors include previous disaster experience, trust in authorities, financial savings, insurance coverage, risk knowledge and information, and cultural values and world-views [83]. To simulate the risk perception of the Homeowner Agents, the survey-based model developed by Niforatos et al. [83] is adopted. This regression model, derived from survey data collected in a seismically active region of central-west Greece, estimates the initial seismic risk perception (SRP_0) as a function of age, gender, education level, household structure, income, savings, earthquake insurance status, and building construction period, as follows:

$$\begin{aligned} SRP_0 = & [\beta_{\text{age}} \times \text{Age (years)}] + \beta_{\text{gender}} + \beta_{\text{education}} + \beta_{\text{household}} \\ & + \beta_{\text{income}} + \beta_{\text{savings}} + \beta_{\text{insurance}} + \beta_{\text{year built}} \end{aligned} \quad (3.1)$$

The coefficients of the regression model are presented in Table 3.1. Each β coefficient represents the estimated influence of a specific variable (e.g., age, gender, income, etc.) on the overall seismic risk perception score. Positive β coefficients indicate that the corresponding variable increases the seismic risk perception score. Negative β coefficients indicate that the variable reduces the seismic risk perception score. For example, men have a $\beta_{\text{gender}} = -0.88$, suggesting that they have a lower seismic risk perception than women (the reference category with $\beta = 0$). The overall seismic risk perception is computed by summing the contributions from all included variables. The seismic risk perception coefficient in Eq. 3.1 is a number between -1 and 1. Homeowner Agents are assigned a risk

perception coefficient at the beginning of each simulation. The initial value can be dynamically updated as agents interact with each other or are influenced by environmental pressures (e.g., an educational campaign).

3.2.2 Perceived benefit

Perceived benefit is a key determinant of homeowners' decisions to pursue seismic retrofits. Homeowners may not proceed with retrofit measures if they do not understand the tangible benefits of seismic retrofitting. The perceived benefit of Homeowner Agents is set to zero in the baseline scenario, and it responds to external motivators. Homeowner Agents consider the subsidies as a partial return on their investment (retrofit cost), and therefore, the financial incentives enhance homeowners' perceived benefit. To model the increase in perceived benefit, it is assumed that if a policy provides 40% partial coverage of retrofit cost, the Homeowner Agent's perceived benefit increases from 0 to 1 with a probability of 0.4. This modelling assumption reflects survey results conducted by Egbelakin et al. [29] where 92% of owners stated that they are likely to adopt retrofit measures if the initial cost of implementation could be recovered.

3.2.3 Seismic adjustment efficacy

Seismic adjustment efficacy refers to the extent to which people estimate the adequacy of seismic adjustment measures to ensure protection against earthquake impacts and has been shown to influence an individual's decision to adopt mitigation measures [80]. Here, the seismic adjustment efficacy attribute is assigned a value between -1 to 1. A value less than -0.5 represents Homeowner Agents who do not believe in the effectiveness of retrofits in protecting lives and properties. A value larger than 0.5 indicates an agent with a strong positive opinion regarding in effectiveness of retrofits. Similar to seismic risk perception, the Homeowner Agent's seismic adjustment efficacy attribute values are subjected to change when exposed to government education campaigns or social interaction with other agents. The seismic adjustment efficacy attribute for agents is estimated using the results of a survey conducted in Seattle, USA [2], as shown in Table 3.2.

Table 3.1: Coefficients of the seismic risk perception regression model [83]

Demographics	Coefficients
Age	$\beta_{\text{age}} = 0.02$
Gender	$\beta_{\text{gender}} = \begin{cases} 0, & \text{Women} \\ -0.88, & \text{Men} \end{cases}$
Education level	$\beta_{\text{education}} = \begin{cases} 0, & \text{None, primary} \\ 1.84, & \text{Secondary , Technical} \\ 1.55, & \text{University} \end{cases}$
Household structure	$\beta_{\text{household}} = \begin{cases} 0, & \text{Single person} \\ 1.15, & \text{Single parent} \\ -0.006, & \text{Couple/family without children} \\ 0.38, & \text{With children} \end{cases}$
Income (CAD)	$\beta_{\text{income}} = \begin{cases} 0, & \text{income} < 60000 \\ -1.05, & 60000 < \text{income} < 120000 \\ 0.28, & 120000 < \text{income} < 240000 \\ -1.18, & \text{income} > 240000 \end{cases}$
Savings	$\beta_{\text{savings}} = \begin{cases} 0, & \text{Not at all} \\ -0.04, & \text{Slightly} \\ -0.45, & \text{Somewhat} \\ -0.42, & \text{Moderate} \\ 0.54, & \text{Extremely} \end{cases}$
Insurance status	$\beta_{\text{insurance}} = \begin{cases} 0, & \text{Non-insured} \\ 0.36, & \text{Insured} \end{cases}$
Building construction period	$\beta_{\text{year built}} = \begin{cases} 0, & \text{year built} \leq 1960 \\ -0.15, & 1961 \leq \text{year built} \leq 1985 \\ -0.96, & 1986 \leq \text{year built} \leq 1995 \\ -1.10, & 1996 \leq \text{year built} \leq 2000 \\ -1.59, & \text{year built} > 2000 \end{cases}$

Table 3.2: Distribution of the seismic adjustment efficacy [2]

Survey responses	Attribute value	probability (%)
Not at all effective	[-1 , -0.6]	0.6
Slightly effective	[-0.6 , -0.2]	3.3
Somewhat effective	[-0.2 , 0.2]	42
Very effective	[0.2 , 0.6]	51.4
Completely effective	[0.6 , 1]	2.7

3.2.4 Willingness to pay

Willingness to pay (WTP) for retrofitting is one of the key factors influencing the decision to adopt retrofit measures. Willingness to pay is modelled as a function of the household's discretionary income (DI), government subsidies (S), potential insurance premium discounts (IPD) from retrofitting, and retrofit costs (C_r). In this study, DI is a function of the presence of a mortgage, and $IPD = 0$ because insurance companies in Vancouver do not apply general discounts due to retrofits. The willingness to pay attribute takes values between 0 to 1 and is defined as

$$WTP = \begin{cases} \min\left(\frac{DI+S+IPD}{C_r}, 1\right), & \text{presence of mortgage} \\ 1, & \text{otherwise} \end{cases} \quad (3.2)$$

3.3 Policy interventions

In this study, the local government implements retrofit promotion policies to convince homeowners to retrofit their dwellings. These policies act as environmental forces on the Homeowner Agents. These policy interventions target specific Homeowner Agents to expedite intention and decision formation phases, affecting their seismic risk perception, seismic adjustment efficacy, perceived benefit, and willingness to pay. Two types of policy interventions are considered: educational measures and financial incentives.

3.3.1 Government education program

Government-led public education campaigns vary in frequency and reach, influenced by objectives, target demographics, and available resources [54].

In this study, the educational measures are designed over a 5-year time frame with a biannual frequency and a probability of exposure of 0.5, such that each agent is expected to be exposed to an educational campaign once per year. When exposed to these measures, the risk perception and seismic adjustment efficacy of Homeowner Agents increase at a rate referred to as the policy impact factor $\mu_{education}$. The educational measures are assumed to be less influential on individuals with extreme opinions (those with lower uncertainties). This aligns with the relative agreement model assumptions that people with strong opinions have lower uncertainty about their opinions and are less likely to be influenced by other agents or government policies [24, 77].

Additionally, it is assumed that each subsequent exposure to educational campaigns has a diminishing effect on the increase in households' risk perception and seismic adjustment efficacy. This reflects that the novelty of the information decreases with repeated exposure. With this, the increase in risk perception and seismic adjustment efficacy is estimated as

$$\text{attribute increase} = \mu_{education} \times \text{agent uncertainty} \times \log(10 - 2 \times \text{education counter}) \quad (3.3)$$

Where $\mu_{education}$ is the government education impact factor, assumed to be equal to 0.1. This function uses the log function to model the effect of diminishing returns from subsequent exposures. The education counter tracks the number of times an agent has been exposed to the government's educational program. The Homeowner Agent's uncertainty accounts for decreased influence on people with extreme opinions.

3.3.2 Government financial incentives

Financial assistance, modelled after the Earthquake Brace and Bolt (EBB) retrofit in California [17], is also simulated as an external motivator. Financial assistance adds to the household's discretionary income, increasing the Homeowner Agent's willingness to pay. Also, the agent's perceived benefit of the retrofit program is set to increase proportionally to the subsidy amount. For example, if a homeowner's perceived benefit attribute is zero and they receive subsidies equal to 40% of the retrofit cost, their perceived benefit increases to 1 with a probability of 0.4. With this added incentive, the household decides whether to adopt the retrofit measures.

One of the challenges that local governments may face is that a portion of the population holding a negative attitude regarding retrofitting may not consider spending the

budget on promoting seismic retrofitting and the fair use of public resources. To incorporate this into the simulation model, a grievance function is defined such that if a policy involves substantial government subsidies, the opinion of agents who are not in favour of the retrofitting becomes more negative, proportional to the scale of government investment in the program. This group of agents may influence the opinions of other owners during social interactions within their network. In this case, a Homeowner Agent who was initially intended to retrofit their home might change their opinion about adopting retrofit measures. The grievance function acts as the opposite of the education measures, creating a negative wave proportional to the government’s budget expenditure and propagating it among agents through social interactions.

3.4 Agent’s interactions

In this study, the relative agreement model [24, 22, 23, 77] is employed to characterize the change in Homeowner Agents’ opinions regarding seismic retrofits resulting from social interaction with other agents. The choice of the similarity-biased model class is consistent with the existing literature that considered the impact of social interaction among agents in different areas, such as seismic [62] and flood risk mitigation [55, 56, 46], and energy technology adoption [95, 92]. The Homeowner Agent’s attributes, influenced by the social interaction, are seismic risk perception and seismic adjustment efficacy. Consider a population comprised of n agents, and we want to explain the interaction between two agents i and j . Say x_i is the opinion of agent i concerning aspects of the seismic retrofitting adoption process x , e.g., risk perception. The underlying assumption in the relative agreement model is that people have some level of uncertainty in their opinions [24, 77]. Homeowner i ’s uncertainty regarding their risk perception, x , is denoted by U_{x_i} . The combination of opinion and the corresponding uncertainty creates a range $(x_i - U_{x_i}, x_i + U_{x_i})$ in which the agent can change their opinion. This is known as the bound of confidence (BC). According to the relative agreement model, individuals can be influenced by others who share similar opinions. Thus, individuals cannot be influenced by others outside their BC. The mathematical representation of the interaction mechanism, including the extent of influence and the resulting opinion and uncertainty, follows the work of [24]. Figure 3.3 presents the BC of attribute x for individuals i and j . Agent i opinion about earthquake risk initially falls within the range $(x_i - U_{x_i}, x_i + U_{x_i})$. To determine how close (large overlap) or far (small or no overlap) in opinion the individuals are, we estimate the overlap of opinions as

$$O_{ij} = \min((x_i + U_{x_i}), (x_j + U_{x_j})) - \max((x_i - U_{x_i}), (x_j - U_{x_j})) \quad (3.4)$$

where O_{ij} is the overlap between attribute x of individuals i and j ; x_i , U_{x_i} , x_j , and U_{x_j} are the attribute x and the corresponding uncertainty level of individuals i and j , respectively. If the overlap is greater than the uncertainty level of individual i (i.e., $O_{ij} > U_{x_i}$), individual i can influence individuals j . At any time step, the modified value of attribute x and of individual j is

$$x_j(t + \Delta t) = x_j(t) + \mu \cdot \left(\frac{O_{ij}}{U_{x_i}} - 1 \right) \cdot (x_i(t) - x_j(t)) \quad (3.5)$$

and their uncertainty level as

$$U_{x_j}(t + \Delta t) = U_{x_j}(t) + \mu \cdot \left(\frac{O_{ij}}{U_{x_i}} - 1 \right) \cdot (U_{x_i}(t) - U_{x_j}(t)) \quad (3.6)$$

Where $x_j(t + \Delta t)$ and $U_{x_j}(t + \Delta t)$ are modified values of x and uncertainty level U_x of individual j after interaction with individual i ; and μ is a parameter that characterizes the extent of communication influence among individuals and controls the convergence speed of opinions. μ is assumed to equal 0.38 as prescribed by [92].

