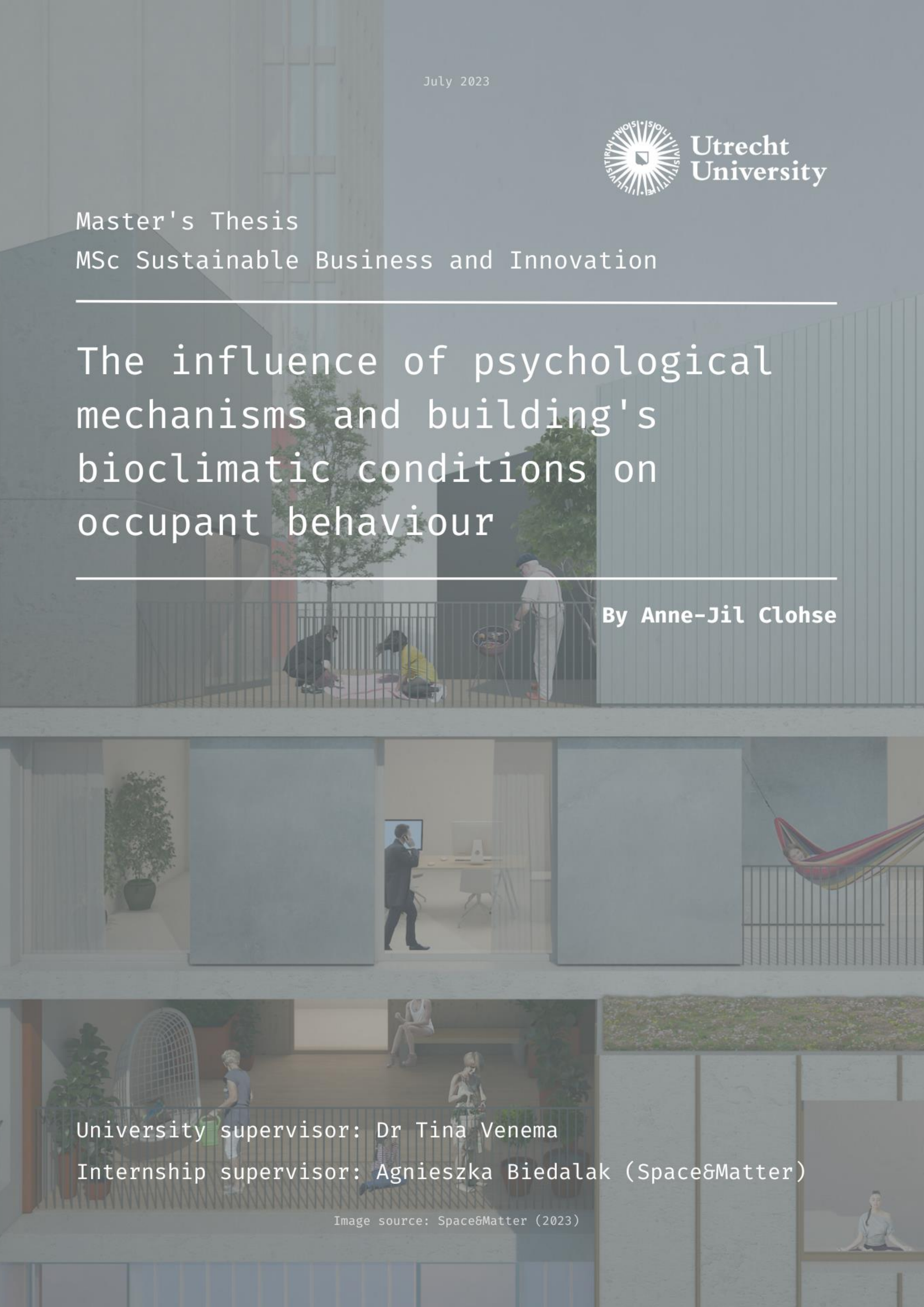


July 2023

Utrecht University

Master's Thesis

MSc Sustainable Business and Innovation

The influence of psychological mechanisms and building's bioclimatic conditions on occupant behaviour

By Anne-Jil Clohse

University supervisor: Dr Tina Venema

Internship supervisor: Agnieszka Biedalak (Space&Matter)

Image source: Space&Matter (2023)

Table of Contents

Abstract

Introduction. The building sector is responsible for about 40% of total energy usage in the European Union, of which 60% can be attributed to residential building energy consumption. Further, the gap that persists between predicted and actual energy consumption of buildings presents an issue for investors. This gap can be partly explained by occupant behaviour not being considered when estimating energy performance of buildings. Hence, this research investigates the influence of bioclimatic conditions, habits, and moral licensing on occupant behaviour.

Theoretical background. Bioclimatic architecture, habits, and moral licensing are the theoretical foundations of this research. *Bioclimatic architecture* refers to a sustainable way of designing buildings that considers the local environmental context of the building (e.g., bioclimatic conditions such as the orientation of a building, solar radiation, or ambient temperature). *Habits* are unconscious behaviour that is triggered by environmental cues and plays an essential role in energy consumption. *Moral licensing* describes the cognitive process in which humans justify acting morally wrong without feeling guilt by having acted morally right previously. It is a cause of rebound effect.

