

# Towards Understanding Home Battery Adoption in the Netherlands

A Discrete Choice Analysis of Household Preferences

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# Towards Understanding Home Battery Adoption in the Netherlands

A Discrete Choice Analysis of Household Preferences

by

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# Executive Summary

## Introduction

The Dutch electricity system increasingly needs flexibility, because electricity generation from variable renewable sources such as solar and wind does not always match electricity demand. Battery Energy Storage Systems (BESS) can provide this flexibility by storing electricity and releasing it later. They respond quickly, scale across system sizes, and are already commercially proven. These properties have led market actors to increasingly deploy utility-scale BESS. At household level, residential BESS, or home batteries, are also growing rapidly and make up ~45% of installed capacity in the Netherlands.

Despite technical similarity, installed capacity of the two types of BESS grows in fundamentally different ways. Utility-scale capacity growth results from a limited number of professional investment decisions and is therefore relatively predictable. Residential BESS capacity growth is more difficult to predict, because it emerges from many separate household decisions shaped by financial and non-financial considerations. Various actors can only influence the conditions under which households evaluate one. In this thesis, these conditions are conceptualized as home battery attributes, such as investment costs, payback time, certainty of payback time, self-consumption and emergency power.

## Literature Review

Existing literature shows that residential BESS adoption follows from many household decisions to invest in a home battery. This decision should not be understood as purely techno-economic. Financial drivers such as costs, payback time and lower electricity bills matter, but non-financial drivers such as energy autonomy, emergency power and environmental motives also shape the household decision. A structured literature search identified a broad set of adoption drivers, which were organized using a framework for categorizing drivers of household investment decisions. Although literature is rich in possible drivers, it does not clearly show which home battery attributes matter most to households, how important these attributes are relative to one another, nor how changes in these attributes affect choices. Existing prioritizations rely mainly on stated importance rather than observed choice trade-offs, and evidence is concentrated in Australian studies, limiting transferability to the Dutch context.

The main research question of this thesis is therefore: *How do changes in home battery attributes affect the household investment decision to buy a home battery?* It is answered through three sub-questions. First, the thesis identifies the most important attributes affecting the household investment decision. Second, it estimates their relative importance. Third, it explores how changes in these attributes affect the probability that a household chooses a home battery.

## Methodology

The research combines a literature analysis with Discrete Choice Modeling (DCM). The literature analysis screened the broad set of drivers down to a set of 12 attributes, from which we derived a subset of five key home battery attributes: **investment costs**, **payback time**, **certainty of payback time**, **energy autonomy**, and **backup power**.

A discrete choice experiment (DCE) was designed where respondents repeatedly chose between Battery A, Battery B and no battery. Each battery was described by a set of these attributes and their levels. The final experiment included eight choice tasks and was completed by 529 usable respondents. From the total pool of respondents, based on household characteristics, a representative sample for the average Dutch household was made. A panel mixed logit model estimated relative importance of the key attributes and the choice probabilities for choosing a baseline home battery with consistent attributes.

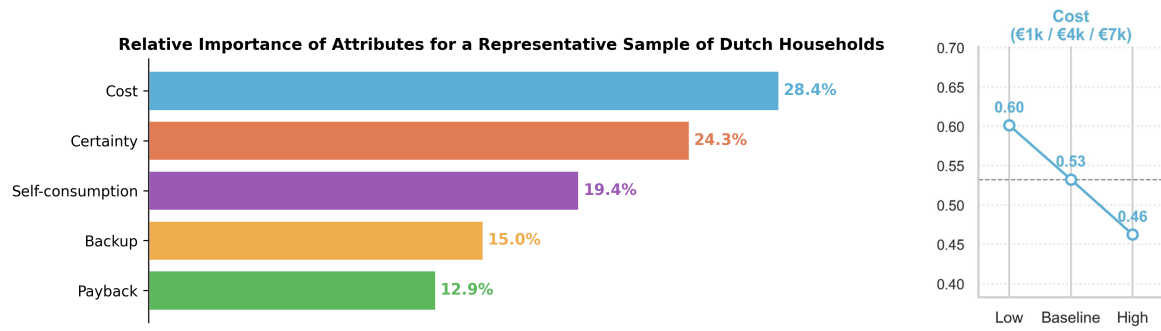


Figure 1: Relative importance and choice probability analysis for the representative sample.

## Results

A panel mixed logit model estimated on the choice data shows that all five attributes have a statistically significant effect on household choices. The model provides significant explanatory power ( $\bar{\rho}^2 = 0.2477$ ). The relative importance of the attributes for the average Dutch household is shown in Figure 1. A choice probability analysis shows the probability for choosing a baseline home battery is 0.60 in a data sample with solar PV owners, and 0.53 in the representative sample. These values should not be interpreted as real market shares, but as controlled model outputs.

## Conclusion

**Changes in home battery attributes affect the household investment decision by changing the probability that a household selects the battery alternative.** The five selected attributes are therefore relevant "knobs" through which residential BESS adoption can be understood or influenced. However, the model only tests the included attributes: it shows that these five matter, not that they are the five most important in every real-world decision.

From the key attributes and their relative importances we found that the household investment decision is **strongly financial, but not purely economically rational**. Costs, payback time and certainty of payback time together account for most of the relative importance, yet households do not appear to evaluate a battery as a simple profitability calculation. Payback time, a key metric for professional investors, is the least important attribute in the representative sample, and households did not accept more risk in exchange for shorter payback.

**Investment costs and certainty of payback time are the strongest attributes.** This has direct implications for policy and market actors. Measures that lower upfront costs, such as subsidies or tax rebates, target the most important part of the household decision. Measures that stabilize or guarantee returns target the second most important attribute. This is relevant because current Dutch policies mainly affect payback time and self-consumption, certainty of payback time is affected only indirectly. Barely any policies affect investment costs and certainty of payback time directly. Grid operators could use this insight by offering contracts that give households more certain returns in exchange for control over battery operation to stabilize grids.

**The attributes do not tell the full picture.** Comparing the representative and solar samples shows that targeting the right households can shift choice probabilities by a similar magnitude as large attribute changes. Actors seeking to promote adoption should therefore not only improve the battery proposition, but also focus on groups already more willing to adopt.

The results should be read within the limits of the method. The experiment simplifies a complex real-world decision, measures stated rather than actual choices, and only tests the included attributes. Future work should expand and formalize the attribute selection, test transferability across countries, quantify how policies change home battery attributes, and connect these preference estimates to diffusion models that translate attribute changes into capacity growth.

# AI Statement

In this thesis several AI tools were used as supportive instruments. **Google Scholar Labs** was used for exploratory literature searches. **NotebookLM** was used to navigate and summarize literature. Lastly, **ChatGPT** was used to refine energy-dense texts, like section titles and sub-questions, assist in formatting in Overleaf and to generate the cover image. **Copilot** was used in VSCode to assist with writing code for model estimations and plot generation. The author is fully responsible for the content of this thesis.

# Contents

<b>Acknowledgements</b>	<b>i</b>
<b>Executive Summary</b>	<b>ii</b>
<b>AI Statement</b>	<b>iv</b>
<b>Nomenclature</b>	<b>viii</b>
<b>1 Introduction</b>	<b>1</b>
1.1 Problem Statement and Knowledge Gap . . . . .	2
1.2 Research Questions . . . . .	4
1.3 Approach . . . . .	5
1.4 Link to the CoSEM Program . . . . .	7
1.5 Research Structure . . . . .	7
<b>2 Background and Literature Review</b>	<b>9</b>
2.1 Background on Residential BESS Adoption . . . . .	9
2.2 Literature Review: Residential BESS Adoption . . . . .	12
2.2.1 Residential BESS Adoption is not a Purely Economic Decision . . . . .	12
2.2.2 Drivers of Residential BESS Adoption . . . . .	12
2.3 Limitations and Research Gap . . . . .	15
<b>3 Methodology</b>	<b>18</b>
3.1 Theoretical Background on Discrete Choice Modeling . . . . .	19
3.2 Literature Analysis to go from Drivers to Key Home Battery Attributes . . . . .	21
3.2.1 Screening and Operationalization of Drivers to Attributes . . . . .	21
3.2.2 Identifying Key Home Battery Attributes . . . . .	23
3.3 Discrete Choice Experiment Design . . . . .	25

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3.3.1	Attribute Terminology and Levels . . . . .	25
3.3.2	Choice Tasks and Experiment . . . . .	27
3.3.3	Survey Instrument and Data Collection . . . . .	28
3.4	Discrete Choice Model Estimation and Analysis . . . . .	30
3.4.1	Data Analysis . . . . .	30
3.4.2	Discrete Choice Model Estimation . . . . .	31
3.4.3	Relative Importance of Key Attributes . . . . .	32
3.4.4	Choice Probability Analysis . . . . .	33
<b>4</b>	<b>Results</b>	<b>34</b>
4.1	Key Home Battery Attributes . . . . .	34
4.2	Choice Data Samples . . . . .	35
4.3	Model Estimation Results . . . . .	38
4.4	Relative Importance of Home Battery Attributes . . . . .	41
4.5	Choice Probability Analysis . . . . .	41
<b>5</b>	<b>Discussion</b>	<b>44</b>
5.1	What the Model Reveals about the Household Investment Decision . . . . .	44
5.2	Heterogeneity and Data Samples . . . . .	45
5.3	Comparing the Dutch and Australian Context . . . . .	47
5.4	Implications for Actors and Policy . . . . .	48
5.4.1	Policies and Relevance for Battery Attributes . . . . .	49
5.4.2	Implications for Actors . . . . .	50
5.5	Limitations . . . . .	51
<b>6</b>	<b>Conclusions &amp; Outlook</b>	<b>53</b>
	<b>References</b>	<b>56</b>
<b>A</b>	<b>Appendix - Full List of Drivers</b>	<b>63</b>
<b>B</b>	<b>Appendix - Code, Ngene Code &amp; Chi-Square table</b>	<b>65</b>
B.1	Link to Github repository: . . . . .	65

- B.2 Ngene Code . . . . . 65
- B.3 Chi-square table . . . . . 66
- C Appendix - Final Survey Version 67**
- C.1 Survey Explanation Text . . . . . 68

# Nomenclature

<b>Abbreviation</b>	<b>Definition</b>
ASC	Alternative-Specific Constant
BRP	Balancing Responsible Party
BESS	Battery Energy Storage System
DA	Day-Ahead
DCE	Discrete Choice Experiment
DCM	Discrete Choice Modeling
DSO	Distribution System Operator
FiT	Feed-in Tariff
ID	Intraday
LFP	Lithium Iron Phosphate
Li-ion	Lithium Ion
LL	Log-Likelihood
MXL	Mixed Logit
MLE	Maximum Likelihood Estimation
MNL	Multinomial Logit
PV	Photovoltaic
RES	Renewable Energy Sources
RUM	Random Utility Maximization
TSO	Transmission System Operator
VRE	Variable Renewable Energy

# 1

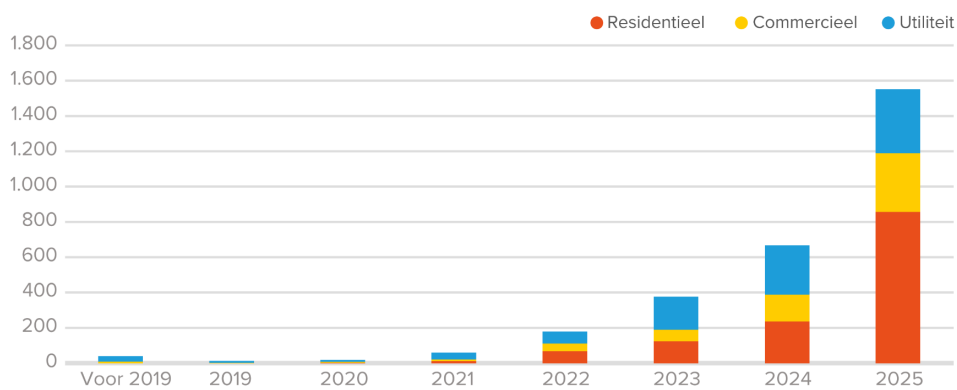
## Introduction

In order to achieve energy autonomy and tackle climate change, Europe must transition towards meeting its energy demand with Renewable Energy Sources (RES) [1]. For many countries, like the Netherlands, this means a high reliance on Variable Renewable Energy (VRE) like solar Photovoltaic (PV) and wind energy [2]. Electricity generation from these renewable sources is highly variable, both throughout the day and throughout seasons and does not always match electricity demand. This mismatch in supply and demand requires the need for flexibility in the energy system [3]. Without sufficient flexibility, congestion, curtailment and other market inefficiencies emerge [4, 5, 6]. These hinder further electrification and economic growth, imposing costs across Europe estimated in the tens of billions of euros annually [7, 8].

Through energy storage, and specifically Battery Energy Storage Systems (BESS), VRE can be stored when supply is available, and released later [9]. BESS are currently the leading solution to provide flexibility [3]. They can respond almost instantly to mismatches in supply and demand, and can store electricity also on longer timescales, up to weeks [10]. This allows higher penetration of VRE, while also enhancing the resilience and autonomy of energy systems [6]. Both have become increasingly important as recent disruptions in oil and gas supply chains have exposed Europe's vulnerable dependence on energy imports, highlighting the need for domestically controlled, electricity-based energy systems [11].

In this study, the terms *battery* and *BESS* are used interchangeably and refer to lithium-ion (Li-ion) battery energy storage systems. Unless stated otherwise, these systems are assumed to be lithium iron phosphate (LFP) technology. These batteries can easily be scaled to all types of system sizes and characteristics [10]. We distinguish two main categories of BESS: *residential- or home batteries*, which are connected to a household electricity system and installed behind the meter, and *utility-scale BESS*, which are typically larger systems, with a direct connection to the grid, deployed by commercial actors or utilities [12, 13, 14]. Both BESS categories have shown exponential growth in capacity (MWh) in the Netherlands over the past years as can be seen in Figure 1.1.

Growth in utility or commercial-scale BESS capacity is driven by investments of professional market actors. These are profit maximizing actors and work out clear business cases [16]. Because of the large size, limited number of systems and clear investment rationale, growth in utility-scale BESS capacity is more predictable and controllable [15]. Growth in residential BESS capacity is different, but grows rapidly and constitutes almost half of total installed capacity in the Netherlands [15]. It does not depend on a few large investment decisions like with utility-scale BESS. It results from adoption by many individual households. Residential BESS adoption, defined as the positive decisions of households to buy a home battery, is not so straightforward to predict and understand. This is because households might consider more than just economic values when buying a home battery, and households might also differ in these values. The decision to adopt is governed by both financial drivers, like costs or



**Figure 1.1:** Installed BESS capacity in the Netherlands by type in MWh. The red chart is residential BESS, yellow and blue are commercial and utility-scale BESS. [15]

payback time, as well as non-financial drivers like energy autonomy or environmental concerns [17]. A driver is defined here as a factor, variable or determinant that directly or indirectly, influences the household decision-maker in their behavior to adopt a residential BESS. Taken together, residential BESS is a significant portion of total installed capacity and is growing rapidly, adoption is however difficult to understand and predict because of the variety of household decisions.

## 1.1. Problem Statement and Knowledge Gap

This complexity of the household investment decision to adopt a home battery, and lack of understanding thereof are problematic for various actors and reasons. Grid operators want to know how many batteries will be installed in the grid in order to know where and what parts of the grid to invest in in the future, and if such investments are necessary [18, 19]. Municipalities also seek to better understand where capacity might be installed, and how to potentially steer growth in the right places in order to relieve local grid pressure [20]. Energy companies, like Eneco, seek to understand this choice for business oriented goals: what contracts to give to customers with home batteries, and how many batteries will be installed in the grid in order to better forecast electricity prices and assess future business cases [21]. Lastly, the ministry of climate and environmental concerns has recently filed a letter calling for increased decentralized developments in the energy system, including home batteries. They stress the need for good capacity planning and better align local energy generation, storage and consumption in order to reduce pressure on the electricity grid and support a resilient and sustainable energy system [22].

These actors cannot directly influence how many households buy a battery. They can only do so indirectly. Ministries can draft new legislation, an example being the end of the net-metering scheme [23] and attempted halt of double energy tax for home batteries [24]. Municipalities may consider subsidies for local batteries and grid operators may change tariff structures, for example through flexible tariffs [20, 25]. The effects of such changes are difficult to assess because, as mentioned, residential BESS adoption follows from thousands of poorly-understood, complex and diverse household investment decisions [24]. This brings us to the problem statement:

**Various actors seek to influence, understand or predict residential BESS adoption, they however do not know how to do so because of the complexity and variety of household investment decision-making processes.**

The household investment decision mentioned in the problem statement can be shaped by many factors, such as the interaction between household members, financial expectations, environmental motives, perceived uncertainty, social influence, and the specific decision-making context [26, 27]. These factors differ between households, which makes it difficult to generalize the full decision-making process [17].

A common factor of all these household decisions is the type of investment: a home battery with certain characteristics [28]. In this thesis, these characteristics are conceptualized as home battery *attributes* like investment costs of a battery, self-consumption value the battery brings or payback time the battery has. The actors mentioned above can affect the battery attributes through different measures. For example the phase out of net-metering might increase self-consumption value [24, 23]. Subsidies may reduce investment costs, tariff structures may affect payback time [20, 24, 25]. This thesis defines these measures that the different actors can take to affect home battery attributes as **policies**. So, these policies can affect the home battery attributes. These attributes are considered by households when making an investment decision. And this results in a certain amount of residential BESS adoption. This logic is shown in Figure 1.2.



**Figure 1.2:** Schematic flowchart showing how policies affect residential BESS adoption through influencing battery attributes and the investment decision of households.

Several parts of the shown logic could be studied. We will focus on studying how battery attributes influence household investment decisions. This is because understanding this link is a necessary intermediate step to assess how policy affects household investment decisions and quantify how capacity growth might result from that [29]. For example, some work has also been done that researches the impact of different policies on revenue models for home batteries [24]. Without first understanding whether, and to what extent revenue influences the household investment decision to buy a home battery, such research is limited in explaining how market adoption might develop. By studying attributes and underlying preferences of the household investment decision, some implications can of course be made for the first and last part of the logic in Figure 1.2, this is however not the main goal of this research.

With this new focus, existing literature on what drives the household investment decision to buy a home battery is reviewed. It was found that the household investment decision is not purely economic, but is also influenced by non-financial drivers such as environmental motives, feeling of energy autonomy and uncertainties [16, 13]. Existing research identifies drivers of residential BESS adoption but does not make a transparent selection of key home battery attributes. Literature also does not prioritize and quantify the importance of these attributes, and the studies are also geographically concentrated in Australia [17, 30, 31, 32]. As a result of these limitations, the following knowledge gap is formulated:

**There is limited understanding of which home battery attributes matter most to households, how important these attributes are relative to one another, and how changes in these attributes affect the household investment decision.**

An elaborate review of literature and argument for the knowledge gap is presented in Chapter 2. This study addresses this knowledge gap in a more contemporary time and new context, the Netherlands. It also dives deeper into which attributes are considered most important by households, and how important they are relatively quantitatively. This provides fundamental information to assess how changes in these attributes will affect the household investment decision, and therefore adoption at a wider scale.

## 1.2. Research Questions

To reach this goal and address the knowledge gap, this research aims to understand how changes in home battery attributes affect the household investment decision to buy a home battery. The main research question is therefore formulated as:

*How do changes in home battery attributes affect the household investment decision to buy a home battery?*

Before this main research question can be answered, we first need to answer other questions that build up towards the main research question. We therefore divide the main research question in three sub-questions. These sub-questions move from identifying the relevant attributes, to quantifying their relative importance, and finally to assessing how changes in these attributes affect the household choice. Before we can understand how a change in a home battery attribute affects the investment decision of a household, we have to know which attributes the households even consider. This brings us to the first sub-question:

*SQ1: What are the most important attributes affecting the household investment decision?*

The first sub-question focuses on identifying the key drivers that affect the household investment decision to buy a home battery. These drivers are then translated to home battery attributes. This step addresses limitations of literature by extensively reporting on all potential drivers affecting the household decision, and how they were screened and selected for inclusion as key attributes in this study. This step is also necessary to simplify and scope the research and its analysis since including every driver or attribute makes the study highly complex. A clear set of important attributes is needed as the foundation for the next sub-question, where the importance of these attributes are quantified and compared.

*SQ2: What is the relative importance of these attributes?*

The second sub-question quantifies the important attributes for the household investment decision. Besides knowing which attributes may influence households. It is also important to know how important these attributes are relative to one another. This gives insight into which attributes households weigh most strongly when deciding whether or not to buy a home battery. This numerical quantification is necessary for answering the final sub-question:

*SQ3: How do changes in attributes affect the predicted probability that a household chooses a home battery?*

The third sub-question connects the attribute-level quantification to actual household investment decisions. A change in a battery attribute can affect individual households differently, because households have different preferences and decision-making processes. We can however estimate the effects of changes in home battery attributes on the predicted probability that a household will invest in a home battery on an aggregated level. This final step allows the main research question to be answered.

These research questions will be answered within the scope of the Netherlands. This is because the research is based in the Netherlands. The household investment decision studied in this thesis is the decision of Dutch households to buy a home battery. Data gathered for this thesis is from Dutch households. By focusing on the Netherlands, the available data, electricity-market conditions and residential BESS development can be treated as one coherent case. Focusing on the Netherlands,

although introducing a geographical constraint for quantitative results, still overcomes limitations of previous literature concentrated in Australia. This study provides a case that can be used to compare results and conclusions of findings of similar literature in the Australian context. So despite an empirical focus on the Netherlands, the findings may also be relevant for other countries.

Answering these research questions will make several contributions to allow further understanding of residential BESS adoption.

- **Identifying key home battery attributes:** This research contributes by identifying a broad set of residential BESS adoption drivers found in literature, and selecting a set of key home battery attributes. This helps to move from a general understanding of what may influence adoption, towards a clearer understanding of which battery characteristics households actually consider in their investment decision. For actors that seek to understand or influence residential BESS adoption, these attributes can be seen as the main “knobs” through which the household investment decision may be affected.
- **Quantifying relative importance:** After identifying the key attributes, their relative importance is still important to understand. This thesis estimates the relative importance of the selected home battery attributes. This shows which of the identified “knobs” matter most to households, and therefore where changes in battery characteristics are expected to have the largest influence on adoption.
- **Linking attribute changes to choice probabilities:** This thesis contributes by connecting changes in home battery attributes to choice probabilities. This is relevant because policymakers, grid operators and energy companies are interested in knowing how changing conditions result in residential BESS adoption and therefore capacity growth.

Together, these contributions help address the knowledge gap identified in this chapter. They also provide practical value for the actors that experience challenges from the limited understanding of residential BESS adoption and the complexity and variety of household investment decisions.

## 1.3. Approach

This section explains *why* a modeling approach using Discrete Choice Modeling (DCM) is used in this study. Chapter 3 presents *how* DCM is applied correctly. The aim of this section is not to explain the full method, but to justify why DCM is a suitable approach for answering the research questions.

A modeling approach is used because the main research question asks how changes in home battery attributes affect the household investment decision. Models are suitable for assessing how different scenarios influence the behavior of a system [33]. In this research, the relevant scenarios are changes in home battery attributes. The relevant system behavior is the household decision to adopt a home battery. Different modeling approaches can be used to study socio-technical systems. A broad distinction can be made between top-down and bottom-up approaches, as shown in Figure 1.3. Since residential BESS adoption depends on many individual household decisions, this study uses a bottom-up modeling approach. Residential BESS adoption does not emerge from one central investment decision, but from many separate decisions made by individual households.

Several bottom-up approaches could be considered. Agent-Based Modeling could be used to simulate how residential BESS adoption evolves over time through interactions between households, market actors and institutions. Multi-agent systems could also be relevant, because residential BESS adoption emerges from the behavior of multiple actors in the electricity system. However, both approaches require assumptions about the goals, preferences and decision rules of the agents. In this research, these are exactly the elements that first need to be understood. Before simulating adoption over time, it is necessary to know which home battery attributes households respond to, and how important these attributes are in the investment decision [34].

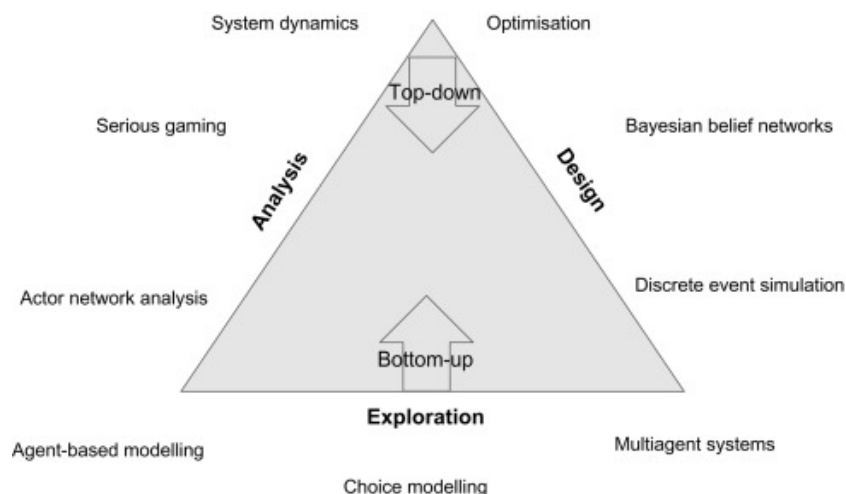


Figure 1.3: An overview of different modeling approaches in socio-technical systems, from [34].