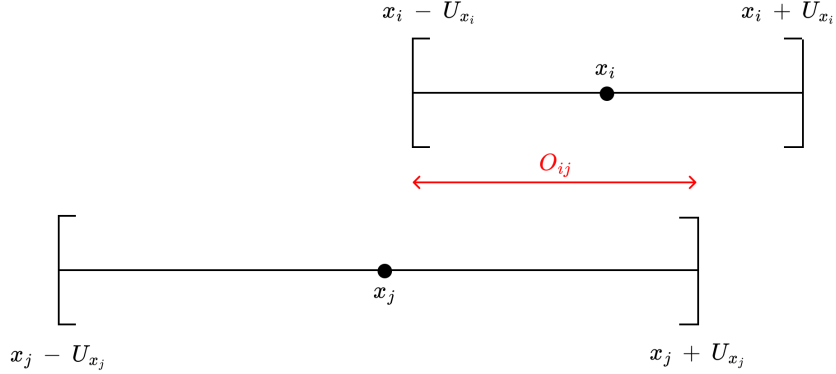


Figure 3.3: Interaction mechanism between agents i and j with attribute x (adapted from [24])

The relative agreement model accounts for the asymmetric influence of individuals with lower uncertainty about their beliefs [24, 22, 77]. These agents, due to their higher confidence, are more persuasive and capable of influencing others' opinions. Risk perception and seismic adjustment efficacy attributes are subject to change during agents' social interactions. The corresponding uncertainty level for each attribute is assumed to be proportional

to the inverse of the absolute attribute value [24, 77]. For the social interaction model, the opinion of an individual is between -1 and 1, where -1 and 1 represent agents with extreme negative and positive opinions, and its uncertainty is between 0.0 and 2.0 [77]. At each time step, each agent interacts with a network of connections. Each network is assumed to consist of 10% local connections, which are located within the same neighbourhood, and 90% non-local connections, which may be located anywhere in the city [92]. The probability of interaction among agents in a social network is defined as the probability that agents exchange opinions about seismic risk and the effectiveness of retrofit measures at every time step. The social interaction among agents influences their attributes and beliefs, which may lead to changes in their behaviour or decisions regarding the adoption of seismic retrofitting over time.

Chapter 4

Case Study

The developed agent-based model is applied to a case study of Vancouver, British Columbia, Canada, to evaluate homeowners' response to government-led seismic retrofit promotion policies. The case study is restricted to owner-occupied, detached dwellings built between 1900 to 1972. Dwellings built after 1973 were designed under upgraded seismic regulations in the building code, and dwellings built before 1900 require more advanced seismic retrofitting than common methods [50]. The assumption is that the local government aims to maximize the number of retrofitted dwellings in Vancouver by running educational campaigns and providing subsidies. The effectiveness of the policy interventions is evaluated in the context of the reduction in total annual earthquake-induced losses to residential dwellings in Vancouver. A scenario-based approach examines how various seismic retrofit promotion policies compare to a baseline scenario with no policies in place. An overview of the simulation framework is shown in [Figure 4.1](#). The agents' attributes are estimated using the adopted models from literature and employing Census data for Vancouver detached homeowners. Homeowner Agents may be exposed to government intervention policies, which influence their decision whether to retrofit their dwelling, considering the effect of interacting with other Homeowner Agents within their social network to determine the overall retrofit take-up rate upon implementing each policy. Then, the reduction in total annual losses to residential building structures and contents is estimated to evaluate and compare the effectiveness of the retrofit promotion policies.

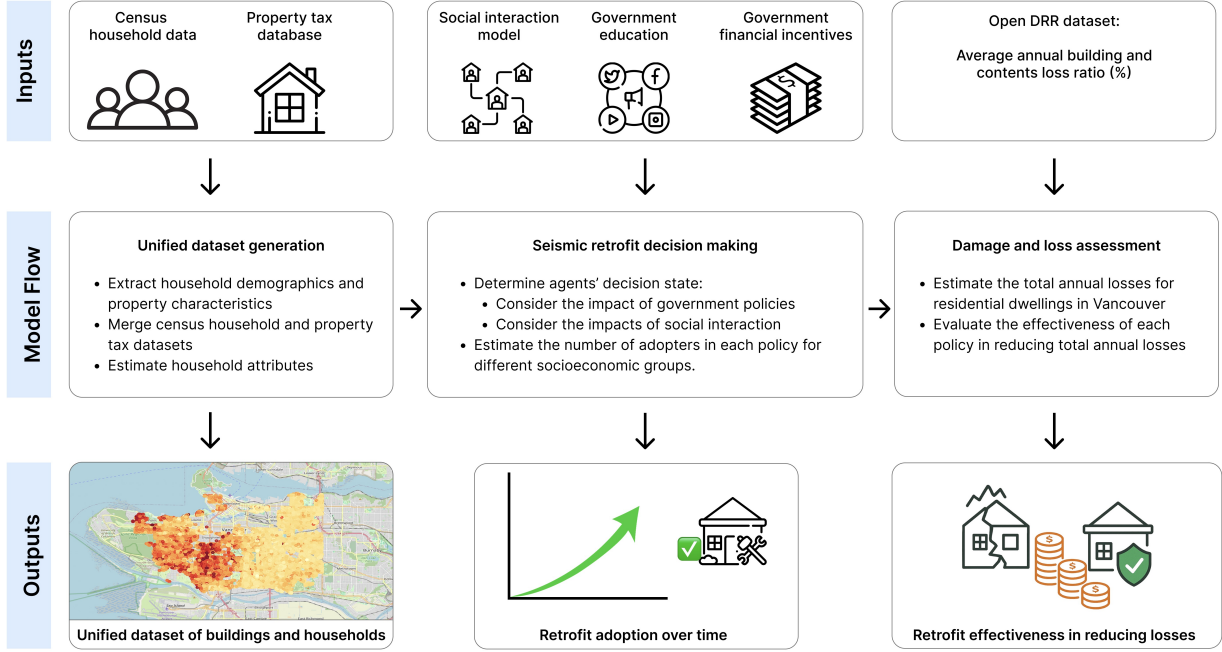


Figure 4.1: Overview of the simulation framework

4.1 Datasets used in the study

This section describes the datasets used in the study, which include the 2021 Census Public Use Microdata (PUMF) [107] and the 2022 City of Vancouver property tax database [20]. The 2021 census PUMFs provide access to non-aggregated socioeconomic demographic data covering a sample of the Canadian population. In this tabular dataset, each row represents the anonymized responses of one household. PUMFs are collected for the Vancouver Census Metropolitan Area (CMA) code, filtering by tenure status and type of dwelling. We collected data on household income, size, and type, as well as age, gender, and the highest level of education of the householder. Household incomes were adjusted from 2021 to 2022 using consumer price indices to match property values from the 2022 property tax database. The median household income of Vancouver detached homeowners in 2022-dollars was CAD \$158,000. Households are separated into three income tiers relative to area median income (AMI): low-income (less than 80% AMI), moderate-income (between 80% and 120% AMI), and high-income (above 120% AMI). The 2022 City of Vancouver property tax database provides information on land value, improvement value,

civic address, and year of construction. The property’s civic addresses are used to geolocate them in Vancouver. [Figure 4.2](#) represents the distribution of single detached homeowner income and property values in Vancouver.

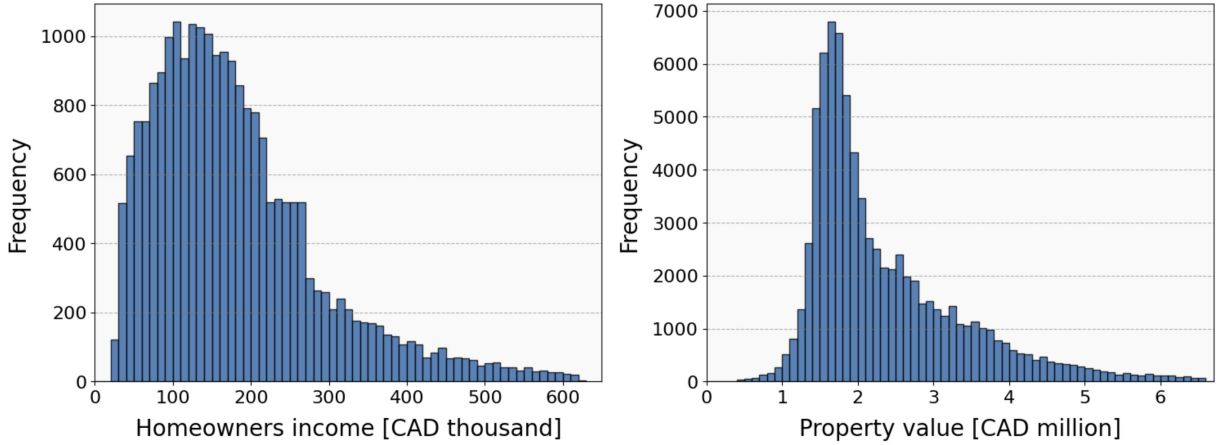


Figure 4.2: Distribution of single detached homeowner income and property values in Vancouver

Ideally, each dwelling in the tax assessor data could be connected to one household in the Census PUMFs. However, the PUMFs represent only a subset of all respondents and do not contain location information. To merge the two databases, it is assumed that a perfect correlation between household income (in the PUMFs) and property values (in the tax assessor data). This method yields a unified dataset with household demographics and property characteristics. In this method, once a property value is matched with an income, the corresponding household, along with its full demographic profile, will be assigned to that property. Although the perfect correlation assumption between property value and household income is not ideal, it allows us to preserve the correlation between household demographics (i.e., income, age, gender, household type and size, and education level). The distributions of household demographics further illustrate this before and after merging with the property tax database. [Figures 4.4–4.6](#) illustrate the distributions of household size, household type, and highest education degree variables before and after merging with the property tax database. The description of possible values for household type and highest education degree variables is presented in [Table 4.1](#) and [Table 4.2](#). [Figure 4.3](#) demonstrates the detached dwellings in the City of Vancouver along with the distribution of households’ income, where each dot on the map represents a property and

the corresponding household assigned to it.

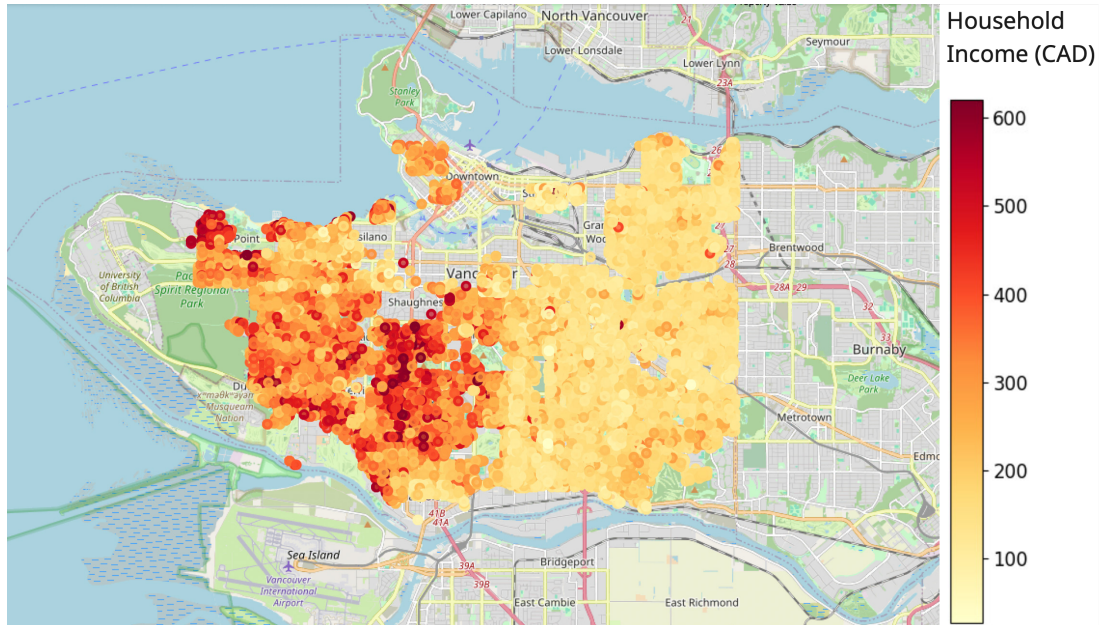


Figure 4.3: Detached dwellings in the City of Vancouver along with the distribution of households' income.

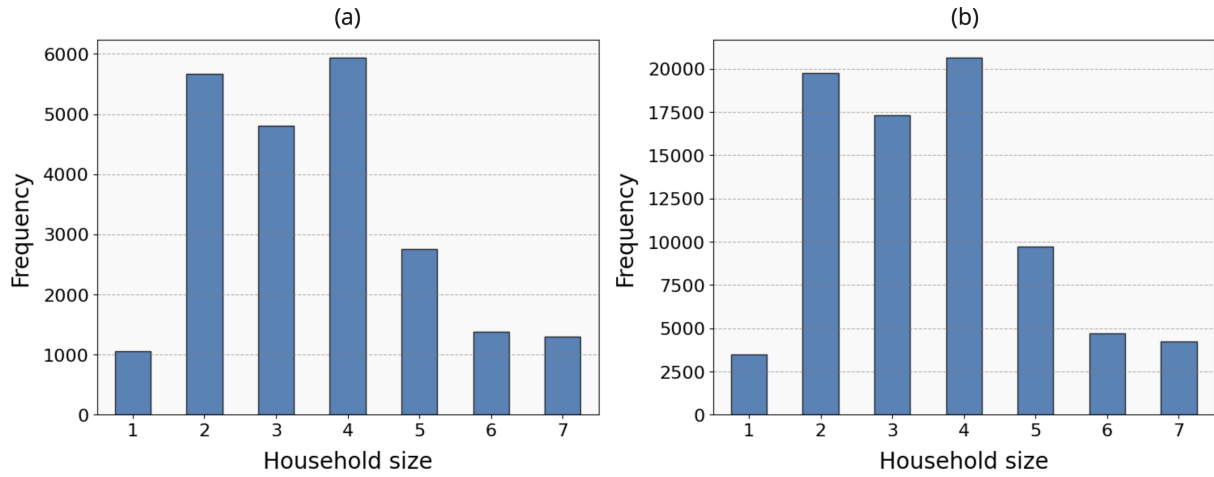


Figure 4.4: Distributions of household size before and after merging with the property tax database; (a) Household size distribution in Census PUMF (b) Household size distribution after merging with the property tax database

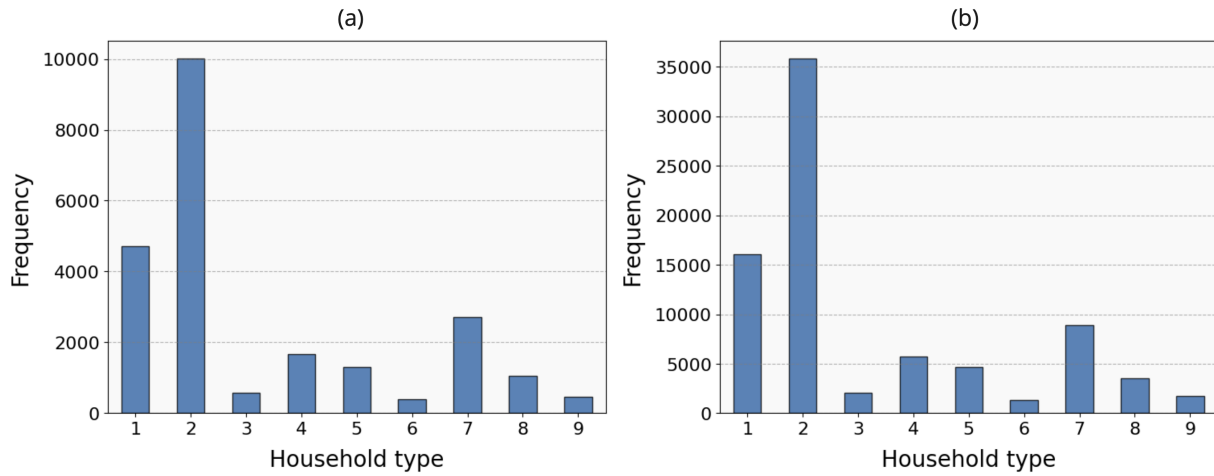


Figure 4.5: Distributions of household type before and after merging with the property tax database; (a) Household type distribution in Census PUMF (b) Household type distribution after merging with the property tax database

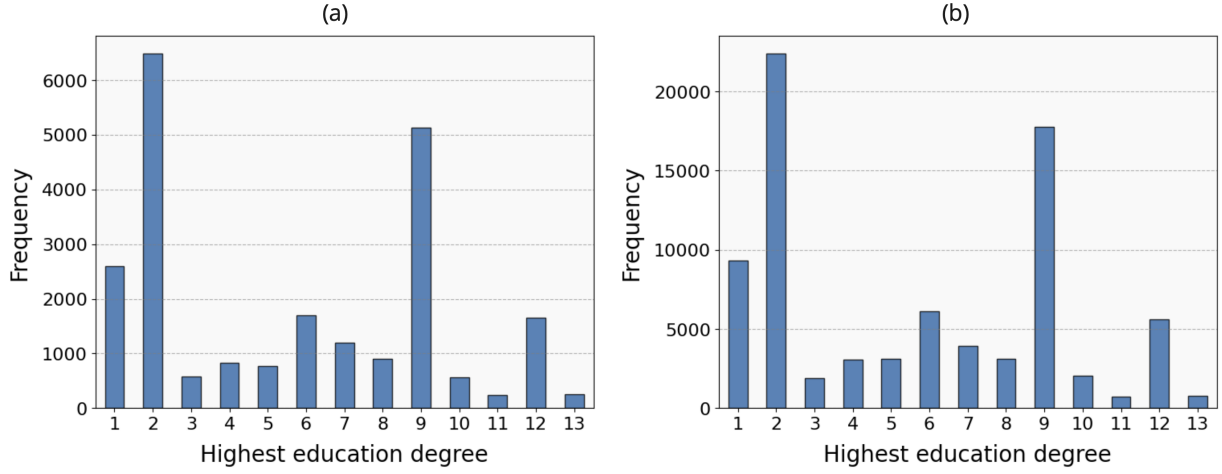


Figure 4.6: Distributions of highest education degree before and after merging with the property tax database; (a) Highest degree distribution in Census PUMF (b) Highest degree distribution after merging with the property tax database

Table 4.1: Household type

Code	Description
1	One-census-family household without additional persons: Couple without children
2	One-census-family household without additional persons: Couple with children
3	One-census-family household with additional persons: Couple without children
4	One-census-family household with additional persons: Couple with children
5	One-census-family household without additional persons: one parent family
6	One-census-family household with additional persons: one-parent family
7	Multiple-census-family household
8	Non-census-family household: one person household
9	Non-census-family household: two or-more-person non-census-family household

The discretionary income, $D(I)$, for Vancouver homeowners is calculated using the distributions of household economic accounts, income, consumption and saving data from Statistics Canada [108] as

Table 4.2: Highest education degree

Code	Description
1	No certificate, diploma or degree
2	High (secondary) school diploma or equivalency certificate
3	Non-apprenticeship trades certificate or diploma
4	Apprenticeship certificate
5	Program of 3 months to less than 1 year (College and other non-university diplomas)
6	Program of 1 to 2 years (College and other non-university diplomas)
7	Program of more than 2 years (College and other non-university diplomas)
8	University certificate or diploma below bachelor level
9	Bachelor's degree
10	University certificate or diploma above bachelor level
11	Degree in medicine, dentistry, veterinary medicine or optometry
12	Master's degree
13	Earned doctorate

$$D(I) = \begin{cases} 0, & \text{if } I < 145,000, \\ \left(\frac{0.095}{30,000} \cdot (I - 145,000) \right) \cdot I, & \text{if } 145,000 \leq I < 175,000, \\ \left(0.095 + \frac{0.09}{155,000} \cdot (I - 175,000) \right) \cdot I, & \text{if } 175,000 \leq I < 330,000, \\ 0.185 \cdot I, & \text{if } I \geq 330,000, \end{cases} \quad (4.1)$$

where I is the household income in Canadian dollars. The willingness to pay is estimated using discretionary income and the amount of government contribution in covering the retrofit cost in each policy using Eq. 3.2. The seismic risk perception of Vancouver homeowners is calculated using Eq. 3.1 and is shown in Figure 4.7. The initial perceived benefit is set to zero but is subject to change upon receiving financial incentives. The seismic adjustment efficacy attribute is calculated using the multinomial distribution in Table 3.2.

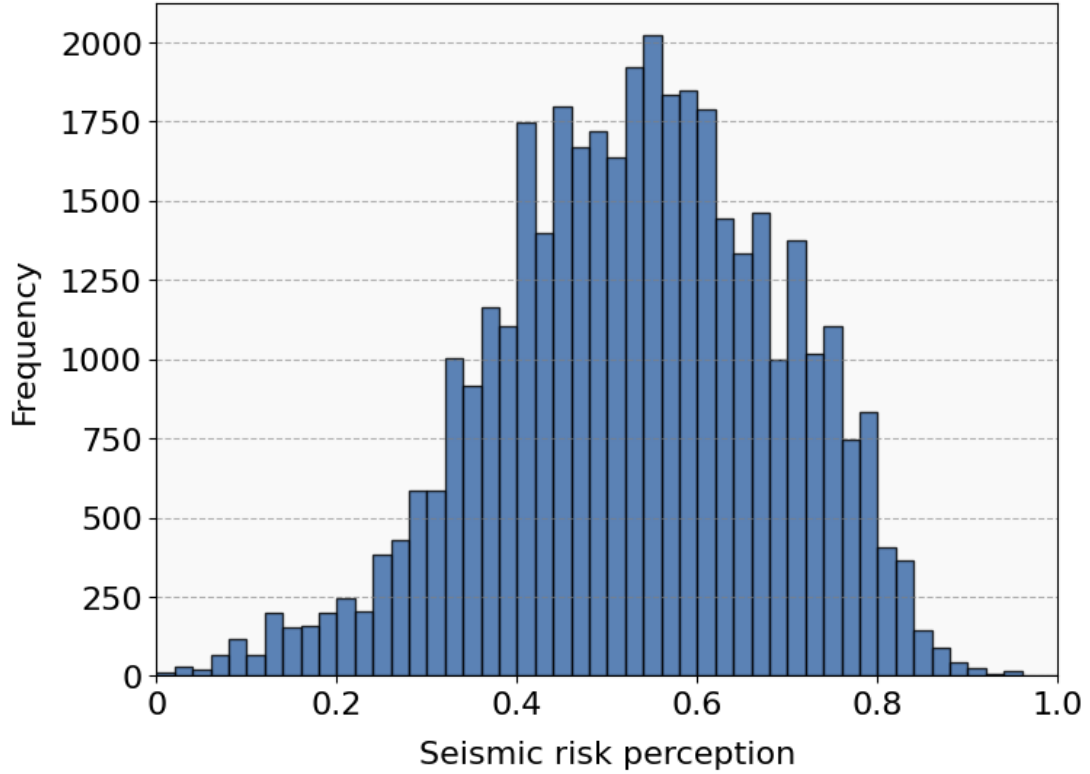


Figure 4.7: Distribution of seismic risk perception of Vancouver detached homeowners.

4.2 Policies

The summary of the policy intervention parameters considered in this study is provided in [Table 4.3](#). Policy 0 serves as a baseline case for comparison. Similarly, Policies 1 and 2 were selected to observe the results of the educational campaign and financial incentive programs separately. The EBB initiative inspired the cost coverage ratios in Policy 2 in California, where 40% of the retrofit cost is covered for moderate and high-income households and 80% for low-income households [\[16\]](#). Policy 3 examines the effects of joint educational measures and financial support for low-income homeowners (100% retrofit cost coverage) on maximizing the retrofit take-up at a lower cost.

Table 4.3: Parameters across the different policies

Policy	Educational Program	Financial Incentive
		Low-moderate-high income
Policy 0	No	None
Policy 1	Yes	None
Policy 2	No	80%-40%-40%
Policy 3	Yes	100%-0%-0%

4.3 Results

This section presents the results of the agent-based simulation model across each policy. A sensitivity analysis is presented in Figures 4.12–4.13 to assess which variables contribute more heavily to the observed simulation results.