This study applies Discrete Choice Modeling (DCM). DCM is suitable because it represents the household investment decision as a discrete choice between alternatives. In this thesis, these alternatives are different home batteries, each described by a set of attributes. DCM is grounded in the theory of Random Utility Maximization (RUM) [35]. RUM assumes that agents, or in our case, the decision-maker of energy investments in the household, will choose the alternative that maximizes their perceived utility. It does not necessarily imply that households are fully rational economic optimizers [36]. It splits the utility of an alternative into a part which depends on observed attributes, and a random error term, which captures everything we do not observe [35, 37]. Households are in reality bounded rational: they rely on limited information, time and cognitive capabilities [38]. Under RUM, such bounded-rational behavior is absorbed into the random error term rather than assumed away [37]. This is why DCM remains suitable for this study. It does not require households to maximize utility perfectly, only that their choices reflect a systematic component that can be estimated from observed attributes. RUM also does not assume utility maximization is limited to financial attributes, so DCM can also investigate non-financial attributes. This fits the problem, because the household decision to adopt is driven by both financial and non-financial factors [17, 13].

DCM has been widely used to study household adoption of energy investments and the underlying preferences for such investments [17, 29, 30, 39]. By observing household choices between alternatives with different attribute levels, DCM allows the relative importance of these attributes to be estimated. It also allows choice probabilities to be estimated for different attribute combinations. This reliance on stated choices in hypothetical scenarios, which may not perfectly reflect real investment decisions, is the main limitation of this method [40]. Despite this, DCM performs well in extracting preferences if applied correctly [41]. It also provides information on the probability of uptake of products, making it suitable for this research [42].

The use of DCM for this research question is not innovative per se. This study will however make a novel contribution by addressing a recurring shortcoming in DCE design. Attribute selection in DCEs is often poorly reported and lacks a transparent justification of which candidates were considered and why certain attributes were included or excluded [43, 44]. This is partly because a standardized approach for attribute selection in DCEs is missing [43]. This makes existing studies difficult to replicate and leaves open the question of whether different selection choices would have led to different conclusions. This research addresses this by documenting the full attribute selection process: starting with a broad literature-based driver list, screening of drivers using the framework of Kastner and Stern [26], and reporting the arguments used to select the final set of key attributes. The study does not propose a methodological contribution to DCE design in itself, but it does respond to a broader limitation DCE literature has identified.

Another limitation related to the selection of relevant attributes makes the method suitable for quantifying and validating the importance of attributes, but less suitable for discovering "unknown unknowns". DCM can show how strongly households respond to the attributes included in the experiment, but it cannot identify attributes that were not included. This limitation is acceptable in this research, because previous work has already identified a wide range of possible drivers of residential BESS adoption. A literature analysis is therefore done first to identify and translate these drivers into a focused set of home battery attributes. DCM is then used to quantify their relative importance and their effect on choice probabilities. An overview of the methodological framework is presented in Chapter 3.

## 1.4. Link to the CoSEM Program

This thesis fits within the CoSEM program because residential BESS adoption is a socio-technical process in a complex system: the Dutch electricity system. The technical domain is clearly visible, since the research focuses on home batteries as a relatively new technology that can provide flexibility in the electricity system. At the same time, the problem studied in this thesis is not purely technical. Residential BESS adoption depends on values and investment decisions of household decision-makers, but also on market incentives, regulation and the broader institutional context. The thesis therefore combines technical, economic, institutional and social insights.

The contributions of this thesis are also relevant for both public and private actors. A better understanding of residential BESS adoption can help companies, grid operators, municipalities and policymakers, but for different reasons. These actors also have different values, roles and power. Households make the final investment decision, while grid operators have to facilitate future capacity growth, municipalities may want to manage local effects, and companies may want to anticipate market development. This combination of multiple actors, different interests, unequal decision power and a technical energy-system context makes this research a true CoSEM thesis.

## 1.5. Research Structure

The remainder of this thesis is structured as follows.

**Chapter 2** discusses the role of residential BESS in the Dutch electricity system and explains why the household decision to adopt a home battery should not be understood as a purely economically rational investment decision. It then reviews existing literature on residential BESS adoption and identifies the drivers that influence the household investment decision to buy a home battery. The chapter concludes with a full argument for the knowledge gap by showing that existing research identifies many possible drivers, but does not sufficiently explain which home battery attributes matter most, how important they are relative to one another, and how changes in these attributes affect the household investment decision.

**Chapter 3** presents the methods used to answer the research questions. It first explains the theory behind DCM. It then shows how the drivers from literature are translated into key home battery attributes. After that, it describes the design of a choice experiment and survey to collect data. Finally, it explains how the models are estimated from this data and how the relative importance and choice probabilities are calculated.

**Chapter 4** presents the results. It first shows the key home battery attributes, thereby answering the first sub-question. It then presents the raw choice data and model estimation results. The chapter ends with the relative importance of the attributes and a choice probability analysis.

**Chapter 5** interprets the results by reflecting on the chosen methods and their main limitations and assumptions. It also compares and synthesizes results with relevant literature in this field of research. It discusses what the key attributes mean, how the model results should be understood, and how the

results differ over the data samples. It also compares the findings to the Australian literature, reviewing conclusions and assessing which can be transferred or generalized to other contexts. It will also argue the main implications for different actors mentioned before, and what the results imply for residential BESS adoption. The chapter concludes with a reflection on the limitations that affect the whole study and main conclusions.

**Chapter 6** concludes the thesis. It first answers each sub-question in turn, then synthesizes these into an answer to the main research question. It summarizes the main findings and reflects on their academic and societal relevance. The chapter closes by suggesting how attributes might be selected in future DCE designs concerning household investments, and recommends what further research is needed to understand residential BESS adoption on a wider scale.

# 2

## Background and Literature Review

This chapter gives the background and literature review. It works towards the knowledge gap of this study. Section 2.1 starts with a background on residential BESS adoption, explaining the need for understanding residential BESS adoption from the perspective of the different actors introduced in 1.1, why understanding it is so complex in contrast to utility-scale BESS growth, and which measures the different actors can take to steer residential BESS adoption. Section 2.2 then reviews existing research on home battery adoption, where we find that adoption follows from a household investment decision influenced by both financial and non-financial drivers. Following that we present the search process identifying such drivers. The drivers that are found are then organized in categories following Kastner & Stern's framework to examine decision-making processes of household energy investments [26]. This synthesizes existing literature on residential BESS adoption into an organized list of drivers. This list will serve as the input for the literature analysis in Chapter 3 Section 3.2.1, where we will select and operationalize these drivers into key attributes to include in the DCE. The chapter ends with Section 2.3, discussing limitations of the existing literature, and presenting the knowledge gap addressed in this thesis.

### **2.1. Background on Residential BESS Adoption**

Residential BESS, also referred to as home batteries, are battery systems installed at household level and connected behind the meter. They can store electricity produced by the household through solar PV, or electricity bought from the grid. This electricity can then be used later by the household, or exported back to the grid. Residential BESS are relevant in the Netherlands because Figure 1.1 shows combined capacity already composes 45% of installed battery capacity in the Netherlands and capacity is growing rapidly [15].

Several factors contribute to this rapid growth [15]. First, home batteries are becoming more accessible for households due to decreasing battery costs and the development of smaller plug-in systems [45, 46]. Second, Dutch households have a large installed capacity of solar PV. These households produce electricity during the day while most of their demand is in the morning and evening. A home battery can shift part of this electricity over time and thereby increase self-consumption. Until now, the Dutch net-metering scheme reduced the financial need to do this, because households could offset electricity exported to the grid against electricity consumed later. When the net-metering scheme stops in 2027, home batteries will become more attractive for households with solar PV [23]. However, a home battery can also be interesting for households without solar panels, for example when it is used in combination with dynamic electricity prices [46]. Household electricity demand is also changing. Electric vehicles, heat pumps and other forms of electrification increase the amount of electricity used by households and

shift temporal demand patterns. This also strengthens the role of home batteries, because batteries can help households match local production and local consumption [47].

The rapid increase in installed residential BESS capacity is not beneficial per se for all parts or actors in the electricity system. Indeed, when operating to maximize self-consumption, it charges from surplus solar generation during the day and discharges in the evening, smoothing the household's own demand profile [48]. If they are operated in such a grid-supportive way, they can reduce pressure on the electricity grid [49]. However, when operating to maximize profits from price arbitrage, it charges when the electricity price is low and discharges when it is high. Because many households face the same price signal, all these batteries will charge in the same low-price hours [50]. This creates congestion at the local level, which would require grid reinforcement, costing the Dutch DSOs and TSO billions [24, 19]. Whether residential BESS helps or harms the grid therefore depends on how batteries are controlled, which is why grid operators do not aim to prevent adoption but to anticipate it: by better understanding what drives households to invest in home batteries, adoption can be predicted more accurately, allowing better spatial planning of grid investments [51, 18].

Governmental and legislative actors are concerned with residential BESS adoption as well, although for different reasons. The Ministry of Economic Affairs and Climate has called for stronger decentralized developments in the energy system, including home batteries, and stresses the need for capacity planning that better aligns local generation, storage and consumption to reduce pressure on the grid and support a resilient and sustainable energy system [22]. Municipalities have limited insight into the local growth of home batteries and seek to understand and steer this growth in order to manage its effects on local congestion [20, 24]. At the European level, the EU Commission is responsible for ensuring that electricity markets function properly and that the transition towards a renewable energy system continues [6, 52].

Energy companies are interested in residential BESS for two business reasons. First, understanding which households are likely to adopt helps energy companies market and sell batteries and design contracts that profit from how those batteries are used [53]. Second, the total installed capacity of residential BESS affects future electricity prices and therefore the business cases and investments of energy companies [54]. Forecasting this effect is difficult, because the value of storage can decline as more storage enters the market and narrows the price spreads it relies on [55, 56].

Altogether, we have shown that the externalities of large-scale residential BESS adoption can be relevant from the perspectives of multiple actors. Understanding the decision of a household to invest in a home battery is therefore relevant for grid operators, energy companies, municipalities and policymakers [18, 20, 22, 53]. We will now explain why understanding this decision is not straightforward by contrasting growth in residential BESS capacity to growth in utility-scale BESS capacity.

We can distinguish residential BESS adoption from utility-scale BESS growth [14, 57]. Utility-scale BESS and residential BESS are technically similar because both store electricity and release it later. The main difference is not the battery technology itself, but the actor owning the system [58]. Utility-scale BESS are owned by professional market actors, such as utilities, energy companies or power producers. These actors make investment decisions based on economic returns [16]. Residential BESS, in contrast, are adopted by individual households. Capacity growth therefore follows from many separate household investment decisions instead of a smaller number of professional investment decisions. Table 2.1 summarizes the main differences. These differences show some of the complexities of residential BESS adoption.

**Table 2.1:** Main differences between residential and utility-scale BESS

<b>Dimension</b>	<b>Residential BESS</b>	<b>Utility-scale BESS</b>
Owner	Households	Utilities, energy companies or power producers
Connection	Behind the meter, connected to the household electricity system	Direct connection to the electricity grid
Decision-maker	Individuals in the household	Professional market actors
Market access	No direct access to DA, ID or balancing markets; indirect access possible through contracts	Direct or professionally organized market participation through a BRP
Investment logic	Diverse, differs per household	Uniform, based on economic returns
Capacity growth	Many small adoption decisions	Fewer large investment decisions

Taken together, we find that residential BESS is hard to predict because it emerges from many heterogeneous household decisions. The actors discussed above cannot directly decide whether a household buys a battery. They can only influence residential BESS adoption indirectly, through policies that change the conditions under which households evaluate a battery. Examples of such policies, and the responsible actor, are shown in Table 2.2 [15, 24, 59].

**Table 2.2:** Policies and regulations that may affect residential BESS adoption.

<b>Policy or regulation</b>	<b>Actor</b>
Abolishment of the net-metering scheme [23]	Ministry of Economic Affairs and Climate
Feed-in remuneration and feed-in costs [24]	TSO & ACM*[60]
Flexible or time-dependent grid tariffs [24]	DSO designs, ACM* approves
Preventing double energy taxation for stored electricity [24]	Ministry of Economic Affairs and Climate
Rules on participation of small-scale batteries in imbalance or flexibility markets [24]	TSO, DSO
Independent aggregation and improved access to electricity markets [24]	EU Commission
Capacity remuneration mechanisms [24]	EU Commission, Ministry of Economic Affairs and Climate
Investment subsidies or tax rebates for home batteries [24]	Municipalities, Ministry of Economic Affairs and Climate, EU Commission
EU Battery Regulation [52]	EU Commission
Physical safety standards for battery installation and operation [52]	EU Commission
Stricter cybersecurity standards [52]	EU Commission
Environmental requirements for battery production, use and recycling [52]	EU Commission

\* The ACM, the Authority for Consumers and Markets, is an independent actor that controls the tariffs set by grid operators [60].

The examples above show that various actors can take different measures that influence residential BESS adoption. The relation of the actors and policies mentioned here, and how they connect to the household investment decision will be elaborated upon at the end of the next section. Note that apart from these policies, many other things can influence residential BESS adoption: BESS costs are declining worldwide [45], and companies could offer discounts or attractive contracts [53]. We will not go further into this as this lies beyond the scope of this research. The key takeaway here is that residential BESS adoption can be shaped by developments outside the household, but not determined by them directly. Because external developments can change the attributes of home batteries, it is important to know how households value those attributes. The next section will review scientific literature on residential BESS adoption in order to identify what has been done to understand the household investment decision to buy a home battery.

## 2.2. Literature Review: Residential BESS Adoption

Section 2.1 showed that residential BESS capacity grows through many household adoption decisions. It also showed that it is important to understand how households value the attributes they base their decision on, as these attributes can be affected by relevant actors. This section reviews existing literature surrounding this topic to answer the question: **What does existing research already know about household adoption of home batteries?**

### 2.2.1. Residential BESS Adoption is not a Purely Economic Decision

As argued in Section 2.1, residential BESS adoption should be understood as a household investment decision rather than as the outcome of professional business-case optimization. Existing literature supports this distinction. Studies on residential BESS adoption show that households consider financial drivers such as investment cost, payback period, profitability, tariffs and subsidies [13, 30, 61, 62]. However, these studies also show that adoption is influenced by drivers that are not purely techno-economic like energy autonomy, backup power and environmental motives [13, 17, 30, 32]. Although correlated with technical characteristics, like battery size, these drivers also capture values like independentness, environmental awareness or safety and security. The literature shows the relevance of financial attributes, but also identify a broader set of drivers that may shape the household decision to buy a home battery. The next step in this literature review is to do a structured search identifying the drivers of residential BESS adoption.

### 2.2.2. Drivers of Residential BESS Adoption

To identify drivers of residential BESS adoption, a literature search was conducted in Scopus. The search process follows a similar approach to research on drivers of household heat pump adoption [63]. Since this study focuses on household adoption of residential BESS, the search query combines three elements: residential BESS, adoption, and drivers. The driver term was kept broad, so that both direct adoption drivers and broader explanatory variables could be identified. The resulting search query is shown in Table 2.3.

Table 2.3: Search entry in Scopus on March 18, 2026.

Component	Query
Search within	TITLE-ABS-KEY (
Residential BESS technology	("home batter*" OR "household batter*" OR "residential batter*" OR "battery energy storage system*" OR BESS OR "home energy storage" OR "residential energy storage" OR "domestic energy storage" )
Adoption	AND ( adoption OR diffusion OR uptake )
Drivers	AND ( driver* OR barrier* OR determinant* ))

The search yielded 55 results and were screened on their title and abstract to check whether residential or household BESS adoption was a central topic. Excluded studies discussed battery performance, electric vehicles, or other household energy technologies. This screening resulted in an initial set of five relevant studies. During full-text reading of these studies, four more studies were found through the references. One initially selected paper was excluded because a more relevant paper by the same authors was found, which contained the original driver information [30, 31]. The included papers are shown in Table 2.4.

From the selected papers, drivers associated with residential BESS adoption were identified by reviewing the results, tables and discussions. Direct adoption drivers, such as upfront cost, payback period and self-sufficiency were included, but also broader explanatory variables, such as income, home ownership, policy arrangements and tariff structures. In total 79 drivers were found, both financial and non-financial

**Table 2.4:** Papers included in the corpus to identify drivers of residential BESS adoption

Author	Year	Title
Agnew and Dargusch	2017	Consumer preferences for household-level battery energy storage [30]
Agnew, Smith and Dargusch	2019	Understanding transformational complexity in centralized electricity supply systems: Modelling residential solar and battery adoption dynamics [31]
Alipour et al.	2022	Exploring residential solar PV and battery energy storage adoption motivations and barriers in a mature PV market [13]
Alipour et al.	2026	Factors Driving Battery and Solar Purchase Decision of Residents: a Behavioural Choice Experiment Using a Hybrid Discrete Choice and Latent Variable Model [17]
Aniello	2026	What drives disparities in the diffusion of residential PV and battery systems? A spatial econometric analysis in the context of dynamic regulatory arrangements [12]
Best et al.	2021	Actual uptake of home batteries: The key roles of capital and policy [61]
Broese van Groenou, Lovell and Franklin	2018	Household Decision-Making for Home Batteries [32]
Jayaraj, Ananthram and Klarin	2026	Towards Consumer Acceptance of Residential Batteries [62]

drivers.

To structure these drivers, the categories of Kastner and Stern [26] were used. They examined the decision-making processes behind household energy investments in a large review. They defined *explanatory variables* and identified six types of explanatory variables: demographic/housing characteristics/location of residence (I), decision-maker dispositions (II), beliefs about consequences for (III) and beyond (IV) the household, social influences (V) and policy measures (VI). They also note that not all categories are equally important. Their review suggests that beliefs about consequences and policy measures tend to matter most for household energy investment decisions [26]. This categorization is useful for the screening process in the next section because it gives a clearer distinction between variables that correlate with adoption and drivers that are more directly part of household decision-making. The full driver list and categorization can be found in Table 2.5.

**Table 2.5:** Residential BESS adoption driver inventory. Category codes: I = Demographic, housing characteristics, house location; II = Decision-maker dispositions; III = Beliefs about consequences for household; IV = Beliefs about consequences beyond household; V = Social influences; VI = Policy measures.

Driver	Cat.	Source	Note
Battery system cost / upfront cost	III	Agnew [30]	Key determinant of stated preference
Payback period	III	Agnew [30]	Shorter payback raises appeal
Battery safety	III	Agnew [30]	Strongly valued product attribute
Battery size / capacity	III	Agnew [30]	Medium or large systems often preferred
Ease of use / maintenance burden	III	Agnew [30]	Simple set-and-forget operation preferred
Warranty length	III	Agnew [30]	Considered but less important
Design / visual appearance	III	Agnew [30]	Aesthetics considered but least important
Self-sufficiency	III	Agnew [30]	Strong non-financial driver
Environmental impact reduction	IV	Agnew [30]	Important but not the top driver
Grid independence	III	Agnew [30]	Influences self-sufficiency; strong non-financial driver
Reducing reliance on energy companies	III	Agnew [30]	Influences self-sufficiency
Backup during blackouts	III	Agnew [30]	Influences self-sufficiency; relevant resilience motive
Battery price	III	Agnew [31]	Influences cost; falling battery prices accelerate uptake
Rising electricity prices	VI*	Agnew [31]	Influences self-sufficiency
Tariff structures	VI	Agnew [31]	Influences payback time & self-sufficiency
PV system size	I	Agnew [31]	Battery attractiveness depends on onsite generation
Government subsidies / policy	VI	Agnew [31]	Influences payback time & costs
Solar system size (physical capital)	I	Best [61]	Smaller PV systems are less likely to add batteries
Solar feed-in tariff level	VI	Best [61]	Lower feed-in tariffs increase battery uptake
Financial pressure / capital constraint	I	Best [61]	Financially constrained households adopt less
Younger age	I	Best [61]	Control vector with statistical significance
Household disengagement	II	Best [61]	Lower engagement is associated with lower uptake
Lower electricity bills	III	Alipour [13]	Most important battery or PV motivation
Payback period	III	Alipour [13]	Important financial consideration
Profitability of battery system	III	Alipour [13]	Financial return matters strongly
Being self-sufficient / energy autonomy	III	Alipour [13]	Important and stronger than environmental concern

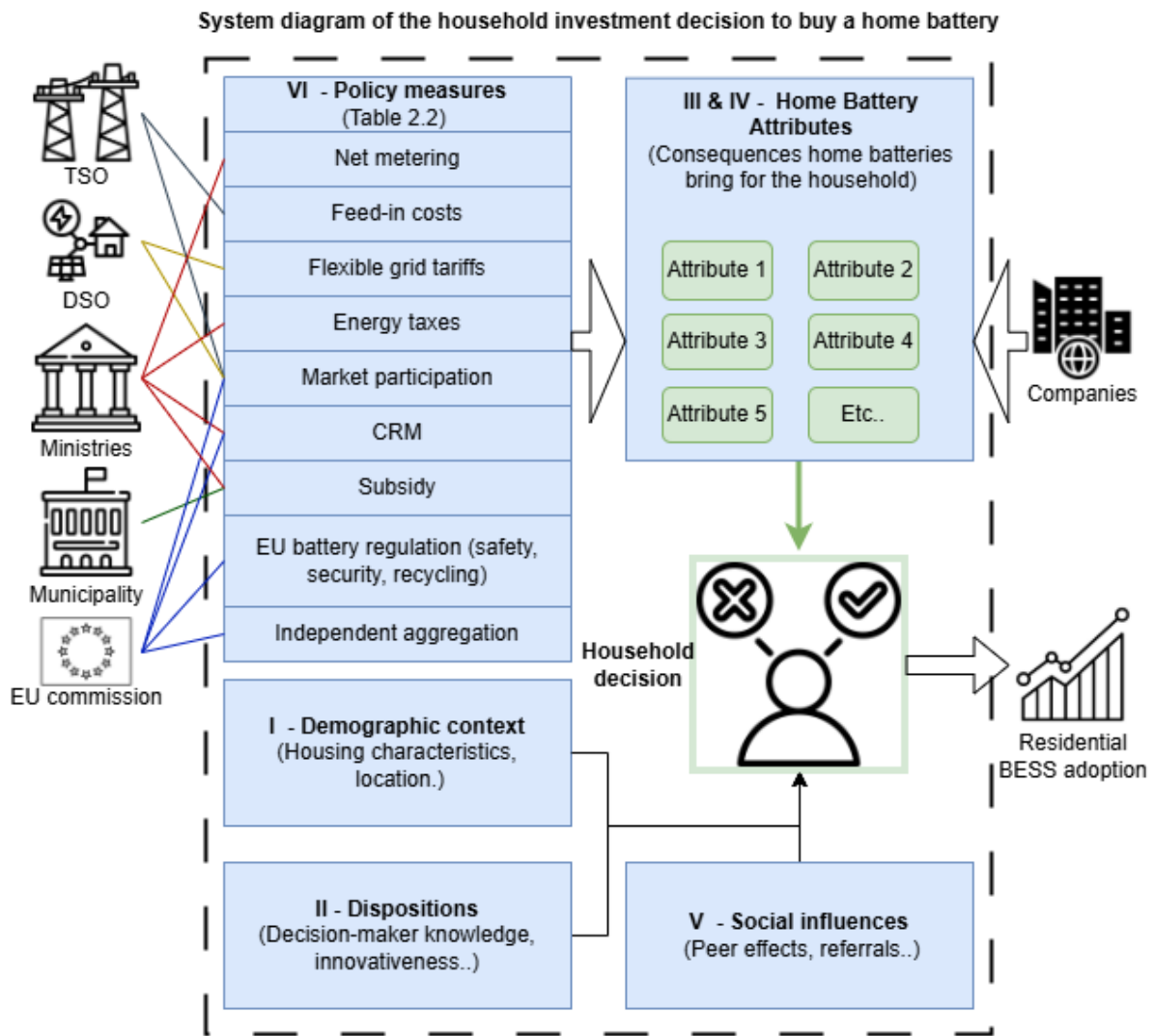
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Driver	Cat.	Source	Note
Avoiding blackouts / power outages	III	Alipour [13]	Relevant resilience motive
Environmental concerns	IV	Alipour [13]	Important but secondary to finance
Interest in the technology	II	Alipour [13]	Matters especially for adopters and innovators
Encouragement by others / peer effects	V	Alipour [13]	Considered least important overall
Annual system cost	III	Alipour [17]	Significant choice-model driver
Battery size	III	Alipour [17]	Critical in PV-owner battery decision
Energy autonomy	III	Alipour [17]	Strong motivator especially for integrated adoption
Peer influence / communicator traits	V	Alipour [17]	Significant through latent communicator constructs
Perceived knowledge about PV or BESS	II	Alipour [17]	Part of significant latent constructs
General innovativeness	II	Alipour [17]	Defines adopter-oriented latent profile
Financial motives / profit-seeking	III	Alipour [17]	Significant latent driver of larger battery choice
Environmental / social attitude	IV	Alipour [17]	Significant through socially conscious investor profile
Age	I	Alipour [17]	Significant sociodemographic influence
Income	I	Alipour [17]	Significant sociodemographic influence
Education	I	Alipour [17]	Significant sociodemographic influence
Employment status	I	Alipour [17]	Significant sociodemographic influence
Gender	I	Alipour [17]	Significant via latent-variable structure
Electric vehicle ownership	I	Alipour [17]	Associated with stronger battery adoption orientation
Owning a pool	I	Alipour [17]	Raises likelihood of battery uptake
House value below AUD 1 million	I	Alipour [17]	Interacts with preference for large battery size
House age	I	Alipour [17]	Increases likelihood of adoption
Acceptable payback period	III	Broese van Groenou [32]	Purchase timing depends heavily on payback
Reducing household power bills	III	Broese van Groenou [32]	One of the main stated reasons to buy
Storing excess solar generation	III	Broese van Groenou [32]	Core functional reason for adoption
Reliability of supply / future outages	III	Broese van Groenou [32]	Motivates a substantial share of households
Environmental considerations	IV	Broese van Groenou [32]	High priority for many but rarely sufficient alone
Rising electricity prices	VI*	Broese van Groenou [32]	Encourages self-reliance and battery interest
Premium feed-in tariff ending	VI	Broese van Groenou [32]	Pushes households toward storage
Trust in information sources	V	Broese van Groenou [32]	Family and friends trusted more than incumbents
Electric vehicle acquisition	I	Broese van Groenou [32]	Expected future EV load encourages larger systems
Homeownership structure	I	Aniello [12]	Strong regional driver of diffusion
Income	I	Aniello [12]	Very important especially for batteries
Education / low education	I	Aniello [12]	Lower education is a barrier
Foreign population share	I	Aniello [12]	Higher share is associated with lower uptake
Elderly population share	I	Aniello [12]	Older populations are associated with lower uptake
Families with minors / under-18 share	I	Aniello [12]	Considered as positive demand proxy
Political inclinations	II	Aniello [12]	Attitudinal-political context shapes uptake disparities
Residential demand	III	Aniello [12]	Considered with mixed or minor effects
PV generation potential	I	Aniello [12]	Considered and found to play only a minor role
Energy prices	VI*	Aniello [12]	Regulatory change materially shapes diffusion
Energy independence	III	Jayaraj [62]	Key adoption motivation
Backup power	III	Jayaraj [62]	Identified as a major performance expectation
Efficient use of solar	III	Jayaraj [62]	Strong functional reason for adoption
Battery system cost	III	Jayaraj [62]	High upfront cost is a primary adoption barrier
Payback period	III	Jayaraj [62]	Belief in acceptable payback period increases adoption
Financial savings / lower electricity bills	III	Jayaraj [62]	Clearest perceived benefits
Rebates / no-interest loans	VI	Jayaraj [62]	Improve affordability
Feed-in tariff reduction	VI	Jayaraj [62]	Lower FiTs make self-consumption attractive
Ease of installation and use	III	Jayaraj [62]	Simple use reduces perceived effort
Installer competence	III	Jayaraj [62]	Poor reputation reduces consumer confidence
Compatibility with current PV system	I	Jayaraj [62]	Whether existing can integrate with storage
Consumer knowledge	II	Jayaraj [62]	Sociodemographic influence
Peer referrals	V	Jayaraj [62]	Positive referrals from others encourage adoption

**Table 2.5:** \* Electricity prices are considered a political driver because of the high influence of regulations on electricity prices [26].