4.3.1 Effectiveness of Educational Campaigns and Social Interactions on Risk Perception

The agent’s attributes can be monitored over different time steps in each realization. Figure 4.8 provides context for the model by illustrating how the risk perception of two Homeowner Agents changes within a single realization. Figure 4.8-a shows an agent’s initial low risk perception. Policies 1 and 3, which include an educational component, substantially improve risk perception. Figure 4.8-b shows an agent with an initial risk perception of 0.47, who has a relatively high risk perception but has uncertainty about it. This uncertainty is reflected in fluctuations in risk perception. In policies 0 and 2, the agent’s risk perception reaches a value close to 0.2, while in policies 1 and 3 it maximizes at 1 after 32 months. The reason why risk perception stabilizes at 0.2 for both agents lies in the principles of the relative agreement model, which stipulates during social interaction, agents influence each other toward reducing the differences in their opinions, eventually leading to the formation of multiple clusters of opinions in the entire population (in this case 0.2 is one of the opinion clusters). A similar pattern exists regarding the influence of educational campaigns on the seismic adjustment efficacy attribute of Homeowner Agents.

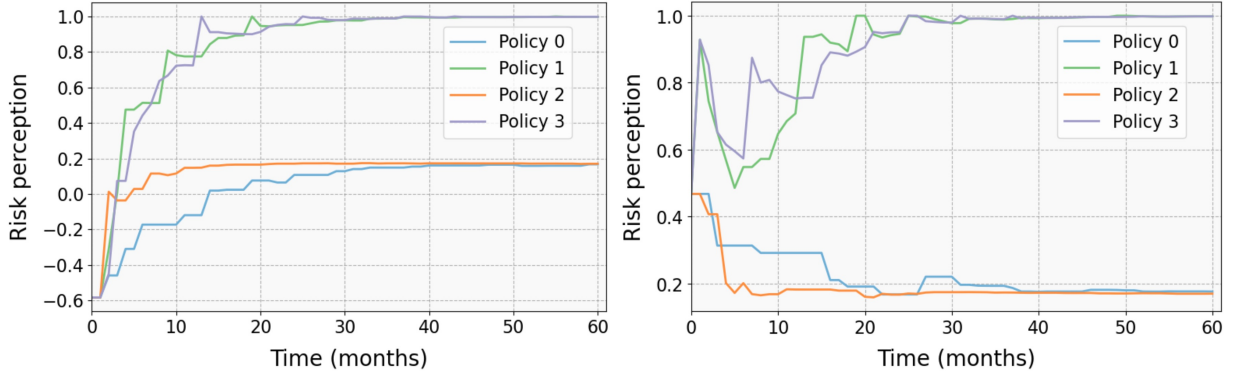


Figure 4.8: Agent’s risk perception over time across all policies; (a) agent with an initial risk perception of -0.59 (b) agent with an initial risk perception of 0.47.

4.3.2 Effectiveness of Educational Campaigns and Financial Incentives on Retrofit Adoption

Figure 4.9 presents the total number of agents in the adopter state across different policies. In policy 0, the number of adopters reaches 8,863 (approximately 23% of the population), which aligns with the findings of [62], showing a similar proportion of agents in the adopter state within the baseline policy within a 5-year time frame. Local governments are often required to update their hazard mitigation plans every five years to remain eligible for certain federal assistance programs [33]. In policy 2, where subsidies are introduced, the total number of adopters increases to 14,936 (39% of the population). The effect of the grievance function when implementing policy 2 is shown with a dashed line. The number of adopters in this case reached 13,000 after 10 months and then reduced to 10,500 after 60 months. This is explained by the negative impact of government investment on the attitude of Homeowner Agents, who are already opposed to the retrofit policy. These agents then influence other agents’ opinions over time, discouraging them from adopting retrofit measures. Policy 1, which involved an education campaign, resulted in a total of 27,679 adopters (72% of the population), while policy 3, which combined education and subsidies, led to the highest overall number of adopters, at 32,887 (86% of the population).

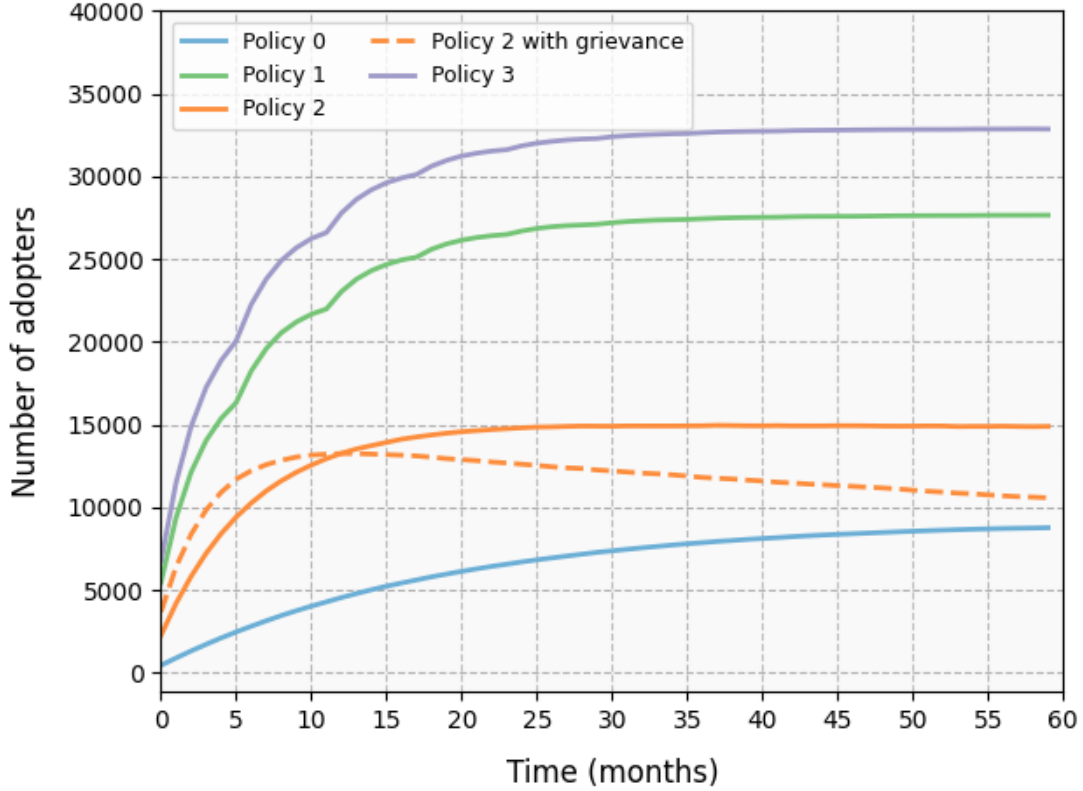


Figure 4.9: Number of agents in adopter state across different policies.

Table 4.4 presents the number of agents in each decision state per policy. In policy 0, where the government does not implement any retrofit promotion or incentive policy, 77% of the population are in *Not Intended*, *Intended*, and *Decided* states and do not adopt the retrofit measures. These results align with the findings of [120] and [29], which state that without government intervention, most homeowners are reluctant to adopt retrofit measures, even though they are aware of their region’s susceptibility to seismic risk. In policy 1, 27.6% and 72.2% are in *Decided* and *Adopter* states, respectively. Government education programs resulted in enhancing seismic risk perception and seismic adjustment efficacy attributes of agents, leading to almost zero percent in *Not Intended* and *Intended* states. The 27.6% in *Decided* state are aware of the seismic risk and benefits of retrofitting but are not willing to pay for the retrofit measures. In policy 2, the largest proportion of the population (45.8%) is in the *Not Intended* state, indicating a level of seismic risk perception that is insufficient for these agents. It is worth mentioning that 4.6% of the population

remains unwilling to pay for the retrofit costs, despite substantial budget allocation to provide 40% of the retrofit costs to moderate and high-income groups and 80% to low-income groups. In policy 3, the majority of agents (85.8%) are in *Adopter* state, indicating a sufficient level of seismic risk perception, willingness to pay, and either perceived benefit or seismic adjustment efficacy attributes.

Table 4.4: Portion of agents in each state per policy (%)

Policy	Not Intended	Intended	Decided	Adopter
Policy 0	48.4	19.8	8.7	23.1
Policy 1	0.1	0.1	27.6	72.2
Policy 2	45.8	10.6	4.6	39
Policy 3	0.1	0.1	14	85.8

Figure 4.10 provides more insight into the effects of the retrofit promotion policies on the retrofit take-up rates across different income groups. In the baseline policy, retrofit adoption rates increase with income, indicating disparities among low, moderate, and high-income groups. Policy 2, which offers partial retrofit cost coverage, significantly enhances the adoption among low-income homeowners but has a smaller effect on higher-income groups. Educational campaigns in Policy 1 substantially improve adoption across all groups, suggesting that the bottleneck in achieving high retrofit take-up rates is educating homeowners about the seismic risk and devastating potential consequences of earthquakes, particularly among moderate and high-income groups. Policy 3, combining full-cost coverage for low-income households with education, yields the highest adoption rates across all income groups. Providing the full coverage of retrofit costs for low incomes helps homeowners who are in intended or decided states to become adopters. These agents have sufficiently high seismic risk perception, seismic adjustment efficacy, and/or perceived benefit, and the cost of retrofitting measures is the main barrier to adoption. High-income owners are those whose income exceeds CAD\$240,000. For these homeowners, the discretionary income calculated using Eq. 4.1 exceeds the cost of the retrofit. Consequently, the only barriers for them adopting seismic retrofits are those related to their perception of earthquake risks and retrofit benefits. Therefore, achieving a 100% adoption rate in Policy 3 demonstrates the impact of education on improving their risk perception/seismic adjustment efficacy attributes. The reason for not achieving a 100% adoption rate among the moderate-income group in Policy 3 is that this group spans a wide income range (CAD 100,000 – 240,000). Some households on the lower end of this spectrum may still require financial assistance to adopt retrofit measures but are not eligible for subsidies under this policy.

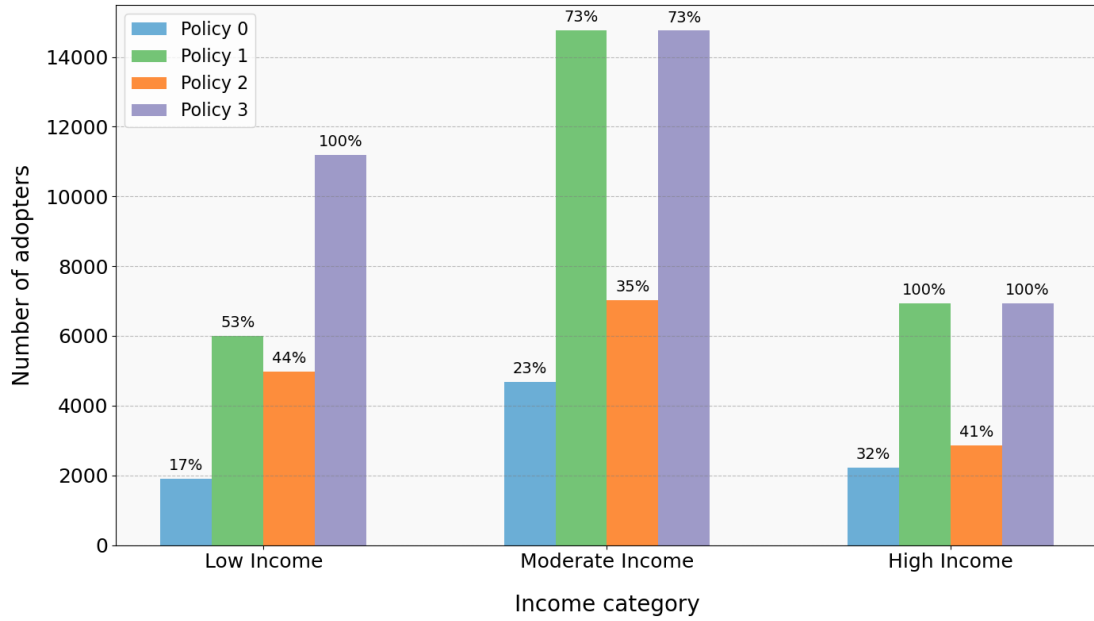


Figure 4.10: Number of agents in adopter state across different income groups.

4.3.3 Effectiveness of Policies in Reducing Earthquake Losses

This section provides a simplified assessment of the effectiveness of seismic retrofitting in reducing earthquake-induced losses. Data representing the average annual (AAL) losses to building structures and contents are extracted from the National Canadian Earthquake Risk Profile developed by the Geological Survey of Canada [94]. This probabilistic risk assessment method accounts for uncertainty in earthquake magnitude, location, frequency, and ground motion propagation. Figure 4.11 illustrates the reduction in total annual losses to the structure and contents of single-family buildings under two scenarios: (i) without insurance and (ii) with insurance. For insured buildings, it is assumed that the insurance will be triggered, and the homeowner will only pay the deductible (12.5% in British Columbia [43]). Moreover, retrofitted homes may still experience losses. Data from the Canadian National Earthquake Scenario Catalogue [50] suggest that for hypothetical M7.0 and M4.9 earthquakes in the Strait of Georgia, seismic retrofitting results in 48.2% and 41.5% reductions in losses for wood-framed single-family dwellings with cripple walls in Vancouver. For completeness, Figure 4.11 shows results for multiple values of retrofit effectiveness. Comparing policy 1, policy 2, and policy 3 under these conditions, a reduction of CAD \$1.8, \$1.0, and \$2.2 million in insured total annual losses for single-family buildings

can be observed. From a policy perspective, this suggests that government investments in retrofit promotion (e.g., through educational campaigns or subsidies) can be cost-effective, provided the total intervention cost is less than the avoided losses. While this exercise provides initial figures, a more robust assessment of costs and benefits would require collaboration between public agencies and private stakeholders, including the insurance and construction sectors.

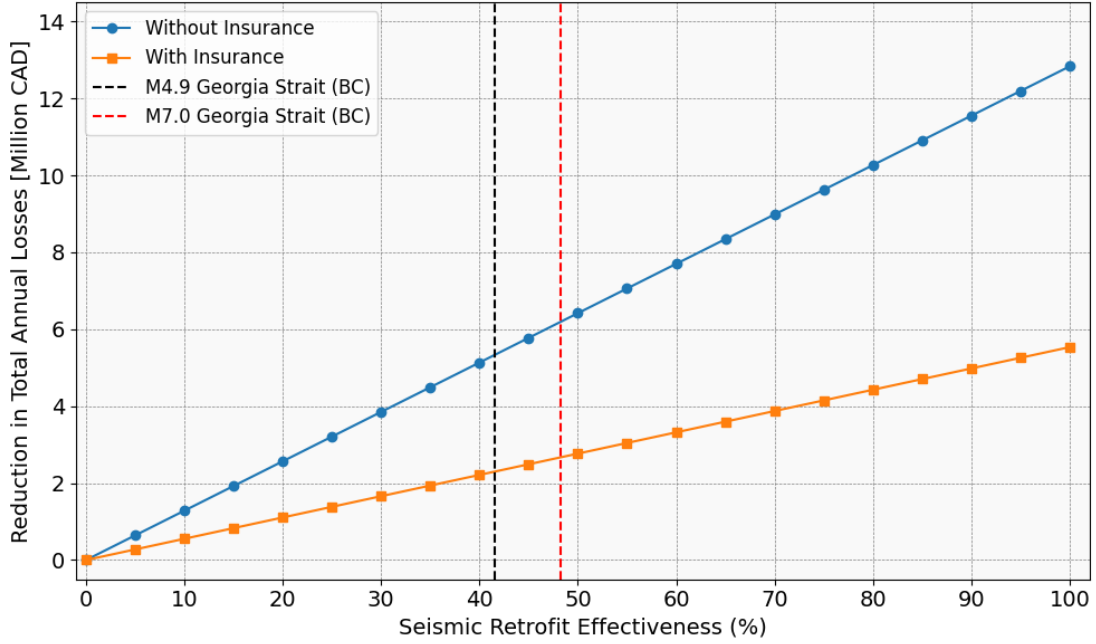


Figure 4.11: Reduction in total annual losses to single-family residential building structures and contents based on retrofit effectiveness in the City of Vancouver.

4.4 Sensitivity analysis

A sensitivity analysis was conducted to quantify the influence of input parameters on the model output. For policies involving education campaigns (i.e., Policy 1 and Policy 3), a Sobol sensitivity analysis was performed using three policy-related parameters: education campaign effectiveness ($\mu_{\text{education}}$), the probability of exposure to education campaigns (p_{exposure}), and the frequency of campaign delivery ($E_{\text{frequency}}$). Figure 4.12 presents the first-order (S1) and total-effect (ST) Sobol sensitivity indices for these parameters under

both policies. In both Policy 1 and Policy 3, the probability of exposure to educational campaigns (p_{exposure}) exhibited the highest first-order and total-effect Sobol indices, indicating it was the most influential factor in explaining the model output variance. The effectiveness of the campaign ($\mu_{\text{education}}$) was the second most important parameter, followed by $E_{\text{frequency}}$, which showed a more modest but non-negligible influence. Second-order Sobol indices, which capture interaction effects between parameters, were consistently small and did not contribute significantly to output variance. This suggests that the model behaviour is largely additive, with minimal interaction between the selected policy levers.

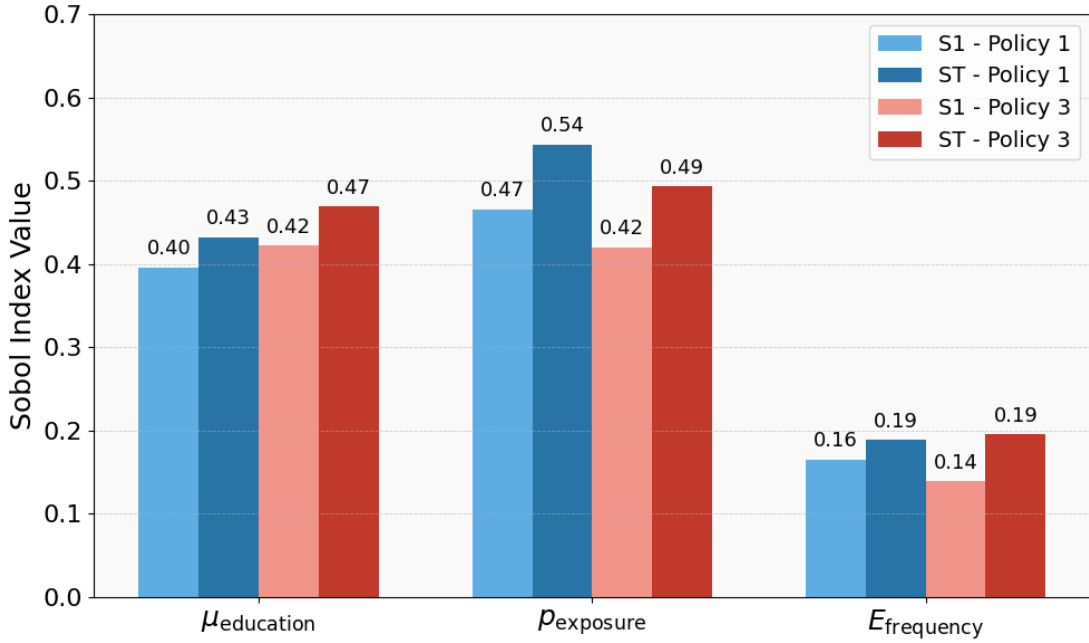


Figure 4.12: First-order (S1) and total-effect (ST) Sobol sensitivity indices for three parameters under Policy 1 and Policy 3.

In policies without education campaigns (i.e. Policy 0 and Policy 2), the impact of varying the probability of interaction between agents on the model output was investigated and is shown in Figure 4.13. A value of 0.05 was selected for the probability of interaction among agents in Policy 0, and the effects of using values in the range of 0.01 to 0.3 were tested and shown in Figure 4.13-a. It can be observed that while increasing the probability of exposure to 0.3 would not increase the number of adopter agents, it would accelerate the rate at which the same number of adopters is achieved (i.e. with 10 months compared to 55 months). Reducing the probability of interaction between agents in policy 0 from 0.05

to 0.01 would decrease the total number of adopters from 8,500 to 4,500 after 60 months. However, running the model with a probability of interaction of 0.01 over a longer time frame can result in approximately the same number of adopters (8,500). This indicates that factors such as the frequency of interaction, size of the social network, and the probability of interaction between agents influence the rate at which the same results are achieved, which aligns with the principles of the relative agreement model [24, 22, 23, 77]. In Policy 2, the value selected for the probability of interaction between agents is 0.15, and the impact of using other values in the range of 0.1 to 0.6 is shown in Figure 4.13-b. Similar to policy 0, changing the probability of interaction among agents in Policy 2 impacts the rate at which the same number of adopter agents is achieved.

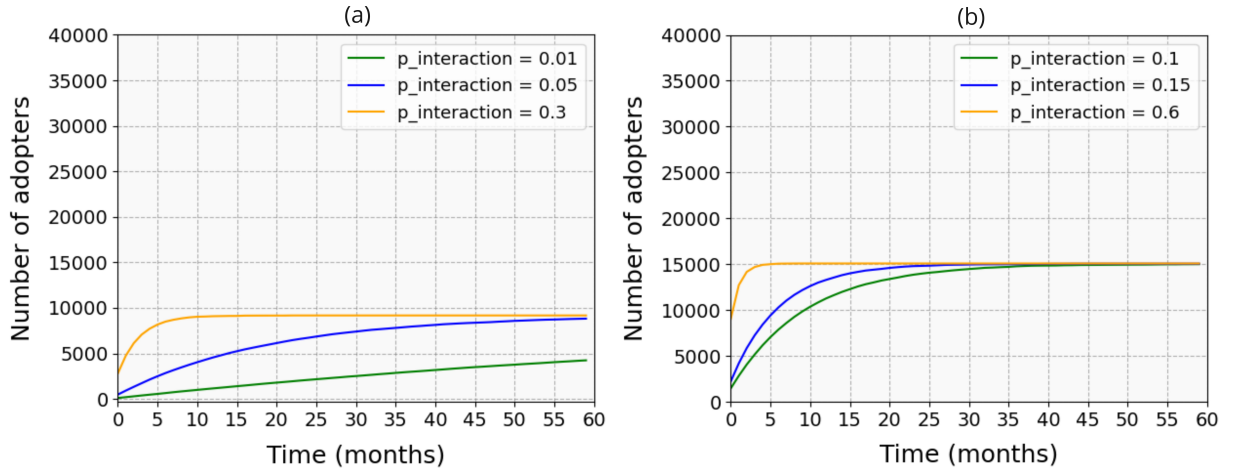


Figure 4.13: Effects of varying simulation parameters on model output: (a) probability of interaction in Policy 0 (b) probability of interaction in Policy 2

4.5 Discussions and Limitations

The developed agent-based model provides a framework for evaluating the effectiveness of potential seismic retrofit promotion policies and is applied to a case study of owner-occupied detached dwellings in Vancouver. Access to such a model would enable decision-makers to examine the potential benefits and drawbacks of seismic risk mitigation strategies prior to their implementation. Detached homes represent 87.8% of Vancouver's 90,014 building inventory and are significant contributors to citywide direct financial losses and extensively and completely damaged buildings in the event of a hypothetical M7.2 Georgia Strait

earthquake. These dwellings are owned by households with a broad range of socioeconomic characteristics. Therefore, the availability of a model that takes into account the demographics of the owners to estimate their attributes would help the decision-makers to target the population with appropriate policies such as subsidies or educational campaigns.

This simulation framework offers policymakers a decision-support tool, which allows them to anticipate how different strategies may perform before committing public funds. The model’s outputs such as adoption trajectories and avoided loss estimates can help local governments evaluate policy trade-offs, engage stakeholders, and design more cost-effective, adaptive, and inclusive seismic risk mitigation strategies. While the model was applied to the Vancouver case study, the general framework can be extended to other regions with suitable local data on housing stock, seismic risk, and resident demographics.

The problem tackled in this study is complex, and its modelling has limitations. First, the results suggest high retrofit adoption rates for policies incorporating educational campaigns (72% in Policy 1 and 86% in Policy 3). However, a limitation of the agent-based model lies in its assumption of the rational behaviour of the agents. That is, it assumes that an individual with the intention and resources to retrofit their home will do so. In reality, human risk-based decision-making might deviate from rational behaviour due to cognitive biases, emotional responses, or misinformation [104, 61].