Having identified and categorized the drivers, the actors and policies from Section 2.1 and the categorized drivers can be combined to create a schematic understanding of the household investment decision, shown in Figure 2.1. The household investment decision is central and is shaped by the several categories of Kastner & Stern [26]. Drivers in categories III and IV, the beliefs about consequences for and beyond the household, can be tied to home battery attributes, because the concrete characteristics of a battery are what gives these consequences for the household. As motivated in the previous chapter, these attributes are the focus of this thesis. The actors and policy measures from Table 2.2 (category VI) do not influence the decision directly but indirectly, by changing these attributes. The remaining categories, demographic context (I), decision-maker dispositions (II) and social influences (V), shape the household decision directly but are outside the scope of this study, as these are different for each household and the relevant actors have little influence on them [26].

The diagram makes explicit both what can influence the household decision (in blue) and what this study focuses on (in green). The exact way in which each policy changes each attribute is itself uncertain and lies beyond the scope of this study [24, 25, 52, 64]. This study will investigate the more fundamental link, which attributes households value, how much, and how this affects the household decision. The next section discusses the limitations in existing literature that do not yet allow us to understand the role of attributes in the household investment decision to buy a home battery.



**Figure 2.1:** System diagram of the household investment decision to buy a home battery. On the left the actors are connected to the possible policies they can influence. These policies can then change home battery attributes that the households consider. Energy companies can also affect the attributes, for example through contracts and discounts. Together with demographic context (I), decision-maker dispositions (II) and social influences (V), the attributes shape the household investment decision, resulting in residential BESS adoption.

## 2.3. Limitations and Research Gap

The driver list shows that existing literature identifies many possible drivers of residential BESS adoption, both financial and non-financial. Different methods were used to identify such drivers, some through stated motivations [13] or interviews [32], and other through statistical correlations [61]. We therefore conclude sufficient work has been done to identify drivers. What remains less well understood is which of these drivers matter most, how households weigh them against one another, and whether findings transfer to the Dutch context. This section discusses three limitations of the existing literature.

A first limitation is that the existing prioritizations are not sufficient to understand how households trade off battery characteristics. Kastner and Stern suggest that beliefs about consequences for the household and policy measures generally matter most in household energy investment decisions [26]. Within the residential BESS literature, Alipour et al. ranked adoption motivations by asking respondents directly about their reasons to install a home battery [13]. However, Best et al. show that such stated interest and actual uptake can differ substantially [61]. Stated importance rankings therefore do not reveal how households actually trade off battery characteristics in an investment decision. Unlike such

rankings, DCE gives information in the strength and probability of adoption, allowing us to overcome such limitations [42]. Agnew and Dargusch provide one of the few studies that ranks home battery attributes by relative importance using a DCE, estimating preferences from choices rather than from stated importance [30]. Their results suggest that cost contributes most, followed by safety, size and payback period. However, their experiment also has limitations. Larger system sizes were connected to higher self-consumption and higher costs, which makes it difficult to interpret whether respondents preferred larger systems because of the battery size itself, higher self-consumption, or the associated cost changes [30].

A second limitation concerns the selection of attributes for a DCE. There is no standardized approach for selecting which attributes to include in a DCE, and the selection step is often reported inadequately, even though transparent reporting is needed for replicability of research [43, 44]. This shortcoming is also present in the residential BESS literature. Agnew and Dargusch selected their attributes from a best-to-worst scaling of motivations and system attributes completed by participants, they however do not report which motivations and attributes were included for scaling [30]. This has two consequences. First, the unreported candidate set limits replicability. Second, selecting attributes from what participants already state to be important risks a bias, because the experiment then measures the importance of attributes that were chosen for being considered important. This study addresses this limitation by selecting attributes using a literature analysis and reporting on the full selection process.

A third limitation is that the existing literature is geographically concentrated in Australia [13, 17, 30, 31, 32, 61]. Some Australian findings might be true for the Netherlands since both countries have high residential solar PV penetration [13, 15]. Some regulations are also similar, Australian feed-in tariffs have ended [32] and the Dutch net-metering scheme is stopping in 2027 [23]. Lastly, time-of-use tariffs, already common in Australia, are now also emerging in the Netherlands [60]. If Dutch and Australian household preferences are similar, residential BESS adoption may follow a comparable path. There are however also differences. Australia receives almost twice as much solar irradiation as the Netherlands, and its seasonal variation in irradiation is smaller [65]. These are relevant because the main value of a home battery for a PV household lies in storing surplus daytime solar for later use. Because of different solar availability, the economics and use of a home battery might differ between the two countries, which can change how households value the battery attributes. Because household preferences differ by location and change over time [66], it will be interesting to confirm whether Australian preferences measured over 10 years ago are similar to contemporary preferences in the Netherlands [30].

Table 2.6 summarizes the limitations of different literature. Not all reviewed literature from previous Table 2.4 specifically concern household battery attributes. Aniello for example uses a spatial econometric analysis to battery adoption with demographic and policy factors [12], and Best et al. explain uptake from capital and policy variables [61]. Table 2.6 therefore compares only the studies that examine household battery attributes and motivations against the three limitations discussed above.

**Table 2.6:** Comparison of studies examining household battery attributes and motivations against the three limitations.

Study	Transparent attribute selection	Attribute prioritization	Geographically & temporally relevant
Agnew & Dargusch (2017) [30]		✓	
Alipour et al. (2022) [13]		✓	
Alipour et al. (2026) [17]		✓	
Broese van Groenou et al. (2018) [32]	✓		
Jayaraj et al. (2026) [62]			✓
<b>This study</b>	✓	✓	✓

In summary, existing literature identifies the drivers of residential BESS adoption but does not establish which concrete home battery attributes matter most to households, how important these attributes are relative to one another, or how changes in these attributes affect the household investment decision. As

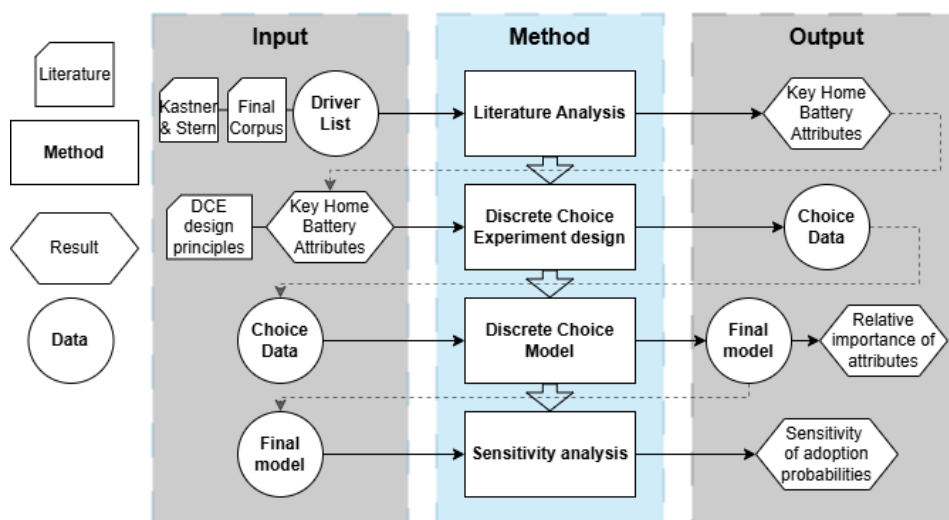
Table 2.6 shows, no existing study combines a transparent attribute selection, a prioritization of attributes by relative importance, and relevance to the current Dutch context. The novelty of this research lies in addressing these three at once: it selects its attributes through a transparent, literature-based process, it quantifies their relative importance and their effect on the household investment decision, and it does so for the Netherlands under current market conditions, for which no equivalent study exists.

Answering this gap requires a method that can quantify trade-offs between attributes from actual choice behavior rather than from stated importance ratings. The next chapter describes how a DCE was designed, and the resulting choice data analyzed, in order to address this gap.

# 3

## Methodology

This chapter explains the methodological approach used to answer the research questions. The goal of the methodology is to move from a broad set of adoption drivers found in literature to a discrete choice model that can quantify how households respond to changes in home battery attributes. The methodological framework is shown in Figure 3.1. The framework consists of four main steps. First, the driver inventory from the literature review is screened and translated into home battery attributes. This step identifies the key attributes used in the experiment and answers SQ1. Second, these attributes are used to design and distribute a discrete choice experiment (DCE). The resulting choice data form the input for the discrete choice model. Third, the choice data are used to estimate the model and interpret the estimated coefficients. This shows whether the attributes systematically affect household choices. Fourth, the estimated model is used to calculate the relative importance of the attributes and to test how choice probabilities change when attribute levels change. These steps answer SQ2 and SQ3.



**Figure 3.1:** Schematic overview of the methodological framework. The middle column shows the main steps. The left column shows the inputs for each step and the right column shows the outputs. Outputs are either inputs for the next step or answers to the sub-questions.

The remainder of this chapter follows this framework. Section 3.1 first introduces the discrete choice modeling theory needed to understand the model estimation and probability calculations. Section 3.2 explains how the drivers are screened and translated into key home battery attributes, in a transparent way. Section 3.3 describes the design and data collection of the DCE. Finally, Section 3.4 explains how the final model is estimated and the choice data analyzed.

### 3.1. Theoretical Background on Discrete Choice Modeling

Discrete Choice Modeling (DCM) is a modeling technique used to explain and predict people's choices between two or more alternatives [37]. In this research, the choice is whether a household chooses one of the presented home battery alternatives or chooses not to buy a home battery. A home battery alternative can be described by a set of attributes, such as investment cost, payback time and the degree to which the battery allows self-consumption. By gathering enough data of choices that households make between alternatives with different attribute levels, a model can be estimated how respondents trade off these attributes. This makes it possible to quantify the influence of the different home battery attributes on the household investment decision.

Collection of choice data is done through a Discrete Choice Experiment (DCE). A DCE consists of four main elements: the decision-maker, the available alternatives, the attributes describing these alternatives, and the decision rule used to make the choice [37, 67]. In this thesis, the decision-maker is the relevant individual or individuals in the household making the choice. The alternatives are the options that can be chosen, either a specific battery type, or no battery. The attributes are the characteristics that describe the battery. The decision rule describes how the decision-maker evaluates the alternatives and selects one of them. This decision rule is based on the theory of Random Utility Maximization (RUM) [35]. RUM assumes the decision-maker chooses the alternative with the highest utility [35, 37]. Real households might however not be consistent in their decisions, they deviate from this because households are bounded rational decision-makers [38]. RUM however does not require households to optimize perfectly: it only requires that their choices contain a systematic component that can be estimated from observed attributes, while deviations from perfect maximization are captured in an unobserved part of utility, introduced below [37]. Utility is a measure for the perceived benefit of an alternative to a respondent. This utility is not directly observed by the researcher. Instead, the researcher estimates the utility based on the choice data. If a respondent chooses alternative  $i$  over alternative  $j$ , the model interprets this as a signal that alternative  $i$  gives more utility than alternative  $j$  in that choice situation. The absolute value of the utility is therefore not directly of interest, the relative difference in utility of alternatives is.

The total utility of an alternative ( $i$ ) for a respondent ( $n$ ) can be written as:

$$U_{ni} = V_{ni} + \varepsilon_{ni}$$

where  $U_{ni}$  is the total utility,  $V_{ni}$  is the observed part of utility, and  $\varepsilon_{ni}$  is the unobserved part of utility. The observed utility contains the effect of the attributes included in the choice experiment. The unobserved part contains everything else that may influence the choice but is not included in the choice experiment. This can be personal preference, other attributes that are not shown in the choice experiment, but also results from bounded-rational behavior. Deviations from perfect rationality are absorbed in this term, rather than assumed away. This means that DCM does not predict one perfectly certain choice. It can however, predict choice probabilities through the logit transformation. By assuming that the unobserved part of utility is independently and identically extreme value type I distributed, the probability that respondent  $n$  chooses alternative  $i$  can be written as [35, 37]:

$$P_{ni} = \frac{e^{V_{ni}}}{\sum_{j \in J} e^{V_{nj}}}$$

where  $P_{ni}$  is the probability that respondent  $n$  chooses alternative  $i$ ,  $V_{ni}$  is the observed utility of alternative  $i$ , and  $J$  is the set of available alternatives.

When designing a DCE, the goal is to make the observed part of utility as informative as possible. This is done by selecting relevant attributes, using realistic attribute levels, and presenting respondents with clear and believable choice tasks. In that way, the choices made in the experiment are more likely to

reflect the trade-offs respondents would also make in a real decision context, which increases the validity of the model outcomes [41, 40]. The observed utility  $V_{ni}$  is specified by the utility function and can take many forms, depending on how people subjectively determine utility of an alternative. The basic form is the linear-additive utility function, meaning that each attribute adds or subtracts utility linearly [40]:

$$V_{ni} = ASC_i + \beta_X X_{ni} + \beta_Y Y_{ni}$$

Here  $X_{ni}$  and  $Y_{ni}$  are attribute levels, and  $\beta_X$  and  $\beta_Y$  are coefficients that have to be estimated. These coefficients show the direction and strength of the effect of each attribute on utility. A positive coefficient means that a higher value of the attribute increases utility. The  $ASC_i$  is the alternative-specific constant. It captures the basic preference people have for, or against an alternative. In this research the utility function for the no-battery alternative would include an ASC to capture the tendency of people to either like or dislike a battery. The coefficients are estimated through maximum likelihood estimation (MLE) [40]. This means that the model searches for the coefficient values that make the choice data most likely. Once these coefficients are estimated, the utility function can be used to calculate the probability that each alternative is chosen using the logit transformation [35]. Together, the RUM assumption, the linear-additive utility function, and the logit choice probability form the standard RUM-MNL model [40].

The RUM-MNL model can be extended upon in several ways. The utility function can be adjusted to test whether attributes have non-linear effects, or whether the effect of one attribute depends on another attribute through interaction effects [40]. These models can then be estimated and their performance compared to see if such effects are actually considered by the participants.

A significant limitation of the RUM-MNL is that it assumes all choice observations are independent data points. This is usually not true for consecutive choice tasks filled out by the same respondent. The answers of the same respondent are likely to be correlated [40]. We can account for this correlation by estimating a panel mixed logit model, or panel MXL, [37, 68]. A panel mixed logit model treats the repeated choices of one respondent as connected and allows preferences to differ between respondents. It still estimates  $\beta$ -coefficients similar to the RUM-MNL, but it can treat coefficients as a distribution, thereby capturing heterogeneity.

The estimated  $\beta$ -coefficients can be interpreted by looking at their sign, size and statistical significance. First, the sign shows whether an attribute increases or decreases utility. Second, the size represents the size of the slope of that attribute in the utility function, and thus is a measure of how impactful the change in that attribute is on the utility. Third, the statistical significance. This is commonly assessed using a t-statistic, which compares the estimated  $\beta$ -coefficient to its standard error. If the absolute value of the t-statistic is large, typically larger than 1.96 for a 5% significance level, the estimated coefficient is large relative to the uncertainty of the estimate [40].

The size of  $\beta$ -coefficients themselves do however not directly show the relative importance of an attribute. Attributes could be measured in different units, and the estimated coefficients are connected to the scale of the utility function. Therefore, directly comparing coefficient magnitudes can be misleading [40]. Lancsar et al. describe several methods to assess relative attribute importance from choice data [69]. In this research, probability analysis is used because the final goal is also to estimate choice probabilities. This method fits the research because it measures how much each attribute changes the predicted probability of choosing a home battery.

The probability analysis is done by changing one attribute at a time while keeping all other attributes fixed at a certain baseline. For each attribute, the estimated DCM is used to calculate the choice probability at the different levels of that attribute. The relative impact of an attribute is then calculated as the difference between the highest and lowest predicted choice probability caused by that attribute. This gives the relative contribution of each attribute to changes in predicted choice probability. This number does not represent absolute psychological importance. It is a measure for the relative importance of different attributes, as measured within the assumptions and range of the experiment [69].

A second method proposed by Lancsar et al. to compare the relative impact of attributes is to compare the drop in log-likelihood of the estimated model when removing one of the attributes from the utility function [69]. The log-likelihood is a measure for how well the model predicts the observed data. It can be compared with the null log-likelihood, which is the logarithm of the probability of guessing all the observations correctly, if all alternatives have an equal chance of being chosen. The log-likelihood uses the estimated  $\beta$ -coefficients and the logit transformation to assign probabilities to the different alternatives based on their observed utility, and therefore predicts the choices better [35]. The larger, i.e. less negative, the log-likelihood is compared to null-log likelihood, the better the model fit. Therefore if removal of one attribute causes a larger drop in log-likelihood than another attribute, it can be concluded that this attribute had a higher explanatory power [69]. The likelihood-ratio test can be used to systematically compare the fit of two models, with one model containing less attributes than the other, based on their maximum log-likelihoods. By taking drop in log-likelihood and multiplying by 2 and comparing this value in a Chi-square table, it can be decided if the removal of the attribute significantly worsens model fit. If the attribute does not significantly worsen model fit, the explanatory power of the attribute can be questioned [40].

## 3.2. Literature Analysis to go from Drivers to Key Home Battery Attributes

This part of the methodology takes the driver list from Chapter 2 Section 2.2.2 and translates them into key home battery attributes for the DCE. Drafting a broad candidate list and then reducing it to a manageable set is a common strategy for developing DCE attributes [70]. Section 3.2.1 therefore first screens the driver list using the categories of Kastner and Stern [26]. After this screening, the remaining drivers are operationalized to potential home battery attributes. The second step then identifies the key home battery attributes to include in the DCE. Despite the lack of a universal method for attribute selection, we are guided by principles such as relevance to the Dutch context, significance in literature, and suitability for the DCE [70]. We are also guided by the general DCE practice that "*less is more*", aiming for a limited number of attributes, often around 3-7 [40, 70]. The goal is not to include every possible attribute, but to include the most relevant attributes for observing household trade-offs [40]. This screening and selection is also where the methodological contribution of this thesis is located. Chapter 2 showed that attribute selection in DCEs is often poorly reported, which limits replicability [43, 44]. This thesis responds to that limitation by documenting the full path from a broad literature-based driver list to the final attributes, not by changing the method itself. A novel contribution is therefore made by transparent reporting of the attribute selection.

### 3.2.1. Screening and Operationalization of Drivers to Attributes

Because the literature search used a broad definition of drivers, the initial set of drivers will be screened for suitability in this research in several steps. First, demographic and contextual variables are removed. This mostly concerns variables in category I, II and V of Kastner and Stern. This is because although these variables can help explain adoption patterns, they are not necessarily part of the decision considered by the household [26]. They are therefore out of the scope of the bottom-up modeling approach that is taken in this research. Second, policy measures or regulatory drivers are removed, corresponding to category VI in the categorization. These drivers are still relevant for the later institutional analysis, but they influence adoption only indirectly through other drivers, such as payback time or costs. Lastly, similar concepts are merged. An overview of this screening process is shown in Table 3.1. What follows now is an elaboration on this screen-out process.

**Table 3.1:** Screening steps of the driver inventory

Step	Drivers remaining	Reason for exclusion
Initial driver count	79	-
Removing demographic and contextual variables	45	Removed because they describe households or regions rather than household adoption decisions. Not part of bottom-up modeling approach.
Removing policy instruments and regulations	36	Removed because they influence adoption only indirectly through other drivers
Merging duplicates	12	Similar concepts are superfluous

The first step removed demographic and contextual variables like age, income, education, gender, employment status or house value. These variables can be relevant for explaining adoption at a wider scale, but they are not direct reasons that households consider when choosing a battery. These variables are not selected as DCE attributes because they describe households or social context rather than battery alternatives. They remain relevant as screening variables, sample descriptors, possible covariates, or limitations. Also, Kastner and Stern note that demographic, housing and location characteristics are generally weaker drivers and less direct than beliefs about consequences for the household [26]. They may explain why some groups adopt earlier than others, but they do not directly influence the behavior at an individual level. The same applies to variables such as PV system size, home-ownership or owning a pool. These variables may affect the technical or financial attractiveness of a battery, but they describe the household context rather than the battery proposition itself. They also cannot be accounted for as attributes in a DCE.

The second step removes policy instruments and regulations from the driver set. These variables are relevant for this thesis, but they are not treated as household adoption drivers directly. A household does not usually evaluate a subsidy or FiT as an isolated driver. Instead, these institutional arrangements affect other characteristics of the battery. For example, a subsidy lowers investment costs and a FiT changes the expected payback time.

The third step removes duplicates and merges similar concepts. This was necessary because several studies use different terms for the same underlying driver. For example, payback period, acceptable payback period and payback time all describe the time needed for the investment to earn itself back. These were therefore merged into payback time. The same was done for battery system cost, upfront cost and battery price, which were merged into investment costs. Self-sufficiency, energy autonomy, grid independence and reducing reliance on energy companies were also merged, since they all describe the wish of households to have more control over their own electricity use and to become less dependent on the grid.

The remaining drivers are all directly connected to the home battery proposition. They describe what a battery costs, what it financially delivers, what functions it provides, or what product and installation characteristics come with it. Therefore, these can all be operationalized as potential home battery attributes. The potential home battery attributes are shown in Table 3.2. This table defines the pool of attributes from which the final DCE attributes are selected in the next subsection.

**Table 3.2:** List of home battery attributes after screening and translation of drivers found in literature.

Home battery attribute	Cat.	Merged with:
Investment costs	III	Battery system cost, upfront cost, battery price
Payback period	III	-
Financial savings	III	Lower electricity bills, reducing household power bills, profit-seeking, annual system cost
Battery capacity	III	Battery size
Battery safety	III	-
Ease of use	III	Maintenance burden, ease of installation
Warranty	III	-
Visual Appearance	III	Design
Energy Autonomy	III	Self-sufficiency, grid / energy independence, reducing reliance on energy companies, efficient use of solar, storing excess solar generation
Emergency power	III	Backup during blackouts, avoiding blackouts / power outages, reliability of supply during outages
Environmental impact	IV	Environmental impact reduction, environmental concern, environmental or social attitude
Installer competence	III	-

### 3.2.2. Identifying Key Home Battery Attributes

The last step of literature analysis is to select a minimal set of key home battery attributes to be included in the DCE from the list of home battery attributes. By keeping the experiment on the lower side of the 3-7 attribute range we improve the comprehensibility of the experiment, decreasing validity but improving reliability [40]. The number of attributes shown also affects choice variability. Presenting more attributes tends to increase choice variability, while presenting fewer attributes tends to produce more consistent choices [71]. This priority is given because if no consistent trade-offs are observed, problems will arise when quantifying importance of attributes and computing predicted choice probabilities, compromising the second and last sub-questions of this study [40]. Candidate attributes are selected based on three characteristics. First, the attribute should recur across the reviewed literature as a reported driver of residential BESS adoption. Second, the attribute should be relevant for the Dutch context and the scope of this research. Third, the attribute should be suitable for a DCE, meaning that it can be varied clearly between battery alternatives and is not already captured by another attribute. This selection does not replace the DCE. Instead, it defines which attributes are most relevant to test in the DCE. The DCE is still needed to quantify how Dutch households trade these attributes off against each other and to estimate their relative importance in a choice setting.