Second, educational campaigns and programs are complex interventions with varying effectiveness depending on factors such as content quality, delivery platform, and target population. This study models this effectiveness using a single parameter, $\mu_{education}$, which is agnostic to the target population. A more sophisticated approach could implement a value to $\mu_{education}$ that is conditional on population demographics. Future research could focus on evaluating the effectiveness of specific types of educational interventions and their delivery mechanisms to specific population groups.

Third, the model is comprised of different components that are based on empirical data. For example, the attributes of Homeowner Agents in the agent-based model, including risk perception, seismic adjustment efficacy, perceived benefit, and willingness to pay, are modelled based on available studies in the literature but employed using demographic data from Vancouver homeowners from the Census PUMF and property information from the City of Vancouver tax assessor database. While this approach does not validate the model as a whole, it guarantees that its building blocks are robust. I believe that such a model is better used as a tool to support decisions rather than making them. While the model includes assumptions that may not accurately reflect future realities, these assumptions are consistent across all simulations. Thus, I envision that the relative results between baseline and improved scenarios inform the magnitude of the potential benefits of a policy

because such assumptions will have limited influence on the interpretation of the relative results.

Many of the limitations in the current model could be substantially mitigated by a survey of the population of interest (e.g., residents of Vancouver). Surveys are a common method for estimating population attributes within the community under study. In this research, existing models and surveys from the literature were used to estimate the relevant attributes of Vancouver's detached homeowners for the decision-making model. For example, survey results conducted in Greece and Seattle were used to estimate the seismic risk perception and seismic adjustment efficacy attributes of the Homeowner Agents. However, collecting data through surveys specifically targeting detached homeowners in Vancouver would help better calibrate and validate the model.

Chapter 5

Conclusions

This thesis developed an agent-based model to evaluate the impact of potential seismic retrofit promotion policies. In the proposed framework, households are modelled as agents with attributes reflecting their demographics and behaviours related to seismic retrofitting decisions. Policy interventions, such as subsidies and educational programs, are implemented by local authorities to encourage the adoption of seismic retrofit measures. The effectiveness of the government-led seismic retrofit promotion policies is evaluated in terms of the total number of adopter agents and the reduction in total annual losses to residential building structures and contents in the City of Vancouver. Annual building and content losses, with and without retrofits, are obtained from the Canadian National Earthquake Scenario Catalogue [94].

The results suggest that a combination of educational programs and retrofit cost subsidies for low-income households yields the highest adoption rates and the largest reduction in total annual losses to detached residential dwellings. However, results show that focusing only on an educational campaign can achieve similar results in terms of adopters and loss reduction. Educational campaigns target seismic risk perception and seismic adjustment efficacy attributes of the homeowners. The model highlights that risk perception is the primary barrier for moderate and high-income groups, while the combination of risk perception, willingness to pay, and perceived benefits (tangible financial returns) is the primary impediment to the adoption of retrofit measures among low-income homeowners. Survey results conducted on detached homeowners in the City of Vancouver can be used to calibrate the model and estimate the agents' attributes that influence seismic retrofit decision-making.

The analysis on the effectiveness of retrofit promotion policies in reducing earthquake-induced annual losses suggests that government investment in education or subsidies could be cost-effective, provided that the implementation costs remain below the projected savings in avoided losses. The model results could be used to inform local governments of what the viable annual budget would be for spending on seismic risk reduction strategies. A more comprehensive cost-benefit analysis is needed, involving collaboration between public agencies, insurers, and the construction industry to quantify implementation costs, co-benefits, and risk-sharing mechanisms.

This study makes a significant contribution both methodologically and quantitatively to the development of effective seismic risk mitigation policies. It demonstrates the value of using agent-based simulation as a tool to support policy design and decision-making. By modelling policy impacts before implementation, local governments can more effectively evaluate and refine strategies to minimize damage and losses in future seismic events. Ultimately, this proactive approach enables more resilient urban planning and better-informed public investments in disaster risk reduction.

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APPENDICES

Appendix A

Distribution of agents' attributes over time across different policies

Figures [A.1–A.4](#) illustrate the distribution of risk perception over time across different policies, where panels (a) and (e) represent the initial and final distributions, respectively. It can be observed that during social interactions agents work toward reducing the differences in their opinion resulting in reducing the width of the distribution over time, which is in accordance with the assumptions in relative agreement model [\[24, 77\]](#). The impact of educational campaigns in improving risk perception of agents could be highlighted by comparing [Figure A.1-e](#) (Policy 0) and [Figure A.2-e](#) (Policy 1), where the final distribution of risk perception settles around 0.6 in Policy 0, while it maximizes at 1 in Policy 1. Similarly, Figures [A.5–A.8](#) present the distribution of seismic adjustment efficacy (SAE) over time across different policies, where panels (a) and (e) represent the initial and final distributions, respectively. During social interactions, the differences in agents' seismic adjustment efficacy attributes is decreased over time across all policies. When SAE is targeted in educational campaigns in Policies 1 and 3, a substantial increase is observed in the final distribution of this attribute, as shown in panel (e) in [Figure A.6](#) and [Figure A.8](#) compared to the policies without educational campaigns ([Figure A.5](#) and [Figure A.7](#)).

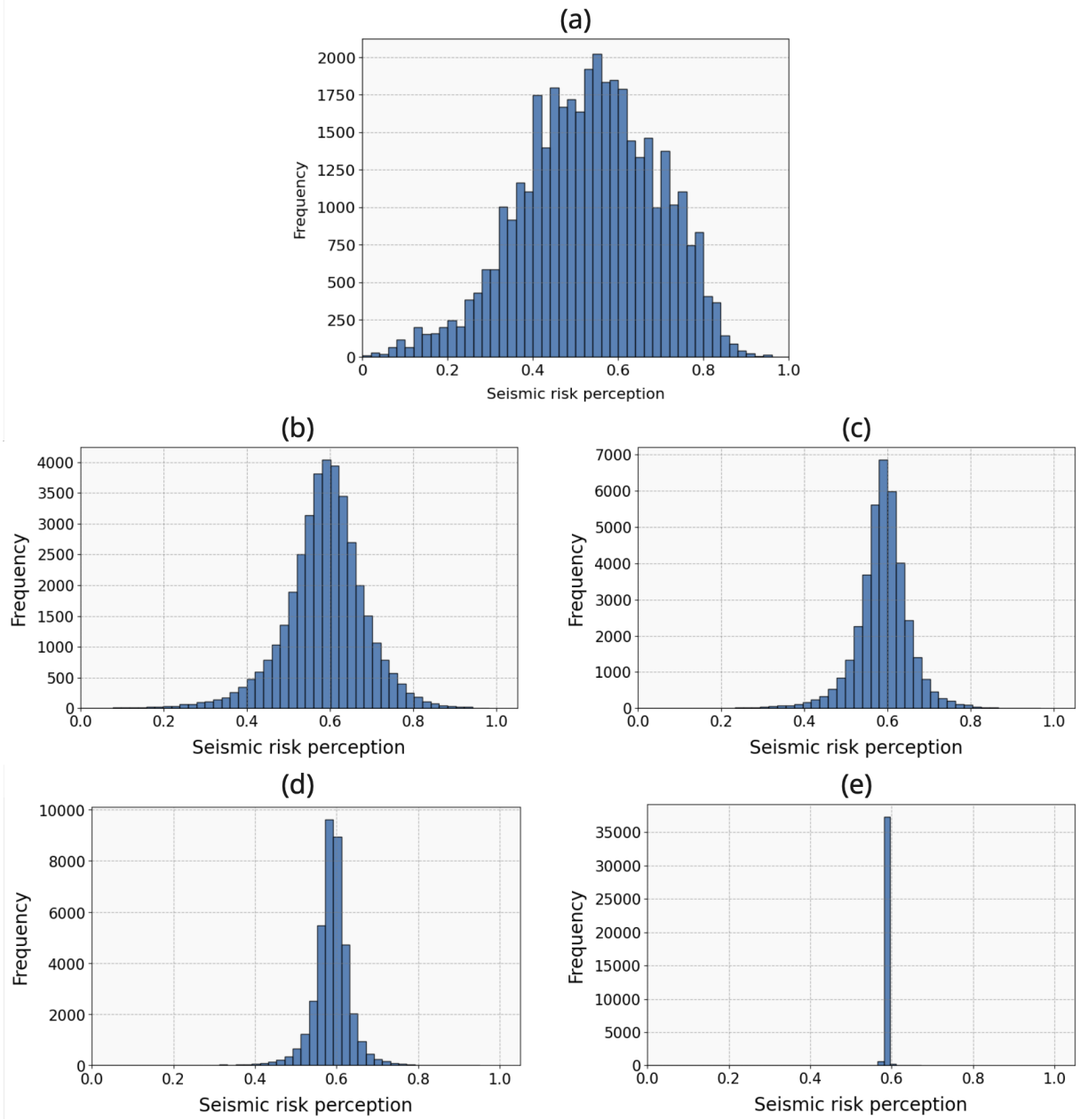


Figure A.1: Seismic risk perception distribution over time in policy 0; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

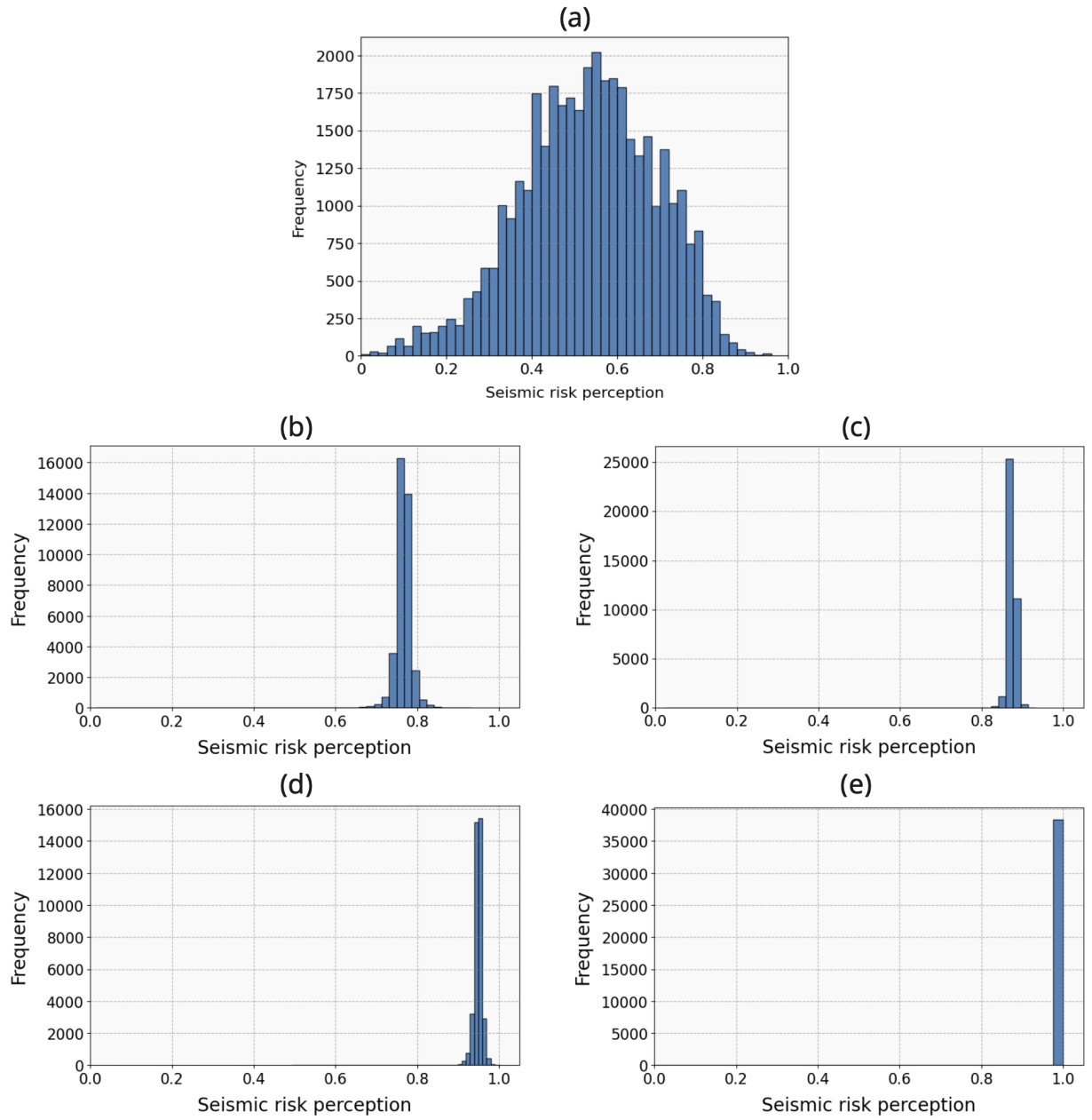


Figure A.2: Seismic risk perception distribution over time in policy 1; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