In the group of financial attributes, investment costs and payback time are retained as key attributes. Investment costs capture the upfront amount that needs to be paid. This is important because investment costs are identified as a dominant barrier for residential BESS uptake [13]. Best et al. also show that capital constraints are an important reason why intention does not always translate into actual installation [61]. Payback time is also retained because it is mentioned frequently in the residential BESS literature [13, 30, 32, 62] and has already been used in an established choice model for home battery adoption [30]. Financial savings and profitability are not included as separate attributes, because they are not treated as separate financial dimensions in the literature and are already represented indirectly through payback time [17].

Battery capacity is an important technical characteristic, but it is not retained as a key attribute. Households evaluate battery systems not by their technical capacity in kWh per se, but through the perceived usefulness and practical benefits a certain battery size will bring, such as self-sufficiency and financial returns [17, 30]. Depending on the function households seek, they may choose a different battery size [30]. A larger battery can increase self-consumption or provide more emergency power,

Agnew and Dargusch therefore include battery capacity in their DCE and correlate it to outcomes such as higher self-consumption [30]. This research, however, is more interested in the value households attach to the underlying motivation to get a battery.

Safety, warranty, ease of use and visual appearance are relevant product characteristics, and the reviewed literature shows they can influence the household decision [17, 30, 62]. They are however not included for the following reasons. Agnew and Dargusch found that design, warranty and ease of use were among the least important attributes in their study [30]. Safety was more important in their study, but it also acts as a proxy for the overall quality of the battery, and it is not identified as a separate driver in the other reviewed studies [30]. Minimum safety requirements are also already regulated through EU battery regulation and priced into the investment costs of the battery [52]. Excluding these attributes has a consequence for the model. Leaving out a relevant attribute can induce a bias on the estimated effects of the attributes that are included, because its influence is not estimated separately but moves into the unobserved part of utility [40, 71]. The consequences of this exclusion are discussed in Section 5.5.

Energy autonomy is taken as a key attribute. It appears in the literature in several forms, including self-sufficiency, grid independence, reducing reliance on energy companies, storing excess solar generation and efficient use of solar electricity. This attribute captures a non-financial value of home batteries. Alipour et al. identify self-consumption and autonomy as strong non-financial motivations, stronger than environmental motivation [13]. The relevance of this attribute is also supported by other studies on residential BESS adoption [12, 17, 30]. In this research, energy autonomy is defined as the household's willingness to control its own electricity consumption and become less dependent on the grid or energy companies.

Emergency power is also retained as a key attribute. It is related to energy autonomy, but it is not the same. Energy autonomy concerns everyday control over electricity use during normal operation. Emergency power concerns electricity supply during power outages. Alipour et al. found that avoiding blackouts can be a significant motivation for home battery adoption [13]. Emergency power is also mentioned by Jayaraj et al. as a relevant motivation [62]. It is included as a separate attribute, because a household may value daily self-consumption and emergency electricity supply differently.

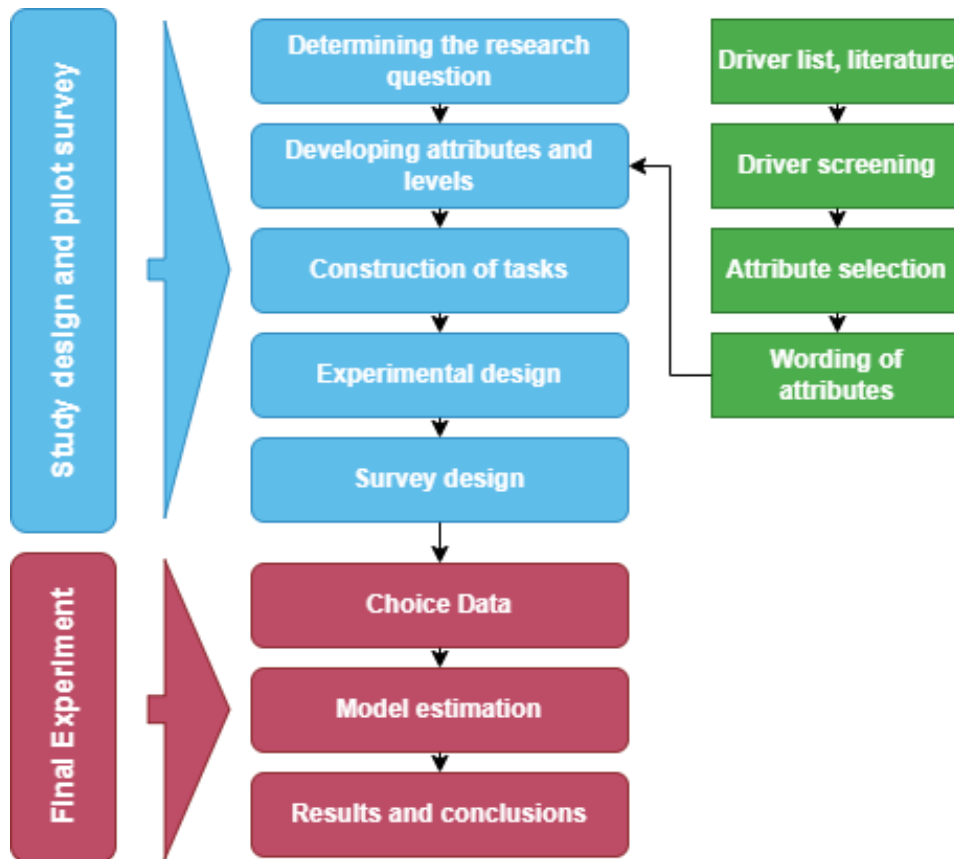
Environmental impact is relevant, but it is not selected as a main attribute. The reviewed BESS literature generally indicates that financial and self-sufficiency motives are stronger than environmental motives [17, 30, 72]. Moreover, this research considers LFP home batteries. The difference in environmental impact between battery alternatives is therefore relatively small compared to differences in costs, payback time, autonomy or emergency power [73]. Environmental impact is therefore unlikely to drive trade-offs between the battery alternatives in this DCE, even though it can matter for the broader decision to adopt at all. Similar to safety, warranty, ease of use and visual appearance, environmental impact is therefore not included as a key attribute.

Lastly, uncertainty of payback time is added as a key attribute. Although this attribute was not found as a separate driver in literature, uncertainty is relevant for investment decisions in renewable energy technologies [74]. Alipour notes that early innovators take risks because the long-term benefits of home batteries are still uncertain [17]. Research on heat pump adoption included uncertainty of performance [63]. For home batteries, the technical performance itself is less uncertain, but the financial performance is uncertain [75]. The payback time of a home battery depends on uncertain future conditions, such as electricity prices, tariff structures, technological developments and household consumption patterns [54, 64].

The final set of selected home battery attributes is shown in Table 4.1. These are the results of the first sub-question, as well as input for the DCE. The next section explains how these attributes were implemented in the DCE.

### 3.3. Discrete Choice Experiment Design

This section describes the design of the DCE. The design followed a structured DCE development protocol, adapted to the aim and scope of this study [76]. The general logic is that the experiment is constructed step by step, from the research question, to attributes and levels, to choice tasks, experimental design, survey instrument, data collection and model estimation [40, 77]. Figure 3.2 gives an overview of this process. The green part of the figure refers to the literature-based driver analysis conducted in the previous section. These steps are therefore not repeated here in detail.



**Figure 3.2:** Framework for the design of the discrete choice experiment. The green steps represent the driver screening and selection described in the previous section. The blue represents steps to design the final survey, the red represents the steps to move from the final choice data to conclusions of the research [76].

Starting with the attribute terminology and deciding on their levels in Section 3.3.1, the next step was to construct the choice tasks, decide on the elicitation format, and create the surrounding experiment, as described in Section 3.3.2. After the raw experiment is constructed, the survey instrument for taking the experiment, as well as the method for collecting data will be motivated in Section 3.3.3. For this study, a total of three experiments were designed: 2 pilots, and the final experiment. The first pilot was used to validate the comprehensiveness of attribute wording and their relevance for respondents. The second pilot was used to estimate prior values for the final efficient design. The pilot studies are not presented as separate results, because they were part of the design process. Their role is only discussed where they influenced the final experiment.

#### 3.3.1. Attribute Terminology and Levels

The first step in designing the DCE is to consider the model goal, and choice context [77]. These have been implicitly described in Chapter 1, but will be repeated here as they are important to consider in many design questions. The goal of the model is to estimate how important home battery attributes are

relative to one another, and how changes in these attributes affect residential BESS choice probabilities. The choice context is the household decision to invest in a certain type of home battery, or not. This goal and context determine the alternatives of the DCE. In a real market-setting, there is always the option to not buy a battery, hence the need for an opt-out alternative [40]. Then, since we are interested in relative importance of attributes, we would like to observe how respondents make trade-offs. This gives the need for two battery alternatives. If only 1 battery alternative would be shown alongside the opt-out, this would yield no information on trade-offs and relative importance [40]. The two battery alternatives are presented as Battery A and Battery B. No brands or labels were included, because the aim of the experiment is to estimate preferences for home battery attributes themselves. The choice task will thus look like:

**Table 3.3:** First step in constructing the choice set: selection of alternatives

Battery A	Battery B	No battery
-----------	-----------	------------

The final experiment was conducted in Dutch. The attribute names and levels described below are therefore translated versions of the actual wording used in the experiment. This is important, because the terminology of an attribute is also a design choice [77]. In the experiment a single term has to be chosen for each attribute, even when the underlying concept is more nuanced or richer than the exact meaning of the chosen term. This creates a trade-off between the experiment's validity and reliability [40]. If a term is too technical, respondents may not understand it. If a term is too simplified, it may measure a broader or slightly different concept than intended. We will motivate and argue for word choices where needed.

The first step was to take the key attributes from Section 3.2 and assign attribute levels to them. The attribute levels were chosen to be linear where possible, this later allows testing for linearity [40]. For qualitative attributes, simple ordered levels were used. The attribute levels also had to cover past, current and possible future market values. This is important because interpolation is generally more valid than extrapolation [40]. Therefore, the chosen ranges should be broad enough to represent current market conditions, but also future lower-cost situations in which home batteries may become more attractive. What follows next is argumentation for the word choice and attribute levels for the key home battery attributes.

**Costs**, in euros, were included as upfront investment costs. In the choice task, this was shortened to costs, because this is simpler and easier for respondents to understand. The cost range was chosen to represent the past and future average costs of a home battery systems, allowing interpolation. In a real market, the final cost of a home battery depends on several factors, such as brand, system size, warranties and installation. Reports indicate that residential battery system costs in 2020 were around €500 per kWh, with average systems of roughly 10 kWh. This corresponds to approximately €5,000, excluding additional costs such as warranties or installation [45]. Therefore, the upper level was set at €7,000. Future expectations can be much lower, with possible costs around €80 per kWh by 2030. Following a similar reasoning, this gives a lower value close to €1,000. Current Dutch market prices also fit within this range [75, 78]. Rounded values were used to reduce cognitive load for respondents, and 4 levels in total were chosen to allow observing non-linearity and reflect realistic market options [40]. The final cost levels were therefore set at €1000, €3000, €5000 and €7000.

**Payback time** of home batteries is a highly uncertain and discussed topic [75]. Some companies claim that a battery can be earned back within a few years, while other sources argue that the investment may take much longer or may not be earned back at all [75]. Many current estimates mention ranges around 6 to 12 years. To cover for uncertainty and avoid extrapolation, the levels were set at a source claiming a broad range [78]. This is also in line with the attribute levels for payback time in previous research [30]. The final levels were *5 years, 10 years and 15 years*.

**Certainty of payback time** describes how certain the expected payback time of the home battery is. This attribute does not change the expected number of years itself, but the confidence around that number. The term certainty was chosen instead of uncertainty to avoid a double negative in the interpretation.

The final levels were *low certainty, moderate certainty and high certainty*. Ranges in payback time were avoided because it adds similar uncertainty, while being more cognitively demanding [40]. These levels were also chosen because they use simple language.

**Self-consumption** was chosen as the attribute to represent the household's willingness to control its own electricity consumption and become more independent from the grid. Although energy autonomy, or energy independence better reflects the underlying value this attribute aims to capture, these are not well-understood terms [79]. It represents the share of electricity use that can be utilized through the battery. This includes both consumption of electricity from storing PV, or from load shifting. This makes the term also relevant for households without rooftop PV. This study recognizes that the actual share of self-consumption a residential BESS delivers is dependent on demand patterns and system size. The purpose of this term is however to include an understandable attribute, that captures the household's willingness to control its own consumption. Self-consumption is typically measured in percentages ranging from 30-90% [53]. Full self-consumption is not realistic, and basic systems show rates starting at 30% [80]. Ensuring linearity thus yields attribute levels of 30%, 60% and 90%.

**Emergency power** describes whether the home battery can provide electricity during a power outage. This term was chosen instead of backup power, because it more clearly refers to an emergency situation for respondents. Emergency power was kept separate from self-consumption, because it concerns a different use of the battery. Self-consumption refers to normal daily operation, while emergency power refers to electricity availability during outages. Many home batteries can provide some form of emergency power [57, 15]. More advanced systems can supply part of the house or the full house [81]. To keep the choice task understandable, only two clear levels were used. The final levels were one socket and full house.

Summing up the selected terminology and attribute levels gives the following shape for the choice sets:

**Table 3.4:** Attribute terms and levels used in the choice sets

Attribute	Battery A / Battery B	No battery
Costs	€1,000 / €3,000 / €5,000 / €7,000	–
Payback time	5 years / 10 years / 15 years	–
Certainty of payback time	Low / moderate / high	–
Self-consumption	30% / 60% / 90%	–
Emergency power	One socket / full house	–

### 3.3.2. Choice Tasks and Experiment

The development of the experiment followed an iterative process. The first two pilot experiments used orthogonal designs. This was because reliable prior parameter estimates were not yet available [40]. Orthogonal designs aim to vary attribute levels independently and, where possible, preserve attribute level balance. This helps reduce correlation between attributes and supports the estimation of separate attribute effects [77, 40]. The first pilot contained 14 respondents and was used to test the comprehensiveness of the experiment. The first pilot used "energy autonomy" as an attribute, which was afterwards changed to "self-consumption" for reasons described above. The second pilot contained 64 respondents and was used to obtain empirical prior estimates for the final experimental design.

The final set of **choice tasks** were generated in Ngene as a D-efficient design, using the prior estimates from the second pilot. Numerical attributes can be entered directly in Ngene. The categorical attributes, uncertainty and emergency power, were dummy-coded because their levels are not directly tied to numerical values. In Ngene, these levels were first assigned numerical labels, such as 0 and 1 for emergency power levels "One socket" and "Full house". This allows the model to estimate differences between the category levels [40]. D-efficient designs use prior information to reduce the uncertainty of the estimated parameters and to maximize the information obtained from each choice task [77, 40]. With one 4-level attribute, three 3-level attributes and a 2-level attribute, 12 tasks would have allowed

attribute level balance, which is beneficial because it increases the odds of estimated  $\beta$ -coefficients of becoming statistically significant [40]. However, the final survey used 8 choice tasks to limit respondent fatigue, since the second pilot revealed all parameters were statistically significant [77]. After generating candidate designs in Ngene, the final design was selected as the lowest D-error design that did not contain dominant alternatives. A dominant alternative is an alternative that scores better than the other alternative on every attribute. The resulting set of choice tasks can be seen in Table 3.5, the first choice task is shown in Figure 3.3. The final Ngene syntax is shown in Figure B.1 in the Appendix. An overview of the final survey is shown in Appendix C.

Table 3.5: Choice sets. Each task also includes a constant “no battery” opt-out.

Set	Battery A					Battery B				
	Cost	Payback	Cert.	Backup	Self-cons.	Cost	Payback	Cert.	Backup	Self-cons.
1	€7,000	10	Low / 0	Full house / 1	60%	€1,000	5	High / 2	One socket / 0	60%
2	€5,000	5	Low / 0	One socket / 0	60%	€3,000	15	Moderate / 1	Full house / 1	60%
3	€1,000	5	Moderate / 1	Full house / 1	30%	€7,000	15	Moderate / 1	One socket / 0	90%
4	€7,000	10	High / 2	One socket / 0	30%	€1,000	10	Low / 0	Full house / 1	30%
5	€3,000	10	Moderate / 1	One socket / 0	30%	€5,000	10	Low / 0	Full house / 1	90%
6	€3,000	15	High / 2	Full house / 1	60%	€5,000	5	Low / 0	One socket / 0	30%
7	€1,000	15	Low / 0	One socket / 0	90%	€7,000	5	High / 2	Full house / 1	60%
8	€5,000	5	Moderate / 1	Full house / 1	90%	€3,000	10	Moderate / 1	One socket / 0	30%

	Battery A	Battery B	No Battery
<b>Cost</b>	€7.000	€1.000	-
<b>Payback time</b>	10 years	5 years	-
<b>Certainty of payback time</b>	Low	High	-
<b>Emergency power</b>	Full house	One socket	-
<b>Self-consumption</b>	60%	60%	-

Figure 3.3: Choice task 1, illustrating how the choice tasks were presented in the DCE.

Before the choice tasks, respondents received an explanation of the decision context and of all attributes. This was done to improve validity and reliability by reducing the chance that respondents make their own assumptions about omitted attributes, and therefore helps the experiment measure the effects of the selected attributes more directly [77, 40]. The explanation was accessible during the survey, an English translation of this is provided in Appendix C.1. Before each choice task, the same question was asked: “Will you buy Battery A, Battery B, or will you not buy a battery?” Respondents then selected one of three answers: “I want to buy Battery A/B” and “I do not want to buy any of these batteries.” Explicitly stating an intention to *buy* the battery is associated with a higher likelihood of the stated behavior [40]. By combining the explanation, with the choice tasks, the actual experiment is designed. The following section explains how the explanation and choice tasks were integrated in a distributable survey. And how data was collected.

### 3.3.3. Survey Instrument and Data Collection

This section will finalize the design of the experiment by explaining how a survey was designed around the experiment designed in the previous section. Following the protocol the survey had to collect choice data from the actual household investment decision-maker, introducing the need for screening questions [77]. Data collection also had to be in accordance with the data management plan of this study. The TU Delft Human Research Ethics Commission has approved the data management plan for this thesis.

The survey was made in Dutch on the platform Analyzer. Analyzer was selected because it provided the required survey functions, such as forced multiple-choice questions and image support for the choice

task. It also allowed anonymous response collection and compatibility with collecting the panel data. Respondents could not return to previous questions and all answers were forced. This was done to avoid incomplete choice sequences and to prevent respondents from changing earlier answers after seeing later choice tasks.

The survey first contained five screening questions. These questions serve two purposes: First, they provide relevant background information allowing to study different heterogenous household groups. Second, they ensured that sufficient survey responses from the relevant target group would be collected since the final choice data sample has to be large enough for model estimation [40]. Table 3.6 presents these screening questions, possible answers and whether that answer is included or not. For solar panels and home type two quotas were included as well. These quotas are targets of shares of respondents answers to the screening question. This was also done to ensure sufficient relevant sample sizes while still allowing a representative sample size for the average Dutch household to be drafted.

**Table 3.6:** Screening questions used in the final survey

Screening question	Included and excluded answer	Reason
What kind of home do you live in?	<b>Included:</b> an owner-occupied home; a rental home. (<25%) <b>Excluded:</b> other.	The sample was mainly only owner-occupied homes because renters are usually not eligible to make investment decisions regarding energy systems [13, 32]. Still a quota of 25% renters was aimed for to be able to get a representative average Dutch household sample.
Who in your household handles energy-related matters?	<b>Included:</b> me; me and my partner. <b>Excluded:</b> my parents; none of the above.	The respondent had to be involved in household energy decisions as defined by the scope of this research. "Me and my partner" was also included, because many households make these decisions together [13].
Do you have solar panels on your home that also generate electricity for your use?	<b>Included:</b> yes (>50%); no. <b>Excluded:</b> I do not know.	At least 50% of households with solar panels was aimed for. Households with solar panels are especially relevant for home battery adoption, which helps prevent too many opt-out choices [17]. Still a quota of 50% houses without was aimed for to be able to get a representative average Dutch household sample
What age group do you fall into?	<b>Included:</b> ages 18-30; 31-40; 41-50; 51-60; 61-70. <b>Excluded:</b> 17 years old and younger; 71 and older.	Respondents outside this age range were excluded because it is highly improbable that they are the household decision-maker for this investment decision [30].
Do you have a home battery, or are you planning to buy one soon?	<b>Included:</b> yes; no, but I plan to buy one within the next six months; no. <b>Excluded:</b> none.	Respondents with a home battery or concrete purchase plans were not excluded. They were asked to answer as if they did not yet have a home battery, to prevent choosing "no battery" only because they already owned one.

Actual respondents were gathered through PanelClix, which recruited respondents from its online panel. Through close communication with PanelClix, quota requirements were met, as PanelClix could specifically open the survey for households with solar panels or renters. The intended sample size was 500 respondents, PanelClix delivered 593 survey responses. The final usable sample contained 529 respondents after removing respondents who were screened out or did not complete the survey. Final data collection took place on 28 April 2026. Respondents were compensated by PanelClix. The researcher only received anonymous survey responses. No names, email addresses, IP addresses, panel identifiers or other direct personal identifiers were included in the research dataset. Data collection and

handling were conducted in accordance with the approved Data Management Plan by TU Delft HREC.

The screening questions were placed immediately after the opening statement of the survey. After the screening questions the experiment itself starts. Altogether this gives the structure and data gathering plan for the final survey used to gather data. An overview of the full survey is presented in Appendix C.

## 3.4. Discrete Choice Model Estimation and Analysis

This Section will explain how a discrete choice model was estimated from the raw choice data. First, the processing and analyzing of the raw data will be explained. Then how the DCM was estimated from the relevant data. After that we will explain how the relative importance of the key attributes was determined. Lastly, the choice probability analysis will be shown.

### 3.4.1. Data Analysis

This section determines the process to estimate the final model. The goal of this step is to make sure that the model is estimated on a relevant data sample for the residential BESS adoption in the Netherlands.

The raw survey data was first exported from Analyzer to a csv file. The data was then cleaned and analyzed in Python. Incomplete responses and respondents that did not pass the screening criteria were removed. After cleaning the data, four samples can be constructed using the screening questions. Creating these samples helps answer the research question by identifying if different groups assess importance of attributes differently, and to assess how the average Dutch household values them. Four samples were drafted:

- **Full data sample:** This sample contains all usable respondents after filtering. It gives the maximum amount of choice observations and is therefore useful for baseline model estimations. The limitation is that this sample is not fully representative for the average Dutch household. As explained in Section 3.3, the survey used quotas for home ownership and solar panel ownership. Hence the need for other samples.
- **Representative sample:** This sample was constructed to represent the average Dutch household more closely. The screening variables that could be used for this were age category, housing type, solar panel ownership and home battery ownership. Home battery ownership will not be used to construct this sample, because it is what this research tries to understand. The representative sample was therefore selected from the full data based on housing type and solar panel ownership. Housing type was matched to an approximate owned-to-rental ratio of 9:7 [82], and solar panel ownership was matched to approximately 42% [15]. Age was not used as a strict representativeness criterion, because no clear data was found on the age distribution of the household decision-maker for energy investments. The age distribution of this sample was therefore kept close to the distribution of the full data sample.
- **Solar sample:** This sample contains respondents that own solar panels. This group is relevant because home batteries are often studied together with solar PV [13, 17, 61]. Solar PV ownership changes the decision context for home batteries, making it interesting to see if attribute importance is valued differently.
- **Revealed preference sample:** This sample contains respondents who already own a home battery, or have concrete plans to buy one within six months. This group is relevant because these respondents are closest to actual adoption. The choices in the DCE are still stated choices, because respondents still answer hypothetical choice tasks. But the sample itself is based on more real adoption behavior. This makes the group useful to compare with the other samples. If this group gives very different answers than the other respondents, it could mean that people answer the survey easier than they would decide in real life. If this group gives similar answers, it suggests that there is a good connection between what people say they would do and what people closer to actual adoption do. Therefore, this sample helps to check the validity of the stated choices [40].

These four samples are used in the later model estimation and relative importance analysis. The resulting sample sizes and screening variable statistics are shown in Section 4.2.

### 3.4.2. Discrete Choice Model Estimation

The full, cleaned choice data will be used to estimate several DCMs. The models were estimated in Python using Biogeme. The full code including documentation is publicly available by following the link in Appendix B. As motivated in theory, first a basic linear RUM-MNL model will be estimated, this serves to compare with performance of other more advanced models with adjusted utility functions. After the base model, fixed-parameter models were estimated. In these models, one attribute coefficient was fixed to zero each time. These models are used to see how much the model fit decreases when an attribute is removed from the utility function. This is done in order to determine if attributes are relevant, and later to investigate the relative importance of the attributes with the log-likelihood drop method described at the end of Section 3.1.

A profitability model was also estimated. This model collapses investment costs ( $C$ ) and payback time ( $PB$ ) into one profitability variable, profitability, through  $C/PB$ . This then represents the yearly financial return that is implied by the battery [17]. It is estimated for two reasons. First, it checks whether excluding financial savings as a separate attribute was justified. If households mainly evaluate a home battery as a financial investment, then this profitability variable should explain choices well. Second, it is used as a check for economic rationality. A higher profitability value should make a battery more attractive. If this model performs similar to the base model this suggests that respondents might also evaluate the battery through this financial return. Similarly, an interaction model was estimated to test whether the effect of investment costs depends on payback time [30, 40]. High investment costs may be more acceptable when the payback time is short. The interaction model therefore adds a cost-payback interaction term. This checks whether respondents make a combined financial trade-off, instead of only responding to costs and payback time separately.

These models all contain linear utility functions, these assume that every additional change in an attribute has the same effect on utility. This may be too simple. For example, the difference between €5000 and €7000 may be evaluated differently than the difference between €1000 and €3000 [40]. The same can apply for the other attributes. Therefore, the base model is re-estimated several times with one squared attribute term added each time. If the squared term improves model fit or is significant, this suggests that the effect of the attribute is not fully linear. These models are included as a specification check before choosing the final utility function. An overview of all models and the corresponding utility functions is shown in Table 3.7. Table 4.3 in the next chapter shows the performances of these models.

A panel MXL model was also estimated because each respondent answered multiple choice tasks and answers are therefore not fully independent from each other. The panel MXL model was estimated using the best performing utility function from the models above. Since the linear base model performed best in the earlier comparison, the panel MXL was estimated with the linear utility function.

A latent class model was also estimated. A latent class model follows a similar approach to the panel MXL model, it however assumes a certain heterogeneity in basic preference for a certain attribute or alternative. Previous studies have shown that some households have a basic preference for home batteries, and other households against batteries [17, 61]. Estimating this model will show whether these groups exist in the Netherlands. The size of these classes can also be estimated, potentially supporting conclusions regarding adoption probabilities.

Estimating the latent class model assumes that respondents belong to one of two classes. Each class has its own distribution for the no-battery ASC. One class with higher no-battery ASC, indicating a stronger basic preference for not adopting a battery. And one with a lower or negative no-battery ASC indicating a preference for a home battery [40].

The class sizes are estimated within the model. Since it is not known beforehand whether a respondent

**Table 3.7:** Model specifications and utility functions. Abbreviations: C = cost, PB = payback time, CT = certainty, SC = self-consumption, BP = emergency power.

Model	Utility function
Base	$V_1 = B_{cost}C_1 + B_{payback}PB_1 + B_{certainty}CT_1 + B_{self}SC_1 + B_{backup}BP_1.$ $V_2 = B_{cost}C_2 + B_{payback}PB_2 + B_{certainty}CT_2 + B_{self}SC_2 + B_{backup}BP_2.$ $V_3 = ASC_{NO\_BATT}.$
Fixed-parameter	<p>The base model is re-estimated several times, each time fixing one coefficient to zero. Full example for no cost:</p> $V_1 = B_{payback}PB_1 + B_{certainty}CT_1 + B_{self}SC_1 + B_{backup}BP_1.$ $V_2 = B_{payback}PB_2 + B_{certainty}CT_2 + B_{self}SC_2 + B_{backup}BP_2.$ $V_3 = ASC_{NO\_BATT}.$ <p>The same is done for no payback, no certainty, no self-consumption, and no backup.</p>
Profitability	$V_{1,profit} = B_{profitability}(C_1/PB_1) + B_{certainty}CT_1 + B_{self}SC_1 + B_{backup}BP_1.$ $V_{2,profit} = B_{profitability}(C_2/PB_2) + B_{certainty}CT_2 + B_{self}SC_2 + B_{backup}BP_2.$ $V_{3,profit} = ASC_{NO\_BATT}.$
Interaction	$V_1 = B_{cost}C_1 + B_{payback}PB_1 + B_{certainty}CT_1 + B_{self}SC_1 + B_{backup}BP_1 + B_{cost\_payback}C_1PB_1.$ $V_2 = B_{cost}C_2 + B_{payback}PB_2 + B_{certainty}CT_2 + B_{self}SC_2 + B_{backup}BP_2 + B_{cost\_payback}C_2PB_2.$ $V_3 = ASC_{NO\_BATT}.$
Non-linear	<p>The base model is re-estimated several times, each time adding one squared attribute term. Full example for non-linear cost:</p> $V_1 = B_{cost\_lin}C_1 + B_{cost\_sq}C_1^2 + B_{payback}PB_1 + B_{certainty}CT_1 + B_{self}SC_1 + B_{backup}BP_1.$ $V_2 = B_{cost\_lin}C_2 + B_{cost\_sq}C_2^2 + B_{payback}PB_2 + B_{certainty}CT_2 + B_{self}SC_2 + B_{backup}BP_2.$ $V_3 = ASC_{NO\_BATT}$ <p>The same is done for payback, certainty, self-consumption, and backup.</p>

belongs to class 1 or class 2, the model estimates class sizes by determining the size of either class that makes the observed choice data most likely. Because there are two classes, only one class size has to be estimated. If the estimated share of class 2 is  $p$ , then the estimated share of class 1 is  $1 - p$ . Conceptually, the model therefore estimates:

$$L_n = (1 - p)L_{n1} + pL_{n2}$$

where  $L_{n1}$  is how well respondent  $n$ 's choices fit class 1, and  $L_{n2}$  is how well respondent  $n$ 's choices fit class 2. The model estimates  $p$ , together with the class-specific coefficients, so that the observed choices of all respondents are explained as well as possible. The estimated class shares are therefore estimates of the share of respondents belonging to each latent preference class. Table 3.8 show the utility functions for these two models.

### 3.4.3. Relative Importance of Key Attributes

To compare the importance of the key home battery attributes, the estimated coefficients of the best fitting model were translated into relative importance scores. Results Section 4.3 shows that the panel MXL model provides the best fit. The relative importance is estimated for all data samples.

Following the probability analysis described in Section 3.1. First, we define the baseline battery profile, following Lancsar et al. this will be set at the mean of the attribute levels [69]. Then, one attribute is changed at a time, while all other attributes are kept fixed at this baseline. For every level of the changed attribute, the predicted probability of adopting a home battery is calculated as:

**Table 3.8:** Panel MXL and latent class model specifications. Abbreviations: C = cost, PB = payback time, CT = certainty, SC = self-consumption, BP = emergency power.

Model	Utility function
Panel MXL	<p>For each choice task <math>q</math>:</p> $V_{1q} = B_{cost}C_{1q} + B_{payback}PB_{1q} + B_{certainty}CT_{1q} + B_{self}SC_{1q} + B_{backup}BP_{1q}.$ $V_{2q} = B_{cost}C_{2q} + B_{payback}PB_{2q} + B_{certainty}CT_{2q} + B_{self}SC_{2q} + B_{backup}BP_{2q}.$ $V_{3q} = ASC_{NO\_BATT} + \sigma_{NO\_BATT}, \text{ with } \sigma_{NO\_BATT} \sim N(0, 1).$ <p>The random ASC is respondent-specific and is kept constant over all choice tasks of the same respondent.</p>
Latent class	<p>Same utility function as the base model, but coefficients are estimated separately for each class <math>k</math>.</p> $V_{1,k} = B_{cost,k}C_1 + B_{payback,k}PB_1 + B_{certainty,k}CT_1 + B_{self,k}SC_1 + B_{backup,k}BP_1.$ $V_{2,k} = B_{cost,k}C_2 + B_{payback,k}PB_2 + B_{certainty,k}CT_2 + B_{self,k}SC_2 + B_{backup,k}BP_2.$ $V_{3,k} = ASC_{NO\_BATT,k}.$

$$P(\text{adopt}) = \frac{e^{V_{\text{battery}}}}{e^{V_{\text{battery}}} + e^{V_{\text{no battery}}}}$$

where  $V_{\text{battery}}$  is the utility of the battery profile and  $V_{\text{no battery}}$  is the utility of the no-battery alternative. Then, for each attribute, the impact is calculated as the difference between the highest and lowest predicted choice probability over the levels of that attribute ( $a$ ).

$$Impact_a = P_{\text{adopt}_{\max}} - P_{\text{adopt}_{\min}}$$

The impacts can then be normalized so that all relative importances ( $RI$ ) together sum to 100 percent:

$$RI_a = 100 \cdot \frac{Impact_a}{\sum_j Impact_j}$$

These scores show how much each attribute contributes to changes in predicted choice probability within the attribute ranges used in the experiment. They should therefore not be interpreted as absolute psychological importance, but as relative importance within the design and model assumptions of this research.

### 3.4.4. Choice Probability Analysis

The choice analysis uses the same probability calculation, but has a different purpose. While the relative importance analysis compares attributes against each other, this analysis shows the predicted choice probabilities and how these choice probabilities change when one attribute moves from its lowest to its highest value. This is done for the representative sample. The results are reported as raw probabilities. This makes the analysis useful for showing the direction and magnitude of the probability change for each attribute, answering the last sub-question.

# 4

## Results

This chapter presents the results of this study. Section 4.1 presents the key home battery attributes resulting from the literature analysis. These attributes answer the first sub-question and were used as input for the DCE and subsequent DCM estimation. Section 4.2 presents the raw data analysis. These results do not directly answer a sub-question, but describe the respondent samples and provide context for interpreting the model results. Section 4.3 presents the model estimation results. These results provide the estimated coefficients and model comparison needed for the following analyses. Section 4.4 presents the relative importance of the home battery attributes, addressing the second sub-question. Finally, Section 4.5 presents the choice probability analysis to answer the third sub-question.

### 4.1. Key Home Battery Attributes

The literature analysis resulted in five key home battery attributes, shown in Table 4.1. These attributes aim to answer the first sub-question "What are the most important attributes affecting the household investment decision?". The results in Section 4.3 will support this selection, by showing all attributes have a statistically significant effect on the observed choices. Importance is established by the choice data, not by the selection step alone. The next chapter discusses to what extent these results answer the first sub-question. These attributes were also used as input for the discrete choice experiment described in Chapter 3. In the survey to collect final data, some attributes were assigned different terminologies following good practices for DCE design.

**Table 4.1:** Key home battery attributes resulting from the literature analysis alongside the term used in the final survey.

Attribute	Survey term	Definition in this research
Investment costs	Costs	The total upfront cost a household has to pay for the home battery.
Payback time	Payback time	The expected number of years before the financial returns of the home battery equal the initial investment costs.
Uncertainty of payback time	Certainty of payback time	The extent to which the expected payback time is uncertain due to future changes in electricity prices, tariff structures, policy conditions, battery performance or household electricity use.
Energy autonomy	Self-consumption	The household's willingness to control its own electricity consumption and become less dependent on the grid or energy companies. This concerns everyday electricity use during normal operation.
Backup power	Emergency power	The ability of the home battery to provide electricity to the household during a power outage.

## 4.2. Choice Data Samples

PanelClix delivered 593 survey responses. After filtering incomplete and invalid responses, 529 respondents remained in the final usable dataset. These respondents form the full sample. As mentioned in Methodology Section 3.4.1, the full sample and three subsamples will be used in the model estimation and later analyses. An overview of the samples, and the amount of respondents per sample is shown in Table 4.2.

**Table 4.2:** Choice data samples used in the results chapter

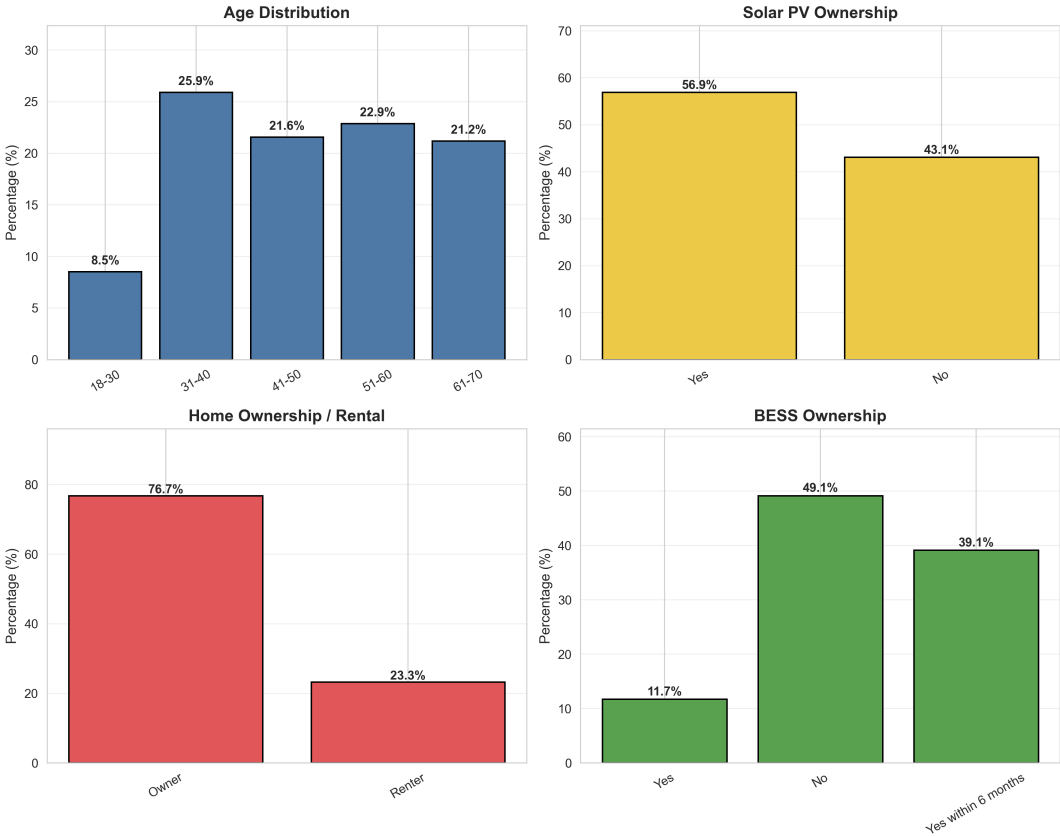
Sample	Sample size	Role in the analysis
Full sample	529	Includes all usable survey responses after data filtering. This sample provides the broadest overview of the collected choice data.
Representative sample	289	Subsample used to estimate adoption share and preferences for a representative group of Dutch households.
Revealed-preference sample	269	Subsample used to compare preferences of respondents that actually adopted a home battery.
Solar sample	301	Subsample of respondents with solar PV. This sample is relevant because home batteries are often evaluated in combination with household solar electricity generation.

Figure 4.1 and Figure 4.2 on the next page show the distributions of the background variables of the four samples. The figures include plots for the different screening variables in the final survey. These results do not directly answer a sub-question, but they provide context for interpreting the model estimation results in Section 4.3 and the sample-specific relative-importance results in Section 4.4.

By comparing the choice data to the Central Bureau of Statistics in the Netherlands, we find the choice data is quite evenly spread across ages, with a slight under representation of the youngest age [83]. The age distributions are broadly similar across the four samples. The full sample has a higher share of solar PV owners, and respondents that will buy a battery in the coming 6 months compared to the representative sample. The goal of 42% of respondents owning solar PV, and a 9:7 ratio of owner versus rental was achieved in the representative sample, while still having a large set of data points (n=289). As expected from implementing quota, the full sample contains more respondents with characteristics that are relevant for residential BESS adoption than the representative sample.

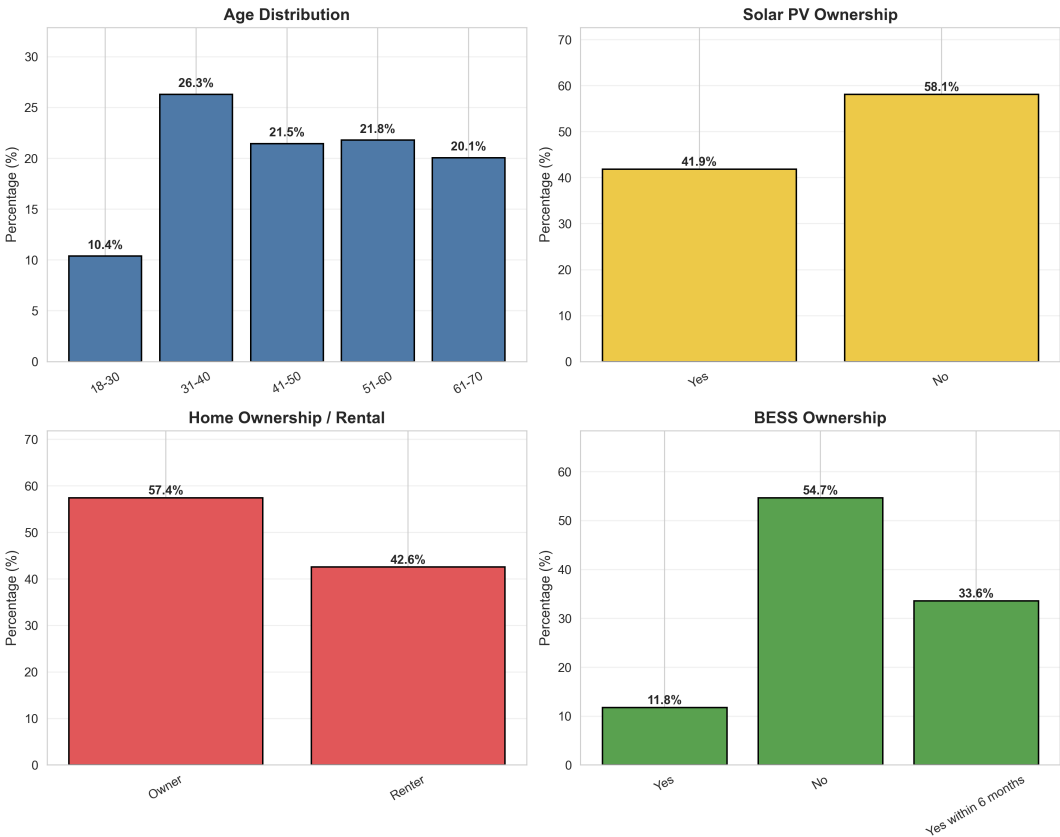
The solar and revealed-preference samples differ more strongly from the representative sample. In the revealed-preference sample, 72.9% of respondents own solar PV and 82.2% own their home. In the solar sample, 84.1% of respondents own their home. BESS ownership is also higher in the solar sample, with 65.1% of respondents either owning or planning to buy a home battery compared to 50.8% in the full sample and 45.4% in the representative sample. This shows that BESS ownership, or intent to buy, is more common among respondents with solar PV, and vice versa. These sample differences are relevant because the following model estimations are performed for multiple samples, allowing the results to show whether preferences differ between the broader respondent group and more adoption-relevant respondent groups.

Full Sample (n=529)



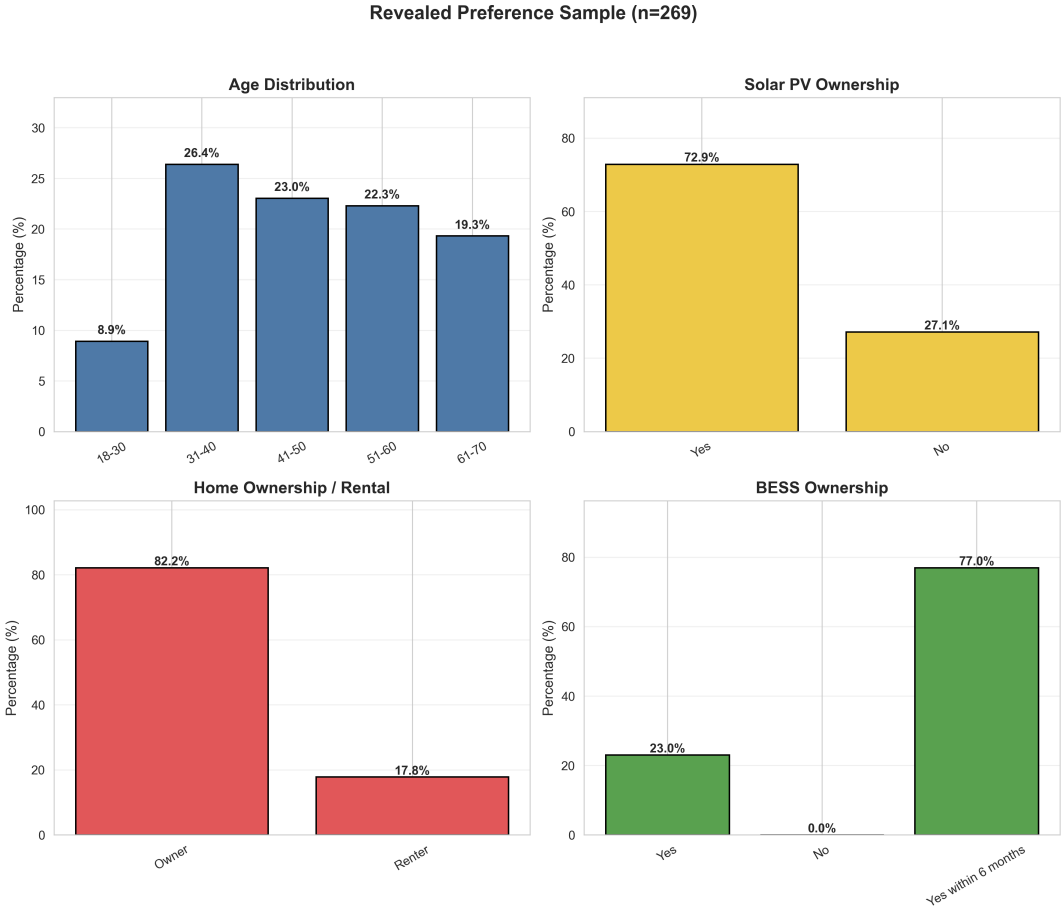
(a) Full sample

Representative Sample (n=289)

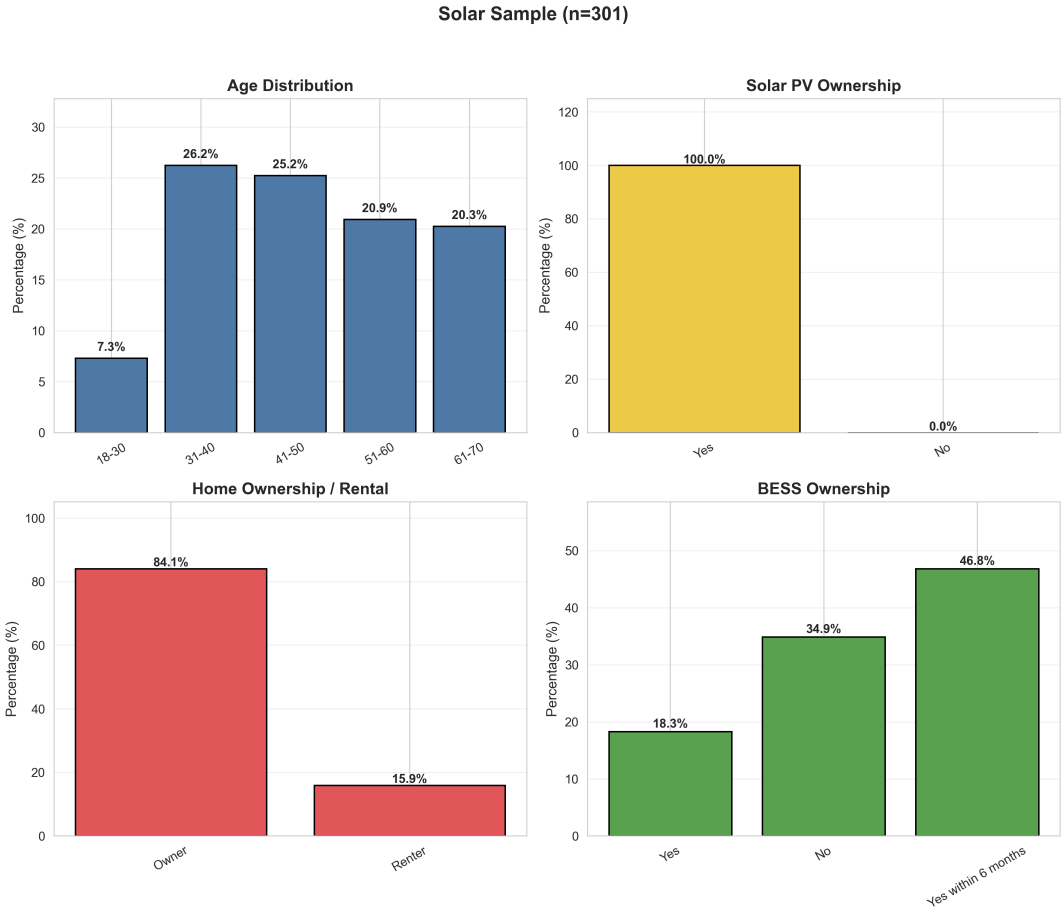


(b) Representative sample

Figure 4.1: Background variables, in percentages, for the full and representative samples.



(a) Revealed-preference sample



(b) Solar sample

Figure 4.2: Background variables, in percentages, for the revealed-preference and solar samples.

### 4.3. Model Estimation Results

This section presents the model estimation results. As described in Chapter 3, the model estimation was done in several steps. First, several basic RUM-MNL versions were estimated to evaluate the contribution of the separate attributes, the profitability specification and the cost-payback interaction. Second, non-linearity tests were performed to check whether the linear utility function was sufficient. Third, panel MXL and latent class models were estimated for the four data samples. The panel MXL model is also selected the final model for the relative-importance and adoption-probability analyses in the following sections.

Table 4.3 shows the results of the RUM-MNL comparison, estimated for the full sample. The null log-likelihood is  $\log((1/3)^{8 \times 529}) = -4649$ . The basic model has a final log-likelihood of -4252.7 and an adjusted rho-square of 0.0838. The other models will be compared with this. All  $\beta$ -coefficients have intuitive signs: higher costs and longer payback time decrease utility, while higher certainty of payback time, higher self-consumption and the availability of full-house emergency power increase utility. Estimated coefficients noted with an **asterisk (\*)** have a t-statistic smaller than 1.96, meaning they are not at a 5% significance level. We will define this as not significant. The ASC of the model estimations are not significant in any of the models. This means that we do not observe a statistically significant baseline preference for or against a battery in the data. This also shows in that for some models the ASC is negative, and for others it is positive.