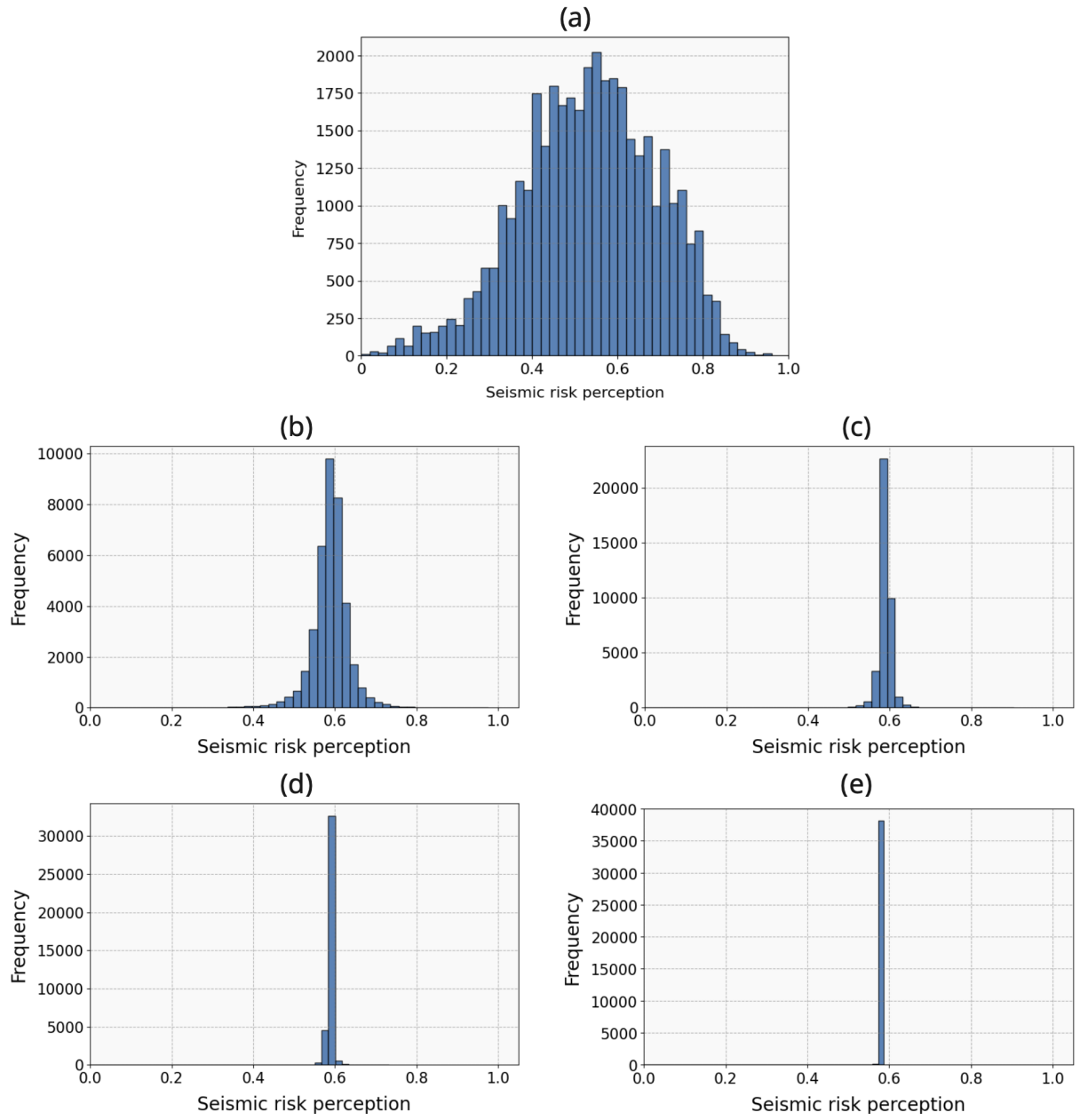


Figure A.3: Seismic risk perception distribution over time in policy 2; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

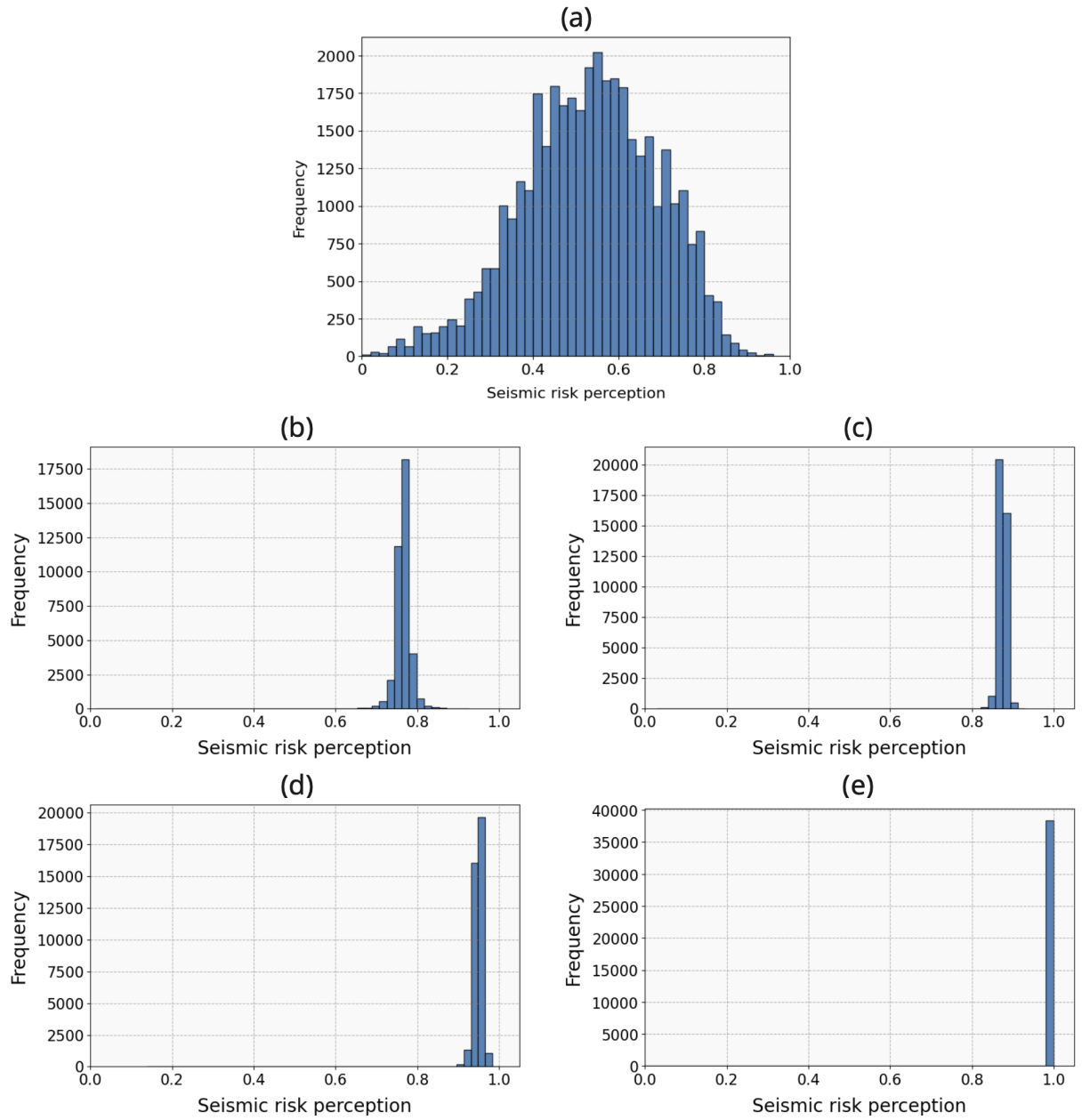


Figure A.4: Seismic risk perception distribution over time in policy 3; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

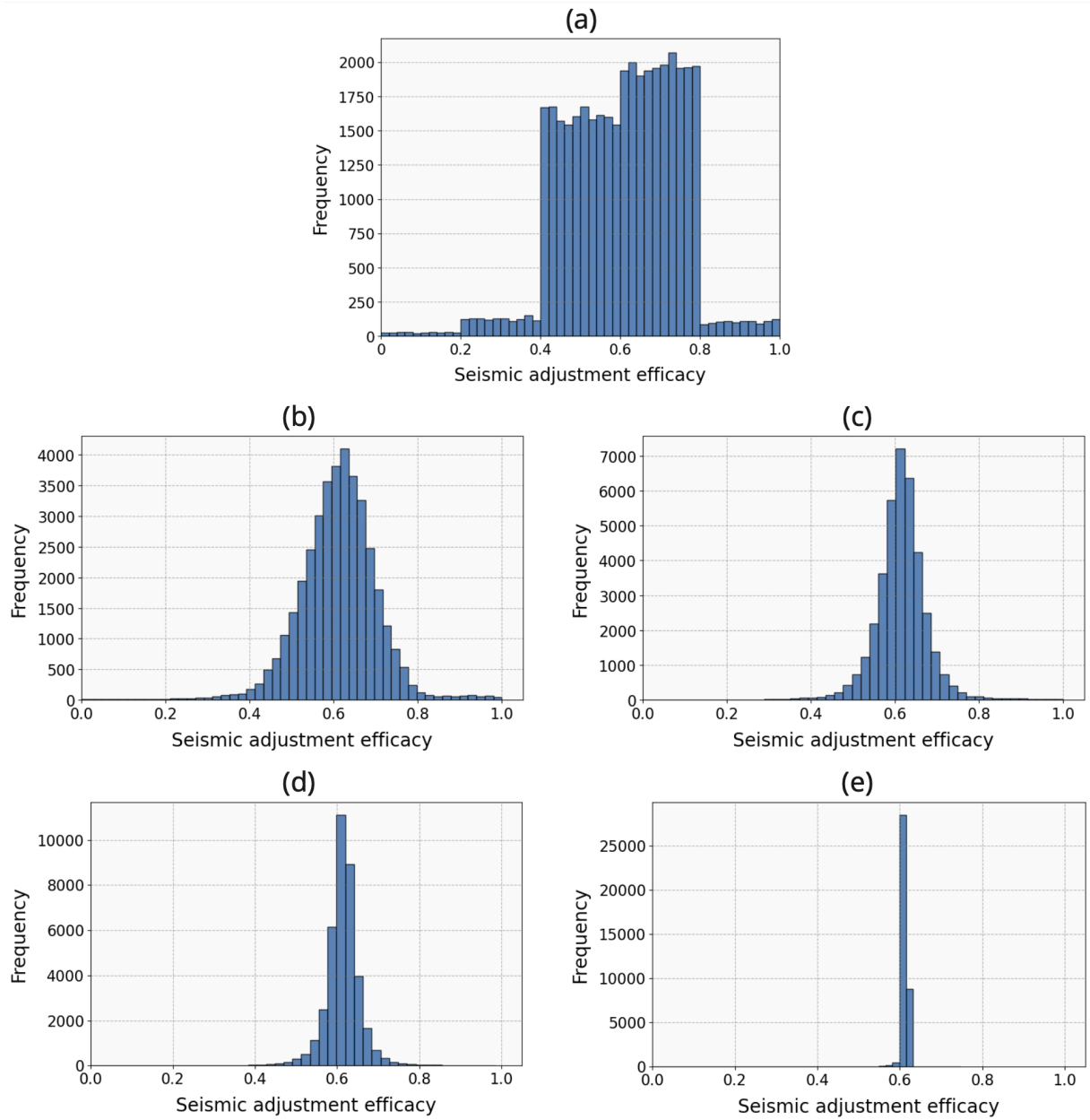


Figure A.5: Seismic adjustment efficacy distribution over time in policy 0; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