The fixed-parameter models show that removing any of the five attributes decreases model fit. Multiplying the drop in log-likelihood of the basic model and fixed parameter models by 2, consistently gives values above 3.84: the chi-square value for 5% significance when removing 1 degree of freedom from the model B.2. This means all attribute significantly contribute to the model fit. The strongest decrease in model fit occurs when costs are removed. The model without costs has a final log likelihood of -4397.1, compared to -4252.6 for the basic model. Removing certainty of payback time and emergency power also causes a clear decrease in model fit. Removing payback time and self-consumption gives a smaller, but still visible decrease. This shows that all five selected home battery attributes contribute to explaining the observed choices.

The profitability model performs worse than the basic model. Its final log likelihood is -4395.6, which is close to the model where costs are removed completely. This indicates that the combined profitability variable does not explain the choices as well as the separate cost and payback-time attributes. Moreover the  $\beta_{profit}$  is actually negative, meaning households perceive less utility from more profit. This is counterintuitive, and further motivates that taking cost and payback time as individual attributes better explain choice data. The interaction model also does not significantly improve the model fit compared to the basic model. The final log likelihood remains -4252.6 and the cost-payback interaction coefficient is very small. Therefore the basic linear MNL model performs best.

**Table 4.3:** RUM-MNL model estimation results. Null log likelihood = -4649.

Parameter	Basic	No cost	No payback	No certainty	No SC	No backup	Profit	Int. C&PB	Int. PB&Cert.
Final LL	-4252.7	-4397.1	-4302.1	-4365.1	-4299.1	-4352.5	-4395.6	-4252.6	-4252.7
$\bar{\rho}^2$	0.0838	0.0532	0.0736	0.0601	0.0743	0.0628	0.0535	0.0853	0.0838
$B_{cost}$	-0.167	fixed	-0.150	-0.153	-0.137	-0.172		-0.185	-0.168
$B_{payback}$	-0.0565	-0.0422	fixed	-0.059	-0.0422	-0.063		-0.064	-0.0591
$B_{certainty}$	0.410	0.358	0.425	fixed	0.372	0.438	0.390	0.407	0.389
$B_{self}$	0.0106	0.00458	0.00751	0.00837	fixed	0.0135	0.00372	0.011	0.0107
$B_{backup}$	0.602	0.620	0.634	0.625	0.682	fixed	0.666	0.607	0.601
$ASC_{no}$	0.283*	0.654*	0.728*	-0.186*	-0.0645*	0.0269*	0.838*	0.219*	0.260*
$B_{profit}$							-0.435		
$B_{cost \times payback}$								0.002	
$B_{payback \times certainty}$									0.00224*

Table 4.4 shows the non-linearity tests. In each model, one squared attribute term was added to the basic linear specification. The purpose of this step was to check whether the effect of an attribute changes exponentially over its range. From LL-ratio test and chi-square distribution, an improvement of at least 1.92 LL-points is needed for the model with the extra squared term to significantly explain the data.

Therefore it can be observed that none of the non-linear specifications meaningfully improve model fit. The adjusted rho-square confirms this by remaining almost identical across all tested models. Therefore, there is no strong reason to use a non-linear utility specification in further analyses.

**Table 4.4:** Non-linearity test comparison. Null log likelihood = -4649.

Parameter	Cost	Payback	Certainty	Self	Backup
Final LL	-4252.6	-4251.2	-4252.1	-4252.6	-4252.7
$\bar{\rho}^2$	0.0838	0.0841	0.0839	0.0838	0.0838
$B_{cost}$		-0.1582	-0.1659	-0.1675	-0.1670
$B_{payback}$	-0.0560		-0.0576	-0.0568	-0.0565
$B_{certainty}$	0.4088	0.3788		0.4010	0.4098
$B_{self}$	0.0107	0.0092	0.0109		0.0106
$B_{backup}$	0.6032	0.6046	0.5968	0.5967	
Linear term	-0.2000	-0.1647	0.5391	0.0148	0.3010
Squared term	0.0042	0.0057	-0.0666	-0.0000	0.3010

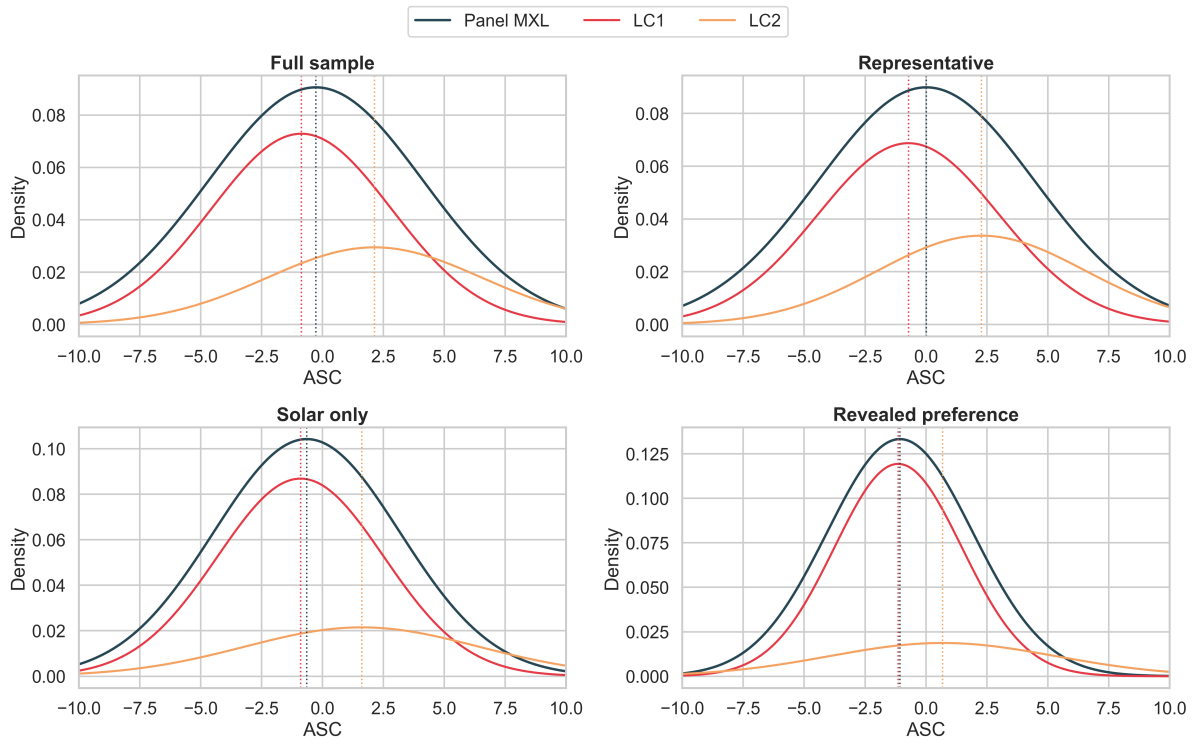
Table 4.5 presents the panel MXL results for the four data samples. This model is relevant because each respondent completed multiple choice tasks. The choices of one respondent are therefore not fully independent. The panel MXL model accounts for this by treating the repeated choices of the same respondent as connected observations. The panel MXL model performs substantially better than the basic RUM-MNL model. For the full sample, the adjusted rho-square increases from 0.0838 in the basic RUM-MNL model to 0.2393 in the panel MXL model. The representative sample has the highest adjusted rho-square, with a value of 0.2477, meaning the model best explains choice data of the sample representing the average Dutch household. The solar sample and revealed-preference sample have lower values, with adjusted rho-squares of 0.2067 and 0.1706 respectively.

The signs of the panel MXL coefficients are stable across all samples. This consistency supports the validity of the attributes and shape of the utility function. The ASC is however not significant for the full and representative data, this again means the model cannot meaningfully distinguish whether the sample has a basic preference for or against a home battery. For the solar and revealed sample the ASC is significant and negative. Meaning these samples on average have a distaste for not choosing a battery, i.e. a basic preference *for* choosing a home battery. The spread in the ASC,  $\sigma$  however *is* significant. This tells us that although the model cannot, with certainty, determine a value for the basic (dis)taste for a home battery, the model can with certainty say that there is a spread in these values. This motivates the estimation of a latent class model where the ASC is split [40].

**Table 4.5:** Panel MXL model

Dataset	$\bar{\rho}^2$	$B_{cost}$	$B_{certainty}$	$B_{payback}$	$B_{self}$	$B_{backup}$	ASC	$\sigma_{ASC}$
Full data (n=529)	0.2393	-0.177	0.448	-0.066	0.012	0.580	-0.272*	2.530
Representative (n=289)	0.2477	-0.191	0.491	-0.052	0.013	0.606	0.017*	2.774
Solar sample (n=301)	0.2067	-0.160	0.435	-0.072	0.013	0.540	-0.645	2.392
Revealed sample (n=269)	0.1706	-0.144	0.362	-0.054	0.010	0.514	-1.068	1.871

Table 4.6 shows the latent class model results. The latent class model separates respondents into two preference classes by assuming different no-battery constants. The latent class MXL has similar  $\beta$ -coefficients but performs slightly worse than the basic panel MXL. For the two classes, the model finds a class with a negative no-battery ASC and a class with a positive no-battery ASC. The class sizes are roughly 2:1. This suggests that the data contains respondents with a basic preference for choosing a home battery, and respondents with a basic preference against choosing a battery. The significance of these classes depends however on the sample. For the solar sample and revealed sample, the ASC for class two is not significant. This means that it cannot be said with certainty that a class of respondents with a basic distaste for batteries is found in these samples. This aligns with the observation that the



**Figure 4.3:** A visualization of the distributions of the no-battery ASC estimated from panel MXL models and the latent class models of the four samples. The dotted lines intersect with the estimated ASC. Areas represent class sizes, meaning the combined area of the latent classes is 1.

ASC for the solar and revealed sample were significant already in the panel MXL. This shows there is no statistical basis for assuming separate classes in the solar and revealed samples. A visualization of the class sizes, the ASC values and distributions can be seen in Figure 4.3. This is a schematic visualization of how basic preference for choosing a home battery are distributed in the different samples.

**Table 4.6:** Latent class MXL model

Dataset	$\bar{\rho}^2$	$B_{cost}$	$B_{cert}$	$B_{payback}$	$B_{self}$	$B_{backup}$	ASC <sub>1</sub>	ASC <sub>2</sub>	Class 1 share	Class 2 share
Full data (n=529)	0.2232	-0.224	0.490	-0.082	0.014	0.718	-0.866	2.138	0.674	0.326
Representative (n=289)	0.2307	-0.232	0.541	-0.070	0.015	0.745	-0.719	2.277	0.641	0.359
Solar sample (n=301)	0.1896	-0.183	0.455	-0.084	0.014	0.582	-0.896	1.612*	0.742*	0.258*
Revealed preference (n=269)	0.1680	-0.159	0.401	-0.069	0.010	0.498	-1.142	0.681*	0.783*	0.217*

Altogether, the model estimation results support four conclusions. First, all five home battery attributes have significant impact on explaining the observed choices. Second, the linear utility function performs best and is therefore used in further analyses. Third, the panel MXL model is the best-performing model and is therefore used as the final model for calculating relative importance and choice probabilities. Fourth, the latent class results suggest that it may be reasonable to assume two classes in the full and representative samples: one group with a base preference for battery adoption, and one group with a base preference for the no-battery alternative.

## 4.4. Relative Importance of Home Battery Attributes

This section presents the relative importance of the five home battery attributes and thereby answers the second sub-question. As concluded in Section 4.3, the linear panel MXL model is used as the final model for this calculation. We used two methods to determine the relative importance. A probability analysis, and comparing the drop in LL when removing one of the attributes. Table 4.3 can be used to compare the LL drop when removing the attributes one by one. Using this method, costs is also the most important attribute. Followed by certainty, backup power, payback time and self-consumption. Figure 4.4 shows the results from the probability analysis for the four data samples.

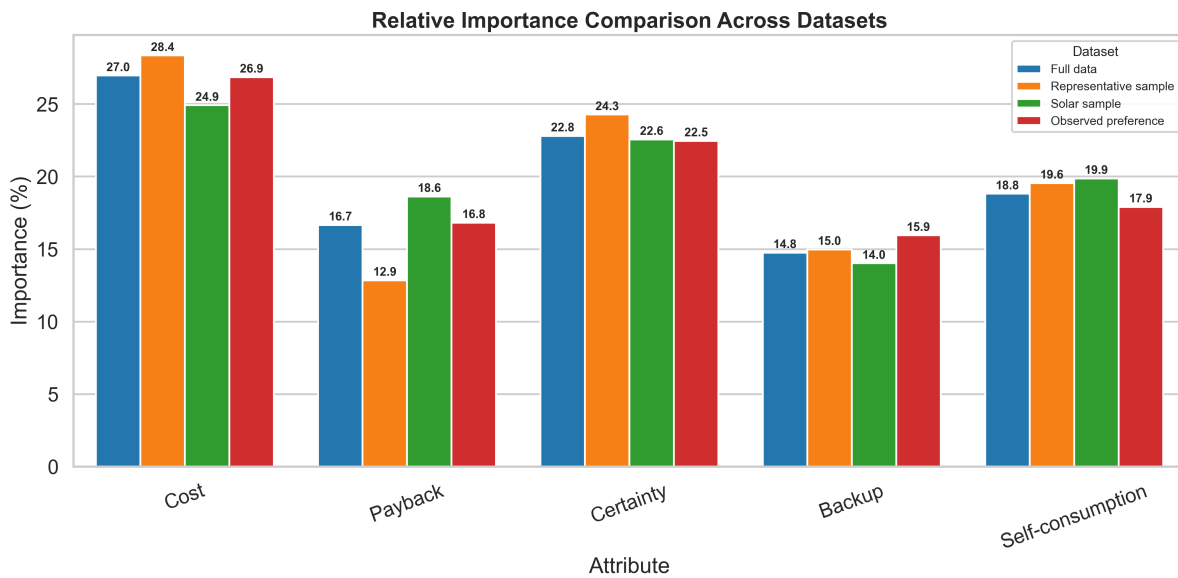


Figure 4.4: Relative importance of home battery attributes for different samples of the data.

Figure 4.4 shows that the ranking of attributes is almost stable across the four samples, Costs are the most important attribute, followed by certainty, self-consumption, payback time and emergency power. Only in the representative sample, backup is considered more important than payback time. Together, costs and certainty of payback time account for almost half of the total relative importance in each sample. This shows that households do not only respond to the expected financial outcome of a home battery, but also to the risk around that outcome. Comparing the samples shows some differences, but no major changes.

## 4.5. Choice Probability Analysis

This section presents the choice-probability analysis, providing the results to answer the third sub-question. The panel MXL model is used as the final model. The baseline home battery has the middle attribute levels: EUR 4k investment costs, certainty level 1, a payback time of 10 years, 60% self-consumption and backup level 0.5. Although EUR 4k investment costs and backup level 0.5 were not directly presented as attribute levels in the DCE, their use is meaningful here because the linear utility specification was selected in Section 4.3. The choice probability analysis then presents the probabilities of choosing the baseline battery, as well as how these statistics change when changing one attribute, while keeping all other attributes fixed at the baseline level.

Figure 4.5 shows the predicted choice probabilities for the four samples. The baseline choice probability differs between samples. It is 0.55 in the full, 0.53 in the representative, 0.60 in the solar and 0.67 in the revealed sample. This pattern aligns with BESS ownership shares presented in Section 4.2. These values should not be interpreted as current real-world adoption shares of home batteries in the Netherlands.

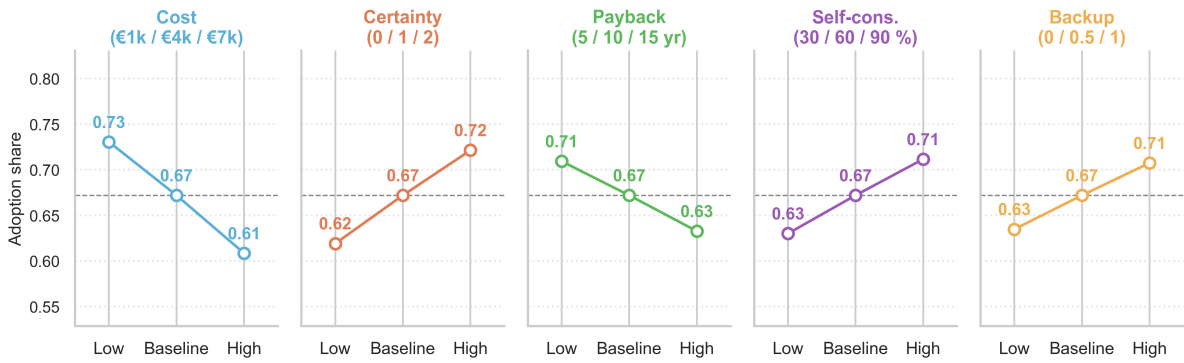
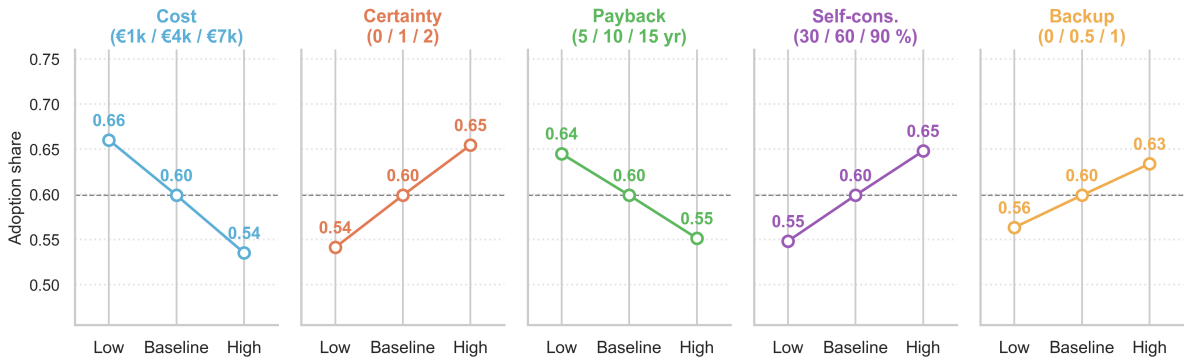
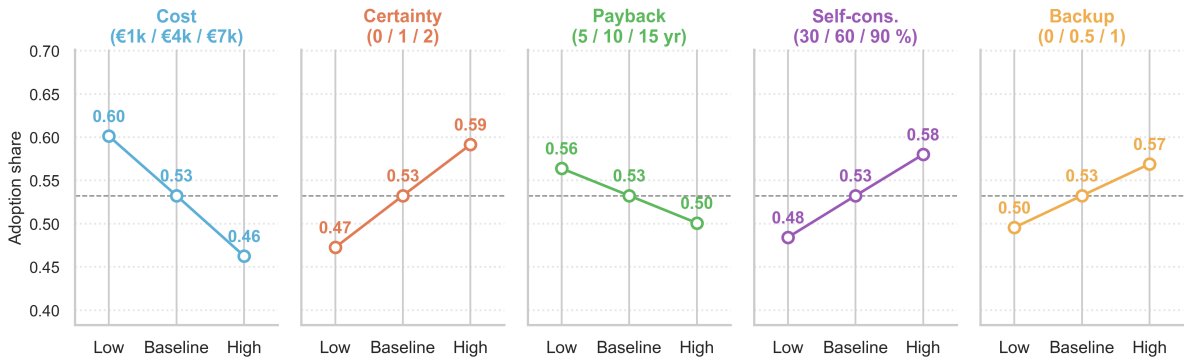
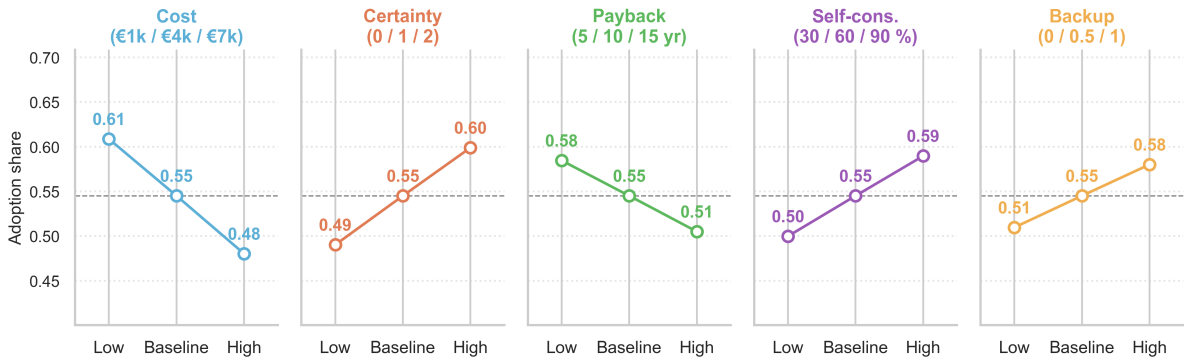


Figure 4.5: Analysis of predicted choice probability by attribute level for full, representative, solar and revealed samples.

They are choice probabilities estimated by the model for the hypothetical baseline battery profile used in this study. It says for example, that there is a 67% chance that someone from the revealed preference sample would choose the baseline battery alternative as opposed to not choosing a battery.

The direction of change in probabilities is consistent with the estimated utility coefficients. Higher investment costs and longer payback time lower the predicted choice probabilities, while higher certainty, higher self-consumption and better emergency power increase the predicted choice probability. This is expected from the signs of the panel MXL coefficients in Table 4.5. The probability analysis illustrates how these estimated preferences translate into predicted choice probabilities under different home battery profiles. The size of the changes do not say anything about relative importance of the attributes. This is because the low, high and baseline levels in the probability analysis are chosen scenario values. It provides an indication how adoption shares might respond to changes in attributes levels [42].

Altogether, the choice-probability results show that changes in the home battery profile lead to meaningful changes in predicted choice probability. The results are model estimations of how probability of choosing a battery alternative changes when individual attributes change. The choice probabilities are best interpreted as controlled model outputs: they show the direction and relative size of changes in predicted choice probability when home-battery attributes change. For actors aiming to influence residential BESS adoption, this means that interventions are most relevant when they improve attributes that households evaluate positively, such as certainty, self-consumption and emergency power, or reduce attributes that households evaluate negatively, such as investment costs and payback time. Since in real market conditions, more factors play a role, the impact of changes in attributes on adoption probabilities in the graph should be considered as the maximum amount of impact an attribute has.

# 5

## Discussion

This research aimed to understand how changes in home battery attributes affect the household investment decision to buy a home battery by identifying key home battery attributes through a literature analysis, and then estimating preferences in these attributes through a discrete choice model. This chapter interprets the results and discusses their implications by considering limitations and assumptions of the study. Section 5.1 discusses what the results say about the nature of the household decision. Section 5.2 interprets the differences between respondent groups. Section 5.3 compares the Dutch and Australian context. Sections 5.4 discusses the implications for actors and for residential BESS adoption in the Netherlands. Section 5.5 revisits the main limitations.

### 5.1. What the Model Reveals about the Household Investment Decision

We first assess the reliability of the model, and then its validity, before we can interpret what the model reveals about the household investment decision. As seen in Table 4.5 the panel MXL model fits the choice data well. Its  $\bar{\rho}^2$  of 0.2477 for the representative sample indicates that the model captures a substantial part of the systematic variation in household choices, while a large share of utility remains unobserved [35, 37]. As a rule of thumb, an adjusted  $\bar{\rho}^2$  above 0.20 already represents an excellent fit for a discrete choice model [40]. Other studies regrettably do not report  $\bar{\rho}^2$  values we can compare this value to [30]. Alipour et al. do report values of 0.87–0.91, but their hybrid model co-optimizes 67–91 background and demographic parameters making a near-perfect fit expected [17, 40]. Despite the lack of comparison, the excellent model fit in this study across all four data samples using only five attributes, and the significance of estimated preference coefficients across samples and utility-function specifications, indicates that the model reliably captures a substantial and systematic part of the household investment decision.

As mentioned we found statistically significant  $\beta$ -coefficients with expected and intuitive signs. The distaste for higher costs and longer payback time and preference for autonomy and emergency power is consistent with findings in literature, supporting our model's validity [13, 30]. The preference for certainty of payback time for a home battery had not been studied in literature. But in line with our findings, policies that guaranteed returns from PV feed-in proved to be successful in Queensland [13]. Results are also consistent with the Random Utility Maximization (RUM) assumption on which DCM is based [36, 37]. This assumption splits utility into a systematic part that responds to the attributes and a random part that absorbs everything the experiment did not measure, such as other attributes, bounded-rational behavior and noise in the choice tasks [84, 37]. The model however cannot prove that households actually follow the decision rule assumed by RUM, other decision rules could generate

similar observed choices [84, 36]. The results therefore do not prove the RUM assumption, but they also do not contradict it. The model explains the observed choices considerably better than random guessing, and the significant, intuitive and stable coefficients indicate that households responded systematically to the battery attributes. So within the limits of the RUM assumption, the model provides a valid and reliable basis for further interpretations.