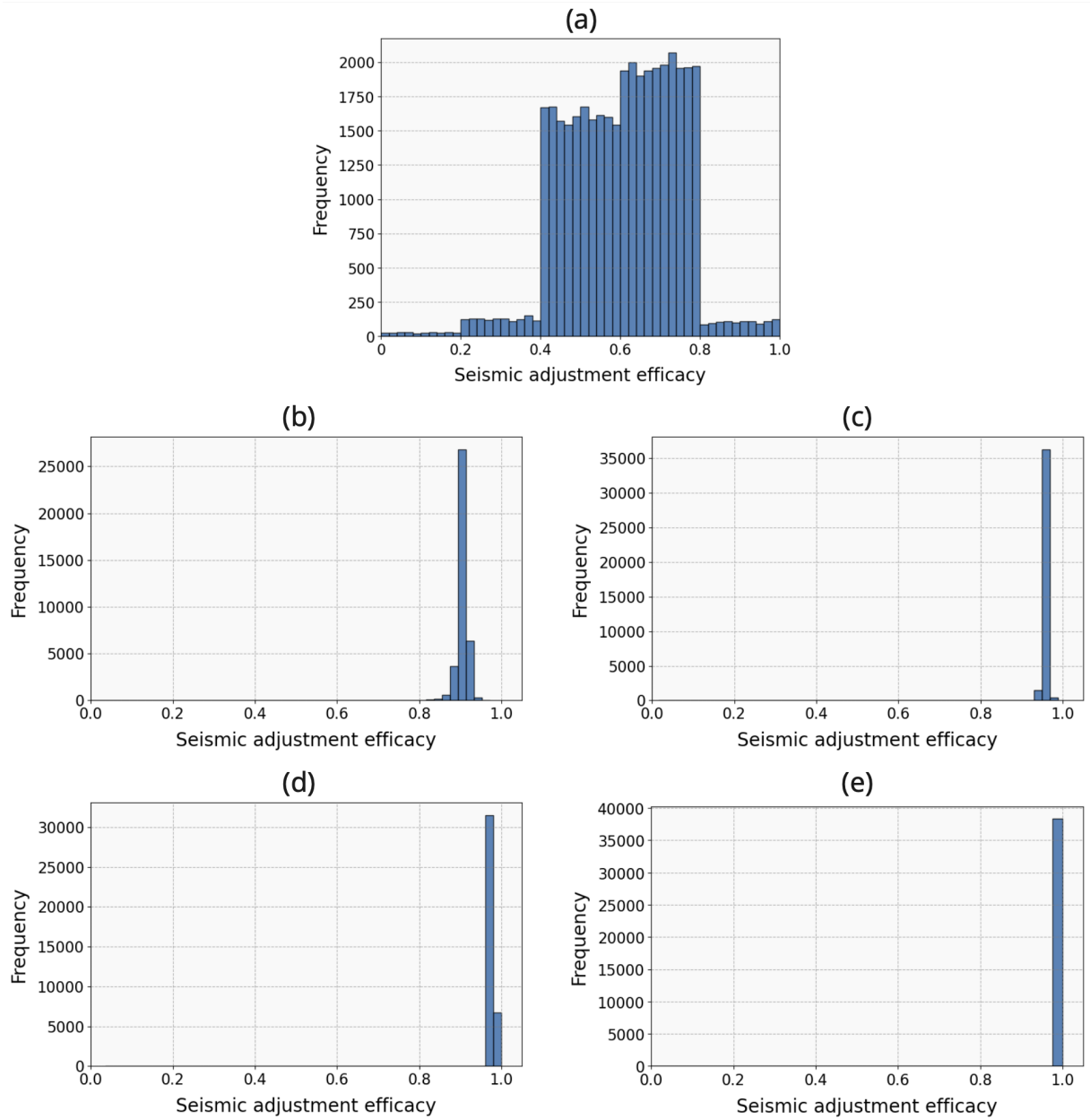


Figure A.6: Seismic adjustment efficacy distribution over time in policy 1; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

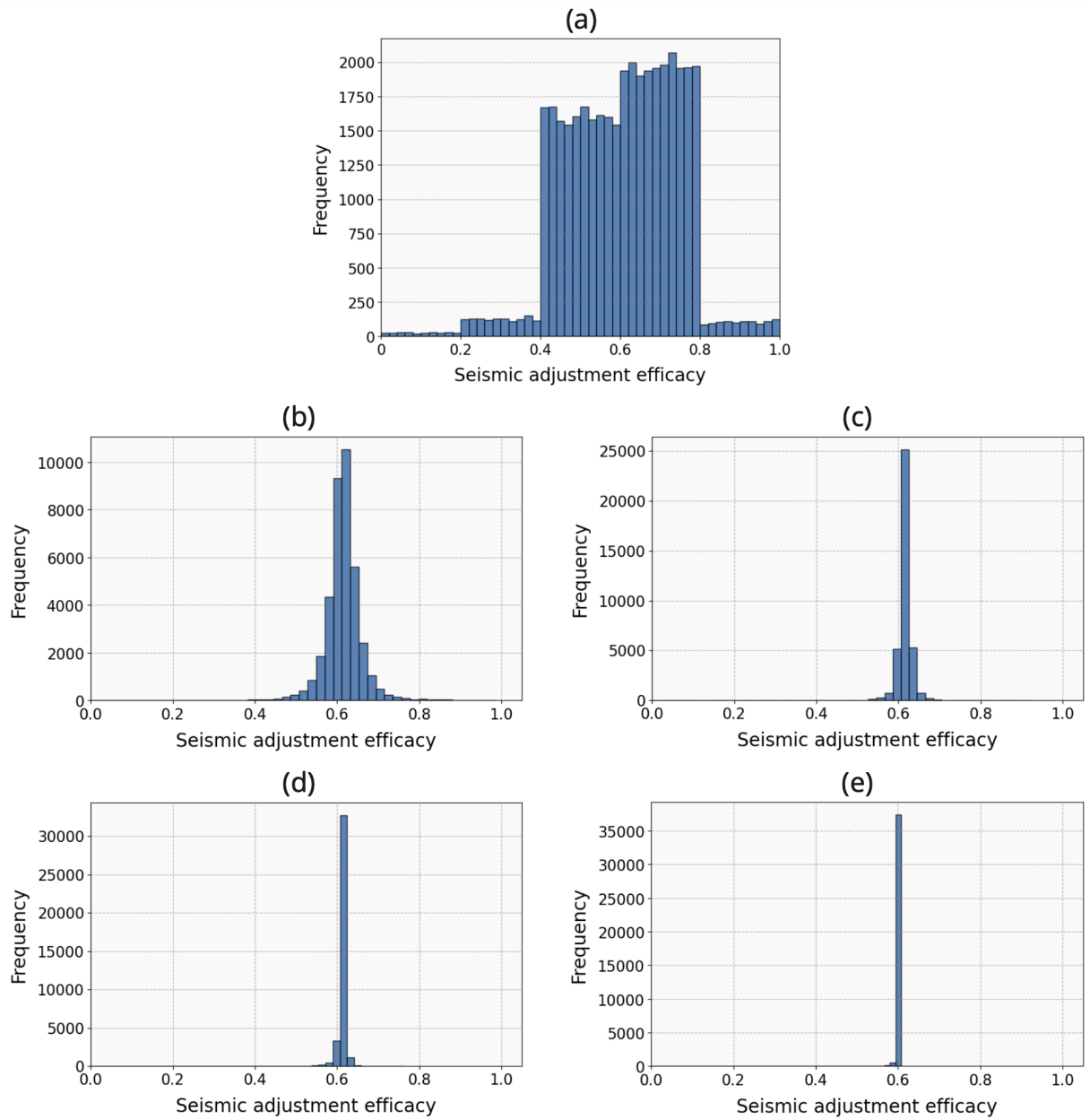


Figure A.7: Seismic adjustment efficacy distribution over time in policy 2; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60

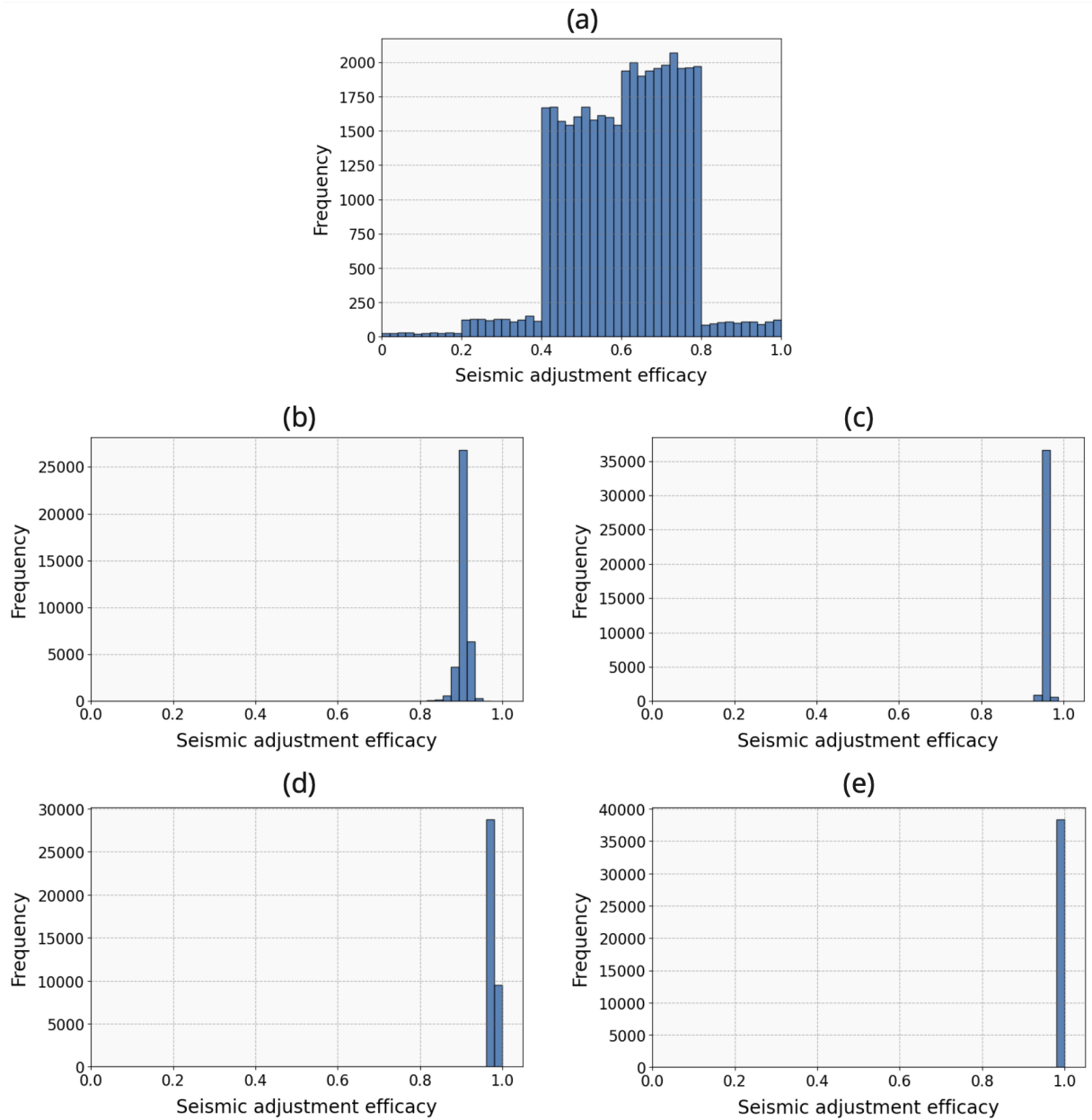


Figure A.8: Seismic adjustment efficacy distribution over time in policy 3; (a) Initial distribution at time step 0 (b) Distribution at time step 5 (c) Distribution at time step 10 (d) Distribution at time step 15 (e) Final distribution at time step 60