We now interpret what these results reveal about the household investment decision. The model shows that households respond consistently to the attributes, in line with a RUM decision logic. Although RUM is grounded in economic theory [35], this does not mean the decision is purely financial. Firstly, Table 4.3 shows the profitability model, which collapses investment costs and payback time into a single profitability variable, fits worse than the basic model. Moreover its  $\beta$ -coefficient takes a negative sign, meaning households prefer less profitability [40]. One could argue this as evidence that the model is unreliable, but since the other specifications fit well and all attributes carry intuitive, stable and significant coefficients, the weakness more plausibly lies in the profitability model itself. Households do not appear to reduce costs and payback time to a single profitability measure. A second piece of evidence is that payback time, which is one of the most important characteristics of investments for market actors, is the least important attribute in the representative sample [16, 85]. However, certainty of payback time, also a return-related attribute, is the second most important of the five, so households clearly still weigh part of the financial return. But testing for interaction finds that households do not accept more risk in exchange for a shorter payback, which is also not what is expected from economically rational market actors, who trade off risk and return [86]. Taken together the evidence supports the statements in Chapter 1 that the household decision-maker is rational, but not strictly economically rational.

A second interpretation concerns how strongly the decision is governed by financial attributes. Three of the five key attributes investment costs, payback time and certainty of payback time, are financial in nature, and together they account for 65.6% of the relative importance found. So although households do not appear to be pure economic optimizers, financial attributes strongly shape the decision. From the non-financial attributes, self-consumption carries substantial weight. Self-consumption may however also be valued partly financially as increasing self-consumption can generate revenue [12, 30, 87]. Although the survey framed it to be exclusively a percentage of control over one's own electricity rather than a financial benefit, it still might be interpreted as bringing financial benefits [76]. Even so, the importance of self-consumption and emergency power provides choice-based evidence for observations in literature that non-economic characteristics of home batteries matter to households [13]. The contribution here is that this support comes from trade-offs and preferences rather than from stated importance rankings, which was a limitation of existing work identified in Chapter 2 [30, 13].

Overall, the results support that the household investment decision to adopt a home battery is shaped by the key attributes identified in this research, and that this decision is strongly financial but not purely so. What these two interpretations mean for residential BESS adoption and for the actors involved is discussed in Section 5.4.

## 5.2. Heterogeneity and Data Samples

The results in Figures 4.1a and below show some heterogeneity between respondent groups. The solar and revealed-preference samples have higher levels of solar PV ownership, home ownership, BESS ownership and BESS purchase intention than the representative sample. The data therefore show a clear association between solar PV ownership and home battery interest, but they do not by themselves establish the underlying mechanism. A likely explanation is that households with solar PV already have the physical system that makes self-consumption valuable, which makes a home battery more relevant for them [24]. This interpretation is consistent with studies from Aniello and Alipour et al., who find that solar PV ownership correlates with home battery uptake and that benefiting from solar PV production is a driver of battery adoption [12, 17]. The present results add to this by showing the same association in a Dutch sample, where the upcoming phase-out of net-metering further increases

the value of self-consumption [23].

Home ownership is also associated with BESS interest. Owner-occupied households have higher levels of solar PV and stronger battery intention than renters, as shown in Figure 5.1. This pattern is expected from the household energy-investment literature. Kastner and Stern describe the principal-agent problem, in which tenants cannot decide on home energy investments even though they would benefit from them, so adoption tends to concentrate among owner-occupiers [26]. Aniello reaches a similar conclusion for residential PV and battery diffusion, finding that ownership structure is a key driver of regional differences in BESS adoption [12]. Despite these findings, the results of this study show that actual BESS ownership is almost identical among renters (11.4%) and owners (11.8%). This is a significant deviation from what is expected from academic and gray literature, which would predict markedly lower uptake among renters [12, 26, 17, 88]. A potential explanation is that the principal-agent problem does not hold for plug-and-play home battery systems. These systems do not require investments or permission from the building owner, and renters can still choose their own electricity contract and so capture the savings themselves [89]. The barrier that the principal-agent literature identifies for solar PV therefore might be weaker for plug-and-play batteries. This suggests that renters might actually be a significant potential market segment for residential BESS.

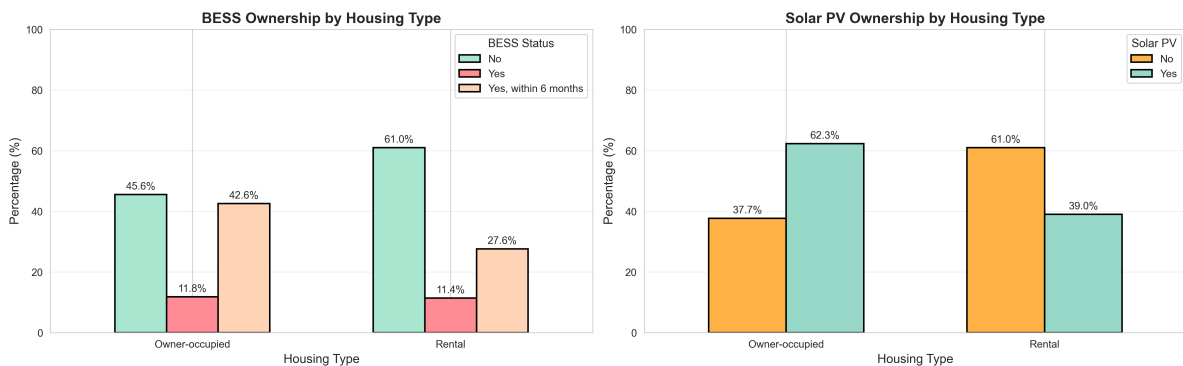


Figure 5.1: BESS (intended) ownership and solar PV ownership by housing type.

The model results also show heterogeneity in the basic preference for adopting a home battery. The ASC distributions in Figure 4.3 and class shares in Table 4.6 suggest that there is a smaller but more resistant group of respondents that do not state to choose a home battery. Several sources present upfront capital costs and financial struggle as the key barrier preventing home battery uptake [13, 61, 32]. In the Dutch context, a recent report stated that 38% of Dutch households struggle financially [90]. This is strikingly close to the 35.9% class share this study produced. This should not be interpreted as causal evidence. However, it does suggest that resistance to adopt could result largely from financial struggles. This might be interesting for municipalities willing to increase installed home battery capacity, because it shows that upfront subsidies could be very effective [20].

The opposite of this pattern is true for the solar and revealed-preference samples. For these samples, the latent class specification does not show the same clear and statistically useful split. This is because these samples already consist of respondents with higher interest in residential BESS or stronger connection to solar PV, again consistent with expectations by Aniello and Alipour et al. [12, 17]. Therefore, forcing the model to split these samples into two classes adds less explanatory value. This supports the interpretation that heterogeneity is strongest in the broader population, where both potential adopters and clear non-adopters are present. These findings are also seen in previous research that identifies different adoption profiles. Alipour et al. distinguish between groups such as adopters, profit seekers and non-adopters, showing that households differ in their general orientation towards PV and battery investments [17].

Heterogeneity shows less in the results on relative importance. Although the representative sample gives a slightly different ordering for some attributes, the overall pattern is similar across samples. A reason for this is that the four samples are not independent groups but partly overlapping subsets of the

same 529 respondents. The representative, solar and revealed-preference samples are each drawn from the full sample. For example, 72.9% of the revealed-preference respondents also belong to the solar sample. The similarity in estimated attribute importance across samples therefore also results from the fact that these samples are statistically dependent [91].

The comparison across samples is therefore better seen as a robustness check than as proof that every group values the attributes in the same way. What can be concluded more clearly is that the samples differ in their basic willingness to choose a home battery at all. This is reflected in the ASC and in the higher predicted baseline choice probabilities for the solar and revealed-preference samples. The solar and revealed-preference samples contain more respondents with a stronger connection to solar PV or home batteries, and therefore have a higher baseline probability of choosing the battery alternative. This supports the interpretation that these groups have a higher basic willingness to consider a battery. For the relative attribute importance, the attribute patterns look broadly similar, but because the samples overlap, this is not independent proof that the groups truly have equal preferences. A stronger claim about preference heterogeneity would require a model that lets attribute effects differ directly between groups, for example through subgroup-by-attribute interaction terms or a latent class model with class-specific attribute coefficients.

The background variables show a large group of respondents intending to buy a battery within 6 months: 42.6% of owner occupied homes, and 27.6% of rental houses. Although reports expect a rapid growth of residential battery storage [15], it is questionable whether capacity will quadruple within 6 months. A reason for this overestimation could be that stated intention is usually higher than actual adoption [61]. In addition, respondents may have had an incentive to signal interest because the survey introduction already mentioned home batteries and because participation was connected to a monetary reward. This may have created a bias. Despite these limitations, this potentially large increase in uptake should not be ignored, because rapid mass adoption of residential BESS in the short term can have detrimental consequences. It could erode the revenues of professional BESS developers through market saturation [54], and it could create problems for grid operators if home batteries are not operated in grid-supportive ways [49].

### 5.3. Comparing the Dutch and Australian Context

As mentioned Section 2.3 of Chapter 2, some parallels can be drawn from the Australian context of several years ago and the contemporary Dutch context. The first comparison concerns the attributes and their relative importance. Because the attributes in this study were identified from a largely Australian literature base, it is not surprising that the most important attributes broadly correspond [13, 30]. This study's relative importance of costs corresponds directly to the number reported by Agnew and Dargusch in their Australian discrete choice experiment [30]. Relative importances of self-consumption, which correlates closely with battery size as motivated in Section 3.2, and payback time also share similar importance as reported by Agnew and Dargusch [30]. These similarities provide evidence that household preferences in home batteries are consistent across different consumers and regions. We would like to make an important note that this study did exclude some attributes, as motivated in Section 4.1, that were actually included in Australian literature [13, 30, 32]. Therefore, we can only draw limited conclusions as to consistency among countries or consumers because we have included different attributes. We can however discuss the common factors: costs, self-consumption and payback time. Future work could compare consumer groups with the same attributes to test whether attributes are valued similarly across countries and regions.

A difference from previous literature is that this study included certainty of payback time as an attribute. Our results show this attribute is highly relevant for Dutch households when deciding between home batteries. We propose two explanations for why Australian literature has not considered this attribute. First, Australia receives almost twice the solar irradiation of the Netherlands and has weaker seasonal variation [65]. This increases the amount of surplus electricity from PV that a battery can shift, making the financial return more consistent and predictable. Second, feed-in tariffs that guaranteed returns,

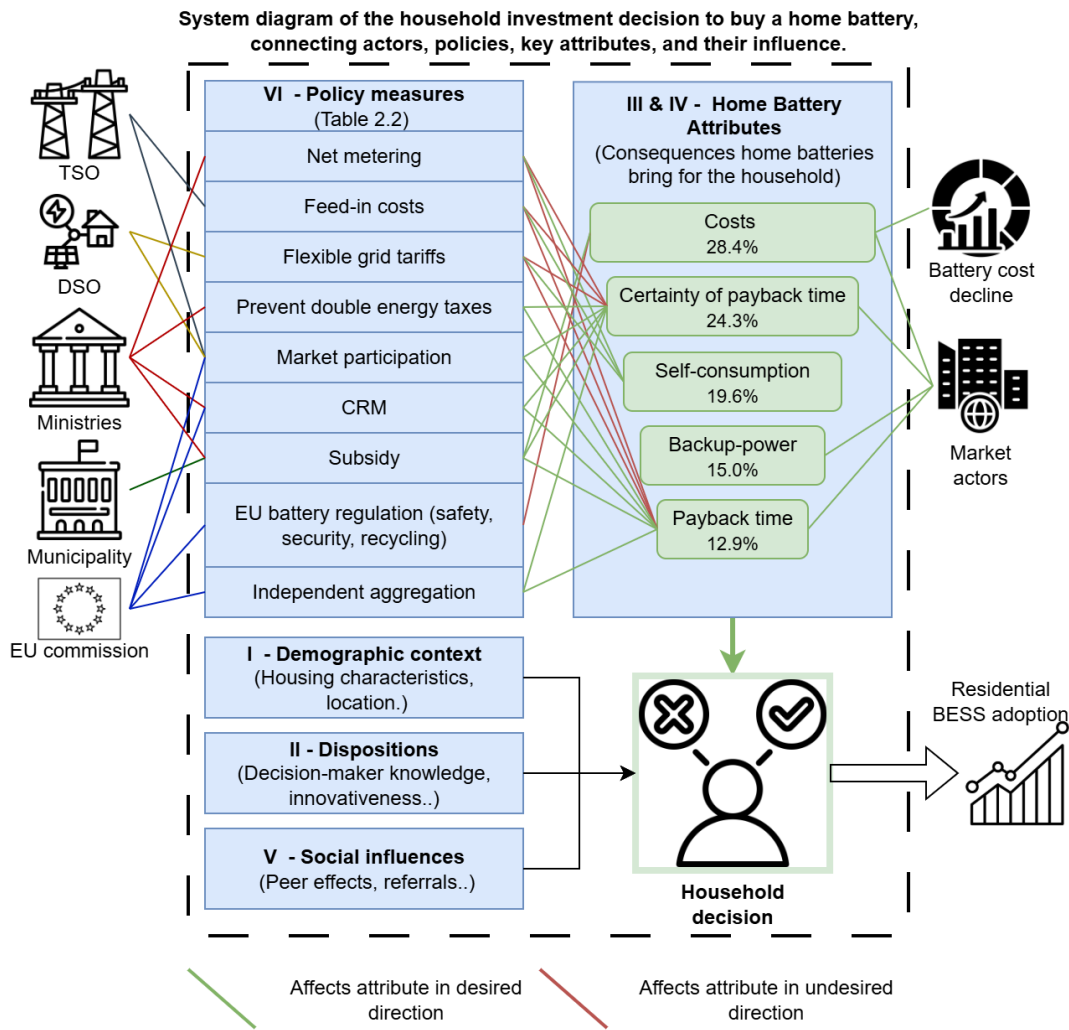
such as the premium fixed feed-in tariff in Queensland, gave households a more certain return and less reason to price in the risk [13]. Under both conditions the expected payback was simply more reliable, so its uncertainty formed a smaller part of the decision. Hence less reason to include it as an attribute in a DCE. This study has identified this risk dimension and quantified its relative importance. In Section 5.4 we will discuss how different actors could use this insight in a Dutch market where returns from home batteries are highly uncertain [24, 78].

A second comparison concerns the similar importance of self-consumption. Two possible explanations fit here. As mentioned, it is possible that similar relative importance of self-consumption results from consistency of consumer preferences through time and location. It could however also be the case that the similar importance is coincidental, and results from a *different* underlying motive. For example, in the Australian literature the strong self-sufficiency motive is tied to distrust in grid operators and energy companies [30, 32]. While the Netherlands does not share this exact history, data for this study were collected in April 2026, a period in which concerns for security and reliability of the electricity systems were prominent. These included the energy-price shock following the conflict involving Iran [11], grid congestion [8], and a warning from TenneT that the Netherlands faces growing risks of electricity shortages [92]. Such a public opinion might create a sense that dependence on the grid and the market is a risk, similar to the previous Australian context. Both explanations seem plausible, a future study that assesses relative importance of the same set of attributes in different countries is needed to confirm either explanation.

A final point follows from this similarity. If the drive toward self-consumption and autonomy holds as it does in Australia, the system-level risks that Agnew and Dargusch tie to it may transfer as well. They warn that widespread self-sufficiency can become a self-reinforcing loop with costly consequences: under-utilized grid infrastructure, stranded network assets, and higher, inequitable costs for the households that remain on the grid [30, 31]. Comparable signals are already visible in the Netherlands. Falling battery costs, the net-metering phase-out, and rapidly growing residential BESS capacity could both saturate storage revenues and strain the grid [7, 15, 23, 45, 55]. They conclude that these risks cannot be managed without a better understanding of consumer motivations for buying home batteries [30]. In this study, we contributed to this for the Dutch context by quantifying how households trade off different attributes feeding these motivations.

## 5.4. Implications for Actors and Policy

This section returns to the starting point of the thesis. Chapter 1 showed that grid operators, municipalities, energy companies and the responsible ministries all need to understand the household decision to buy a home battery, but cannot influence it directly. Chapter 2 organized this in the system diagram of Figure 2.1. This figure was an empty framework where actors take policy measures, those measures affect home battery attributes, and the attributes influence the household decision, resulting in adoption. This section fills that framework with the results of this study, and highlights relevant implications by connecting policies and developments to the attributes we have found. Figure 5.2 shows the diagram with the five estimated attributes, their relative importance and the direction in which they move the predicted choice probability. In the remainder of this section we first motivate the direction of these policy links and how they move the attributes in 5.4.1. We then turn to what this implies for the actors in 5.4.2.



**Figure 5.2:** The system diagram of Figure 2.1, now filled in with the five estimated attributes, and their relative importance in the representative sample. Links between attributes and (policy) developments are made, a green line means that the measure moves an attribute in the direction that increases probability, and thus adoption, more likely, red where it moves it the other way. Falling battery costs and market actors such as energy companies and battery retailers also move the attributes. The selection and direction of the policy links are motivated in Section 5.4.1.

### 5.4.1. Policies and Relevance for Battery Attributes

This section motivates how the policies and developments introduced in Chapter 2 connect to the five attributes estimated in this study. Quantifying how each regulation changes each attribute was not a goal of this research, and the exact size of these effects remains uncertain and a task for future studies. However, by combining the results of this study with reports on the revenue models of home batteries, government and grid-operator documents, we can nonetheless establish some qualitative links [24, 23, 52]. Figure 5.2 shows the result, green line indicates that the measure moves an attribute in the direction that makes choosing a home battery, and thus adoption, more likely. A red line indicates the opposite. We will now motivate the direction of each link, for clarity an overview of policies and their connection to the home battery attributes is also shown in Table 5.1.

Measures that reduce investment costs, such as subsidies or tax rebates, act on the most important part of the household decision and are therefore likely to be effective. This is consistent with research on policies promoting solar PV, where subsidies that lower investment costs led to more installed capacity than subsidies aimed at revenues [93]. The results also show that reducing uncertainty is almost as relevant as reducing costs; uncertainty of payback time can be lowered, for example, by giving

residential BESS access to all electricity markets, which diversifies revenue streams and spreads risk [54, 24]. The mapping in Table 5.1 is not a policy-impact assessment, it shows only which attributes each measure is likely to touch based on existing research [24]. Quantifying the impact of policies on those attributes is left to future research. This study contributes to the next step: linking a change in an attribute to a change in choice probability, and likely adoption [42].

Two observations stand out in Figure 5.2. First, the regulations now arriving act mainly on payback time, certainty of payback time and self-consumption. The net-metering phase-out and the upcoming flexible tariffs make future returns harder to predict. On one hand, phase-out of net-metering promotes self-consumption which by itself is an excellent business case for residential BESS, on the other hand, studies expect this will also decrease revenues from imbalance markets [24]. The introduction of flexible tariffs will also negatively influence payback time because it introduces financial constraints on dispatching, however, it also increases self-consumption value [23, 24]. Again the net effect on payback time is unknown. These examples show many measures touch on certainty of payback time, yet none is designed specifically to provide it. Second, investment costs, the most important attribute, are barely targeted in policies. A plausible explanation is that since residential BESS developments are recent, regulations were not designed with residential BESS in mind.

**Table 5.1:** Connection between policy examples and the home battery attributes.

Policy or regulation	Investment costs	Payback time	Certainty of payback time	Emergency power	Self-consumption
Abolishment of the net-metering scheme	–	×	×	–	×
Feed-in remuneration and feed-in costs	–	×	×	–	×
Flexible or time-dependent grid tariffs	–	×	×	–	×
Preventing double energy taxation	–	×	×	–	–
Rules on participation in imbalance or flexibility markets	–	×	×	–	–
Independent aggregation and improved market access	–	×	×	–	–
Capacity remuneration mechanisms	–	×	×	–	–
Investment subsidies or tax rebates	×	×	×	–	–
EU Battery Regulation	×	–	–	–	–
Physical safety standards	×	–	–	–	–
Cybersecurity standards	×	–	–	–	–
Environmental requirements	×	–	–	–	–

## 5.4.2. Implications for Actors

Referring to the system diagram in Figure 5.2, we can revisit for each actor group from Chapter 1 what these results imply. We deliberately tie these statements to the estimated numbers rather than to expectations that would hold without this research.

Looking at the results of the relative importance of attributes in Figure 4.4, and combining it with the policy overview of previous section, an interesting finding is that certainty of payback time is the second most important attribute, yet no current policies are specifically designed to provide certainty. A policy that would guarantee returns would play well into this highly valued attribute and significantly stimulate adoption [13]. Grid operators could offer households contracts that guarantee returns in exchange for control over their residential BESS, this could on one hand stimulate decentralized storage while also mitigating grid congestion [94]. A similar observation can be made for costs, the most important attribute. A ministry aiming to accelerate adoption outright should develop policies that decrease investment costs. Australia has implemented such a policy in the form of a tax rebate, greatly driving home battery uptake [95].

For battery retailers, the findings suggest a different strategy to increase uptake, or sales. Although we cannot conclude different household groups value preferences differently, we have found that different groups differ in their base willingness to choose for a battery. A change in investment costs from EUR 4,000 to EUR 1,000 in the representative sample gives an adoption-share difference of 0.07. This is about the same as the difference in baseline choice probability between the representative sample and the solar sample. This difference could be because households with solar panels perceive more benefit from

the battery. However, the survey was designed to show the same battery benefits and battery types to all respondents, regardless of whether they had solar panels or not. This shows that changing attributes can sometimes be as influential as comparing different groups of people with different dispositions. Battery retailers can leverage this insight by targeting households that already have a stronger baseline willingness to adopt, such as solar-PV owners. Another interesting strategy following from our results could be to rent home batteries. It removes the dominant cost barrier without touching the uncertain payback dimension, while serving the autonomy motive households reward [61].

A final implication concerns energy companies investing in utility-scale BESS and policymakers, and reaches beyond the household decision. As discussed in Section 5.2, our results indicate an enormous stated intention to install a residential BESS within six months. Given the limitations discussed in that section, this is not alarming per se, but it creates a serious risk for storage investors. As residential BESS adds to total installed storage capacity, the arbitrage spreads and the ancillary-service revenues that storage relies on are decreasing rapidly [55, 56]. If returns keep falling as capacity grows, storage investors may struggle to recover their investments, which might limit the flexibility build-out that the transition toward a net-zero energy system depends on. The implication is that market design cannot be static: revenue mechanisms and policy must evolve as capacity grows to keep storage and other flex investments viable. Agnew and Dargusch conclude that such system risks cannot be managed without understanding what drives households to adopt [30], which is the gap this study addresses for the Dutch context.

## 5.5. Limitations

Several limitations were already raised in the preceding sections and are only briefly recalled here. Section 5.1 showed that the model is consistent with, but cannot prove, the RUM decision rule. Section 5.2 explained that the four samples are overlapping subsets rather than independent groups. Section 5.3 noted that the comparison with Australian work is limited because the studies do not share the same attributes. This section consolidates these points and elaborates on the remaining limitations.

**Only the included attributes are measured.** The most fundamental limitation follows from the approach of DCM itself: the model can only estimate the effect of attributes that were part of the experiment. SQ2 and SQ3 are therefore answered *within* the selected set of five home battery attributes, as the sub-questions themselves state. Everything outside this set, other attributes, household-specific circumstances and bounded-rational behavior, is absorbed into the unobserved utility and the no-battery ASC [37]. The relative importances should therefore be read as conditional on the chosen set and not as context-free truths. Second, the study cannot conclude that excluded drivers are unimportant, nor can it prove that these five attributes are *the* most important ones. It can only show that the included attributes are relevant, and quantify their importance relative to one another. However, based on resemblance with previous studies and excellent model performance many relevant implications can still be extracted from these results.

**The RUM assumption.** DCM is built on Random Utility Maximization, which assumes the household chooses the alternative with the highest utility. As discussed in Section 5.1, the data are consistent with this decision rule but do not prove it. Other rules could generate similar choices [36]. Treated as a limitation, RUM remains a simplification of how households actually decide. Real households are bounded-rational: they rely on limited information, time and cognitive capacity, and often use heuristics rather than full optimization [26, 84]. The purchase is also frequently not made by a single decision-maker, but jointly within the household, which RUM does not capture [27]. RUM does not require perfect optimization, deviations are absorbed into the error term, which is exactly why the method stays appropriate. But the estimated preferences should be read as the systematic part of a decision that is in reality more complex as shown in Figure 5.2.

**Translation of broad drivers into survey terms.** Another limitation of the method is the translation from broad drivers to concrete survey terms. For example, *energy autonomy* was operationalized as

*self-consumption*, and *uncertainty of payback time* as *certainty of payback time*. These terms make the choice task easier to understand, but they also lose part of the meaning of the original driver. Energy autonomy was defined as “*the household’s willingness to control its own electricity consumption and become less dependent on the grid or energy companies*”, whereas self-consumption only measures how much of that control is realized; information is lost and misinterpretation is possible. This attribute is moreover partly economic rather than purely behavioral: as noted in Section 5.1, a higher self-consumption can also generate revenue, so respondents may have read it as a financial benefit despite the framing. This affects SQ1, because the identified attributes are simplified versions of the concepts found in literature.

**The experiment and the model are simplifications.** Both the DCE and the estimated model are a simplified version of the real investment decision. Buying a home battery is a complex real-life decision with real consequences, yet respondents did not spend any actual money and were shown only a small number of attributes, levels and alternatives. This simplification lowers cognitive burden and improves answer reliability at the cost of validity [40]. The consistency between the representative and revealed-preference samples gives some reassurance that the stated choices are meaningful, but this check itself rests on self-reported background variables, which are not always reliable [61]. The model adds a second layer of simplification. Despite the panel MXL model performing very well, especially on the representative data ( $\bar{\rho}^2 = 0.2477$ ), many factors were not captured. This mainly affects SQ3. The choice probabilities show probabilistic effects of changing attribute levels. They only hint towards how adoption may develop in the real market. For this reason the results of Section 4.5 should be interpreted qualitatively rather than as precise values.

**Attribute selection.** The final attribute set is the product of the researcher’s interpretation of the existing literature. This study addressed a recurring weakness in DCEs, namely that attribute selection is often poorly reported, by documenting the full path from a broad driver list to the final attributes [43, 44]. Literature recommends that attributes are not only included based on literature, but also through expert input, and explicit selection criteria [43]. Future research could therefore strengthen the attribute-selection process by combining the Kastner and Stern framework with a structured multi-criteria attribute-selection procedure.

**Data and samples.** A final limitation is the data. Panel data is often treated as the best option for gathering choice data, not because it is perfect, but because the alternatives are usually worse [40, 96]. Apart from general limitations that apply to panel data [96], we would like to mention that the choice data was collected at one moment in time. At that moment, public attention to energy security and electricity markets may have been different than normal, for example due to recent geopolitical events and high imbalance prices [11]. This can affect how respondents value emergency power, certainty and financial performance. The results should therefore be interpreted as preferences measured in that specific context. The samples add a further limitation because these were partly overlapping groups as explained in Section 5.2. Conclusions about household preferences beyond this setting are therefore limited. The representative sample was constructed with the available screening variables, mainly housing type and solar panel ownership. It is therefore closer to the average Dutch household, but not perfectly representative. The solar and revealed-preference samples are useful for comparison, but they represent more specific groups. This means that sample differences help answer the sub-questions, but the results should still be interpreted within the Dutch sample context.

# 6

## Conclusions & Outlook

This chapter concludes the thesis. The aim was to understand how changes in home battery attributes affect the household investment decision to buy a home battery. We first answer the three sub-questions, then synthesize them into an answer to the main research question. After that we reflect on what this means for the actors and problem statement of Chapter 1, and close with an academic reflection and directions for future work.

The first sub-question concerned which attributes most affect the household investment decision. A structured literature analysis, using the framework of Kastner and Stern, translated 79 adoption drivers into five key home battery attributes: investment costs, payback time, certainty of payback time, self-consumption and emergency power. These span both financial and non-financial dimensions, and all five carry significant, intuitively signed coefficients across samples and model specifications. An important limitation however applies: a discrete choice model can confirm that the included attributes matter, but cannot evaluate attributes it never tested. We therefore conclude that these five attributes are relevant, not that they are necessarily the five *most* important.

The second sub-question concerned the relative importance of these attributes. For the sample representing the average Dutch household, investment costs are the most important attribute, followed by certainty of payback time, self-consumption, emergency power and payback time. These findings provide a deeper understanding of the household decision in two ways. First, three of the five attributes, costs, payback time and certainty of payback time, are financial, and together account for roughly two-thirds of the total importance, confirming that the decision is strongly financial. Second, it is not *purely* financial. Payback time, a core metric for professional investors, is the least important attribute for households. Also, collapsing costs and payback into a single profitability term worsened model fit and it was found that households did not accept higher risk in exchange for shorter payback. This is evidence that the household decision-maker is rational, but not strictly economically rational.

The third sub-question asked how changes in attributes affect residential BESS choice probabilities. The probability analysis reflects the households preferences. The baseline choice probabilities between samples reflect differences in basic willingness to adopt a home battery or not. Due to the limited validity of the experiment, these values should not be read as real market shares.

Taken together, these answers resolve the main research question. Changes in home battery attributes affect the household investment decision by changing the probability that a household selects the battery alternative: lower investment costs raise this probability most, followed by greater certainty of payback time, higher self-consumption, better emergency power and shorter payback time. These five attributes are the main "knobs" through which the decision can be understood or influenced.

This addresses the knowledge gap by overcoming limitations of previous studies. A transparent, literature-based attribute selection has found five key attributes that, although not certain to be the most important attributes, together explain household decisions very well. The relative importance of these attributes is also derived from observed trade-offs rather than stated rankings, and relevance to current Dutch conditions. DCM is not in itself a novel approach to extract preferences among decision-makers. The contribution, however, lies in documenting the full path from a broad driver list to the selection of attributes, which responds to a problem in broader DCM literature that attribute selection in choice experiments is poorly reported and hard to reproduce. This study also identifies certainty of payback time as a decision-relevant attribute that earlier work overlooked.

The problem statement of this thesis argued that several actors seek to influence, understand or predict residential BESS adoption, but do not know how to do so because adoption follows from complex and diverse household investment decisions. The results do not solve this full problem and limitations apply, but they do significantly increase understanding of the household investment decision by having quantified important attributes. The attributes however do not explain everything. For example, the solar and revealed-preference samples have higher baseline probabilities of choosing a battery than the representative sample. This shows there are big differences between groups in the basic willingness to consider a home battery. This can have important policy and market implications: if a policymaker, or a company has a goal to install a specific amount of capacity, targeting the right people can result in a similar adoption as reducing prices of the home battery.

For ministries or municipalities aiming to accelerate residential BESS adoption, the results point to two main findings. Investment costs are the single most important attribute, yet they are barely addressed by current Dutch policy. Measures that lower upfront costs, such as subsidies or tax rebates, are likely to be highly effective, which is demonstrated by Australia's home-battery tax rebate. Such subsidies may be especially powerful given that resistance to adoption might for a large part result from the roughly one-third of households facing financial constraints. Another important finding concerns certainty of payback time, the second most important attribute, which no existing regulation is designed to provide. Policies that guarantee or stabilize returns would address a highly valued dimension that current measures, including the net-metering phase-out and flexible tariffs, seem to undermine.

For grid operators, the key opportunity lies in certainty of payback time, the second most important attribute that no current policy provides. Offering households contracts that guarantee returns in exchange for control over their battery could simultaneously stimulate decentralized storage and mitigate grid congestion, while filling this policy gap. This addresses the risk that batteries are otherwise not operated in grid-supportive ways. Our findings also show that energy companies should carefully evaluate whether investing in utility-scale storage provides a business case. The very large stated intention to adopt residential BESS adds to total installed capacity, eroding the arbitrage spreads and ancillary-service revenues that storage depends on. Moreover, if households greatly increase self-consumption of energy, the already competitive energy market might shrink due to decrease in overall demand from centralized production.

The chosen approach in this study limits what can be understood about residential BESS adoption. A central actor, such as an energy company predicting energy prices, or a ministry tracking climate goals, might seek a specific installed BESS capacity figure. For this task a discrete choice model is poorly suited because its outputs hinge heavily on assumptions. For a local actor with a fixed budget trying to encourage as much adoption as possible, this approach is directly useful, since it shows that money is best spent first on lowering costs and increasing certainty. To further understand the household investment decision, future work should quantify how each policy changes each attribute, and then potentially integrating the preferences estimated here in a diffusion model that can translate them into capacity growth over time. To do so we propose the following directions for future research.

- First, the set of included attributes can be expanded and the selection formalized. This study used five attributes, but the results suggest respondents were able to make meaningful trade-offs between them. Future research could therefore test whether a slightly broader attribute set is still manageable and whether this improves validity [76]. The selection of attributes itself

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could be structured through a multi-criteria procedure that scores candidates on relevance in literature, expert interviews, significance and clarity [70]. This improves the selection process methodologically, although it cannot fully remove subjectivity. However, it would still need to define and quantify what is "significant".

- Second, transferability of preferences could be tested across contexts. Repeating the experiment in different countries with identical attributes and comparable timing would reveal whether the preferences found here are stable across regions, and which of them are. This would benefit future researchers who might seek to understand the role residential BESS will play in their context.
- Third, future research should study how policies or measures translate into changes in home battery attributes. For example, the effect of flexible grid tariffs, market access or tax rules on payback time and certainty is not straightforward. This step is needed before the model can be used for stronger policy assessment. The model could also be calibrated with current or historical market data, although this is difficult because the Dutch residential BESS market is still changing quickly.
- Lastly, future research could increase the validity of the DCE by combining a rating or best-worst task with a choice experiment [17]. A broader driver set could first be screened with such a task, after which a DCE can estimate behavioral trade-offs for the most policy-relevant attributes. If the experiment is highly valid, then this type of choice model could be combined with adoption or diffusion models [29]. This would make it possible to use the behavioral results of this thesis as input for broader forecasting of residential BESS growth in the Dutch electricity system.

Altogether, this thesis does not provide a final forecast of residential BESS adoption for the Netherlands, but a transparent and empirically grounded foundation for one. It shows which home battery attributes Dutch households respond to, how strongly and in what order, and how the probability of choosing a battery shifts as those attributes change.

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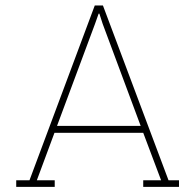
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## Appendix - Full List of Drivers

**Table A.1:** Residential BESS adoption driver inventory. Category codes: I = Demographic, housing characteristics, house location; II = Decision-maker dispositions; III = Beliefs about consequences for household; IV = Beliefs about consequences beyond household; V = Social influences; VI = Policy measures.

Driver	Cat.	Source	Note
Battery system cost / upfront cost	III	Agnew [30]	Key determinant of stated preference
Payback period	III	Agnew [30]	Shorter payback raises appeal
Battery safety	III	Agnew [30]	Strongly valued product attribute
Battery size / capacity	III	Agnew [30]	Medium or large systems often preferred
Ease of use / maintenance burden	III	Agnew [30]	Simple set-and-forget operation preferred
Warranty length	III	Agnew [30]	Considered but less important
Design / visual appearance	III	Agnew [30]	Aesthetics considered but least important
Self-sufficiency	III	Agnew [30]	Strong non-financial driver
Environmental impact reduction	IV	Agnew [30]	Important but not the top driver
Grid independence	III	Agnew [30]	Influences self-sufficiency; strong non-financial driver
Reducing reliance on energy companies	III	Agnew [30]	Influences self-sufficiency
Backup during blackouts	III	Agnew [30]	Influences self-sufficiency; relevant resilience motive
Battery price	III	Agnew [31]	Influences cost; falling battery prices accelerate uptake
Rising electricity prices	VI*	Agnew [31]	Influences self-sufficiency
Tariff structures	VI	Agnew [31]	Influences payback time & self-sufficiency
PV system size	I	Agnew [31]	Battery attractiveness depends on onsite generation
Government subsidies / policy	VI	Agnew [31]	Influences payback time & costs
Solar system size (physical capital)	I	Best [61]	Smaller PV systems are less likely to add batteries
Solar feed-in tariff level	VI	Best [61]	Lower feed-in tariffs increase battery uptake
Financial pressure / capital constraint	I	Best [61]	Financially constrained households adopt less
Younger age	I	Best [61]	Control vector with statistical significance
Household disengagement	II	Best [61]	Lower engagement is associated with lower uptake
Lower electricity bills	III	Alipour [13]	Most important battery or PV motivation
Payback period	III	Alipour [13]	Important financial consideration
Profitability of battery system	III	Alipour [13]	Financial return matters strongly
Being self-sufficient / energy autonomy	III	Alipour [13]	Important and stronger than environmental concern
Avoiding blackouts / power outages	III	Alipour [13]	Relevant resilience motive
Environmental concerns	IV	Alipour [13]	Important but secondary to finance
Interest in the technology	II	Alipour [13]	Matters especially for adopters and innovators
Encouragement by others / peer effects	V	Alipour [13]	Considered least important overall
Annual system cost	III	Alipour [17]	Significant choice-model driver
Battery size	III	Alipour [17]	Critical in PV-owner battery decision
Energy autonomy	III	Alipour [17]	Strong motivator especially for integrated adoption
Peer influence / communicator traits	V	Alipour [17]	Significant through latent communicator constructs
Perceived knowledge about PV or BESS	II	Alipour [17]	Part of significant latent constructs
General innovativeness	II	Alipour [17]	Defines adopter-oriented latent profile
Financial motives / profit-seeking	III	Alipour [17]	Significant latent driver of larger battery choice
Environmental / social attitude	IV	Alipour [17]	Significant through socially conscious investor profile
Age	I	Alipour [17]	Significant sociodemographic influence
Income	I	Alipour [17]	Significant sociodemographic influence
Education	I	Alipour [17]	Significant sociodemographic influence
Employment status	I	Alipour [17]	Significant sociodemographic influence
Gender	I	Alipour [17]	Significant via latent-variable structure
Electric vehicle ownership	I	Alipour [17]	Associated with stronger battery adoption orientation
Owning a pool	I	Alipour [17]	Raises likelihood of battery uptake
House value below AUD 1 million	I	Alipour [17]	Interacts with preference for large battery size
House age	I	Alipour [17]	Increases likelihood of adoption

*Continued on next page*

Driver	Cat.	Source	Note
Acceptable payback period	III	Broese van Groenou [32]	Purchase timing depends heavily on payback
Reducing household power bills	III	Broese van Groenou [32]	One of the main stated reasons to buy
Storing excess solar generation	III	Broese van Groenou [32]	Core functional reason for adoption
Reliability of supply / future outages	III	Broese van Groenou [32]	Motivates a substantial share of households
Environmental considerations	IV	Broese van Groenou [32]	High priority for many but rarely sufficient alone
Rising electricity prices	VI*	Broese van Groenou [32]	Encourages self-reliance and battery interest
Premium feed-in tariff ending	VI	Broese van Groenou [32]	Pushes households toward storage
Trust in information sources	V	Broese van Groenou [32]	Family and friends trusted more than incumbents
Electric vehicle acquisition	I	Broese van Groenou [32]	Expected future EV load encourages larger systems
Homeownership structure	I	Aniello [12]	Strong regional driver of diffusion
Income	I	Aniello [12]	Very important especially for batteries
Education / low education	I	Aniello [12]	Lower education is a barrier
Foreign population share	I	Aniello [12]	Higher share is associated with lower uptake
Elderly population share	I	Aniello [12]	Older populations are associated with lower uptake
Families with minors / under-18 share	I	Aniello [12]	Considered as positive demand proxy
Political inclinations	II	Aniello [12]	Attitudinal-political context shapes uptake disparities
Residential demand	III	Aniello [12]	Considered with mixed or minor effects
PV generation potential	I	Aniello [12]	Considered and found to play only a minor role
Energy prices	VI*	Aniello [12]	Regulatory change materially shapes diffusion
Energy independence	III	Jayaraj [62]	Key adoption motivation
Backup power	III	Jayaraj [62]	Identified as a major performance expectation
Efficient use of solar	III	Jayaraj [62]	Strong functional reason for adoption
Battery system cost	III	Jayaraj [62]	High upfront cost is a primary adoption barrier
Payback period	III	Jayaraj [62]	Belief in acceptable payback period increases adoption
Financial savings / lower electricity bills	III	Jayaraj [62]	Clearest perceived benefits
Rebates / no-interest loans	VI	Jayaraj [62]	Improve affordability
Feed-in tariff reduction	VI	Jayaraj [62]	Lower FiTs make self-consumption attractive
Ease of installation and use	III	Jayaraj [62]	Simple use reduces perceived effort
Installer competence	III	Jayaraj [62]	Poor reputation reduces consumer confidence
Compatibility with current PV system	I	Jayaraj [62]	Whether existing can integrate with storage
Consumer knowledge	II	Jayaraj [62]	Sociodemographic influence
Peer referrals	V	Jayaraj [62]	Positive referrals from others encourage adoption

**Table A.1:** \* Electricity prices are considered as a political driver because of the high influence of regulations on electricity prices, as well as the external nature of the driver.

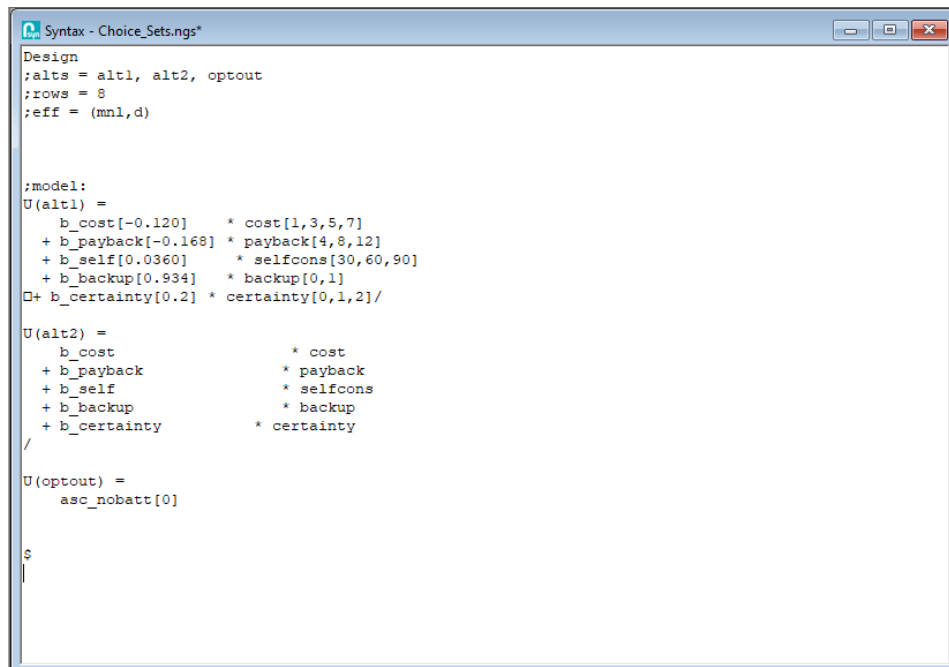
# B

## Appendix - Code, Ngene Code & Chi-Square table

### B.1. Link to Github repository:

<https://github.com/mvketting-TUdelft/MSc-thesis-Mark-Ketting>

### B.2. Ngene Code



```
Syntax - Choice_Sets.ngs*
Design
;alts = alt1, alt2, optout
;rows = 8
;eff = (mnl,d)

;model:
U(alt1) =
  b_cost[-0.120] * cost[1,3,5,7]
+ b_payback[-0.168] * payback[4,8,12]
+ b_self[0.0360] * selfcons[30,60,90]
+ b_backup[0.934] * backup[0,1]
+ b_certainty[0.2] * certainty[0,1,2]/

U(alt2) =
  b_cost * cost
+ b_payback * payback
+ b_self * selfcons
+ b_backup * backup
+ b_certainty * certainty
/

U(optout) =
  asc_nobatt[0]

$
```

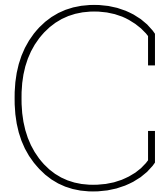
**Figure B.1:** Ngene Syntax to generate final choice sets. The  $\beta$ -coefficients from estimating the second pilot are used to define the betas in the efficient design. Since the ASC in the second pilot was not statistically significant, this prior is set at zero. Note that costs are in k€.

## B.3. Chi-square table

Chi-square Distribution Table

d.f.	.995	.99	.975	.95	.9	.1	.05	.025	.01
1	0.00	0.00	0.00	0.00	0.02	2.71	3.84	5.02	6.63
2	0.01	0.02	0.05	0.10	0.21	4.61	5.99	7.38	9.21
3	0.07	0.11	0.22	0.35	0.58	6.25	7.81	9.35	11.34
4	0.21	0.30	0.48	0.71	1.06	7.78	9.49	11.14	13.28
5	0.41	0.55	0.83	1.15	1.61	9.24	11.07	12.83	15.09
6	0.68	0.87	1.24	1.64	2.20	10.64	12.59	14.45	16.81
7	0.99	1.24	1.69	2.17	2.83	12.02	14.07	16.01	18.48
8	1.34	1.65	2.18	2.73	3.49	13.36	15.51	17.53	20.09
9	1.73	2.09	2.70	3.33	4.17	14.68	16.92	19.02	21.67
10	2.16	2.56	3.25	3.94	4.87	15.99	18.31	20.48	23.21
11	2.60	3.05	3.82	4.57	5.58	17.28	19.68	21.92	24.72
12	3.07	3.57	4.40	5.23	6.30	18.55	21.03	23.34	26.22
13	3.57	4.11	5.01	5.89	7.04	19.81	22.36	24.74	27.69
14	4.07	4.66	5.63	6.57	7.79	21.06	23.68	26.12	29.14
15	4.60	5.23	6.26	7.26	8.55	22.31	25.00	27.49	30.58
16	5.14	5.81	6.91	7.96	9.31	23.54	26.30	28.85	32.00
17	5.70	6.41	7.56	8.67	10.09	24.77	27.59	30.19	33.41
18	6.26	7.01	8.23	9.39	10.86	25.99	28.87	31.53	34.81
19	6.84	7.63	8.91	10.12	11.65	27.20	30.14	32.85	36.19
20	7.43	8.26	9.59	10.85	12.44	28.41	31.41	34.17	37.57
22	8.64	9.54	10.98	12.34	14.04	30.81	33.92	36.78	40.29
24	9.89	10.86	12.40	13.85	15.66	33.20	36.42	39.36	42.98
26	11.16	12.20	13.84	15.38	17.29	35.56	38.89	41.92	45.64
28	12.46	13.56	15.31	16.93	18.94	37.92	41.34	44.46	48.28
30	13.79	14.95	16.79	18.49	20.60	40.26	43.77	46.98	50.89
32	15.13	16.36	18.29	20.07	22.27	42.58	46.19	49.48	53.49
34	16.50	17.79	19.81	21.66	23.95	44.90	48.60	51.97	56.06
38	19.29	20.69	22.88	24.88	27.34	49.51	53.38	56.90	61.16
42	22.14	23.65	26.00	28.14	30.77	54.09	58.12	61.78	66.21
46	25.04	26.66	29.16	31.44	34.22	58.64	62.83	66.62	71.20
50	27.99	29.71	32.36	34.76	37.69	63.17	67.50	71.42	76.15
55	31.73	33.57	36.40	38.96	42.06	68.80	73.31	77.38	82.29
60	35.53	37.48	40.48	43.19	46.46	74.40	79.08	83.30	88.38
65	39.38	41.44	44.60	47.45	50.88	79.97	84.82	89.18	94.42
70	43.28	45.44	48.76	51.74	55.33	85.53	90.53	95.02	100.43
75	47.21	49.48	52.94	56.05	59.79	91.06	96.22	100.84	106.39
80	51.17	53.54	57.15	60.39	64.28	96.58	101.88	106.63	112.33
85	55.17	57.63	61.39	64.75	68.78	102.08	107.52	112.39	118.24
90	59.20	61.75	65.65	69.13	73.29	107.57	113.15	118.14	124.12
95	63.25	65.90	69.92	73.52	77.82	113.04	118.75	123.86	129.97
100	67.33	70.06	74.22	77.93	82.36	118.50	124.34	129.56	135.81

Figure B.2: Chi-square table



## Appendix - Final Survey Version

**Table C.1:** Structure of the survey. The first column names the survey item and question; each item appeared on a separate page, and respondents could not return to previous items. The second column states the purpose of the question, as motivated in Chapter 3. The third column shows the answer options and routing. If no specific routing is given, selecting an option continues to the next item. The final column shows the targeted quota.

Item	Question / content	Purpose	Answers and routing	Quota
Introduction	Study information and consent.	Inform and obtain consent.	Continue	—
Screening 1	Type of home?	Identify housing type.	Owner-occupied Rental Other → exit	~25% renters
Screening 2	Household energy decision-maker?	Select decision-makers.	My parents → exit Me Me and partner None → exit	—
Screening 3	Solar panels generating own electricity?	Record solar status.	Yes No Don't know → exit	>50% solar panels
Screening 4	Age group?	Age screening.	≤17 → exit 18–30 31–40 41–50 51–60 61–70 ≥71 → exit	—
Screening 5	Home battery ownership or purchase plan?	Record battery status.	Yes → Framing Plan within 6 months → Framing No → Explanation	—
Framing	Answer as if not yet owning a battery.	Standardize perspective.	Shown after “Yes” / “Plan” Then → Explanation	—
Explanation	Definitions of the five battery attributes.	Explain attributes.	Continue → Choice tasks	—
Choice tasks 1–8 (See Table 3.5)	Buy Battery A, Battery B, or no battery.	Elicit preferences.	Battery A Battery B No battery Then → next task / end	—
Final page	Completion message.	Close survey.	End survey	—
Target group	Screen-out message.	Inform ineligible respondents.	End survey	—
Quota full	Quota-reached message.	Inform quota closure.	End survey	—

## C.1. Survey Explanation Text

Before respondents completed the choice tasks, they were shown the following explanation of the home battery attributes.

### Explanation

A **home battery** stores electricity. You can use that electricity later. It can come from solar panels or the grid.

You will soon have 8 different home battery options to choose from.

### The batteries differ only on these five points:

1. **Costs** – The total costs, including installation and taxes.
2. **Payback time** – The amount of years before you have earned back the costs.
3. **Certainty of payback time** – How likely it is that you will earn back your costs.
  - *Low* – There is a chance that you will not earn back your costs.
  - *Moderate* – You will earn back your costs, but maybe later than expected.
  - *High* – Likely, you will earn back your costs.
4. **Self-consumption** – How much electricity you can store and use yourself later:
  - “30%” is a small portion.
  - “60%” is more than half.
  - “90%” is almost all.

This is not about power outages.
5. **Backup power** – What the battery can do during a power outage:
  - “One socket” – For one or a few small devices.
  - “Full house” – For your entire home.

You do not need to choose the battery size. It will match the battery you see. You can assume that any battery is suitable for your situation.

Other things, such as safety, warranty, and maintenance, are the same for all batteries.

You will now see 8 options; the question is always:

*What would you do?*

Will you buy Battery A, Battery B, or will you not buy a battery?