Methodology. To research the influence of bioclimatic conditions, habits and moral licensing on occupant behaviour, a quantitative cross-sectional research design was chosen. Data is collected through a survey questionnaire (N = 545) and supplemented by archival data. Further, data is analysed through multiple linear regression.

Results. The results show 7% of occupant behaviour is explained by certain bioclimatic conditions, while 17% is explained by psychological mechanisms. In terms of psychological mechanisms, habits have a larger relative influence on energy-consuming behaviour than moral licensing. Lastly, psychological mechanisms can predict occupant behaviour to a larger extent than bioclimatic conditions.

Discussion. The effect of bioclimatic conditions on occupant behaviour was weaker than expected. A potential explanation for this is the small size and the lacking variety in climatic conditions within the Netherlands. Although some limitations to the research were identified, it presents the first attempt at predicting energy consuming behaviour through bioclimatic conditions of residential buildings and psychological mechanisms which can guide future research.

Conclusion. The findings of this research added to the knowledge on energy-consuming behaviour and how it is influenced. Architects, energy consultants for the built environment

and policy makers can all include the insights of this research to help bridge the gap between predicted and actual energy consumption of buildings.

Executive Summary

This executive summary provides an overview of the key findings and implications of this master's thesis, titled "The influence of psychological mechanisms and buildings' bioclimatic conditions on occupant behaviour". This research was linked to a research internship at Space&Matter, a sustainable architecture and urban design office in North-Amsterdam. The research questions that were answered were:

1) *How is occupant behaviour influenced by the bioclimatic conditions of the residential building they are in?*
2) *How conscious or unconscious is occupant behaviour? And hence, to what extent can occupants be held responsible for their behaviour?*

Bioclimatic conditions and occupant behaviour. The results of Analysis 1 showed that 7% of energy-consuming behaviour can be robustly explained by two building orientations (i.e., East and West), as well as the need for artificial light and the average wind speed around an occupant's home. An Eastern or Western orientation of the building was linked to more energy-consuming behaviour. Additionally, the need for artificial light due to the lack of natural daylight was linked positively to occupants' energy-consuming behaviour. On the other hand, increased average wind speeds were negatively associated with energy-consuming behaviour. Lastly, when energy efficiency decreases (lower energy labels), energy-consuming behaviour decreases too. In other words, the worse the energy label, the less energy-consuming the occupant's behaviour is. This is in line with the prebound effect that explains why buildings with worse energy labels consume (on average 30%) less energy. This can be linked to occupants being conscious of the energy performance of their building and hence, behaving more economically when the energy performance is worse.

Psychological mechanisms and occupant behaviour. The results of Analysis 2 showed that 17% of energy-consuming behaviour can be robustly explained by habits and moral licensing (i.e., the two psychological mechanisms that were considered). Both habits and moral licensing were positively related to energy-consuming behaviour. Hence, the more habitual the behaviour, the more energy-consuming it is too. Equally, the more moral licensing is used, the more energy-consuming the behaviour of the occupant.

Combination of bioclimatic conditions and psychological mechanisms. Overall, psychological mechanisms are a stronger predictor of energy-consuming behaviour than bioclimatic conditions. However, the weak effect of bioclimatic conditions could potentially be explained by the little variation in climatic conditions within the Netherlands. Indeed, the Netherlands is a small country with a relatively stable climate. Hence, the same bioclimatic architecture principles can be used for architectural projects within the Netherland. However, the same might not hold for architectural projects in countries with a very different climate or with more variation in bioclimatic conditions. For example, one of the projects of Space&Matter was located in Abu Dhabi, where climatic conditions differ greatly from the Netherlands.

Research quality. This research presents the first attempt at predicting energy consuming behaviour through bioclimatic conditions of residential buildings and psychological mechanisms. A substantial dataset (i.e., 545 data points) was created which groups data on energy-consuming behaviour, bioclimatic conditions of residential buildings, habitual behaviour, and the use of moral licensing. The sample was representative of the student demographic in the Netherlands. E.g., the presence of 55.3% of females in our sample is in line with the national average, i.e., 54% of female students at university and 53% in higher professional education enrolments (CBS Statistics Netherlands, 2023). Also, the rather equal split between Dutch citizens and internationals reflects the reality of the student population in the Netherlands. Additionally, data was gathered from diverse locations across the Netherlands. Therefore, results are generalizable to the population of residential occupants in the Netherlands, and hence, external validity is high.

Recommendations. For architects and designers, the results imply that bioclimatic conditions and underlying psychological mechanisms can be consciously considered when designing buildings. In terms of habits, they should consider that familiar environments trigger learned habits, which can be inefficient. By considering these points, buildings could be designed such as to optimise energy-consuming behaviour. Space&Matter already involves future occupants in project with the aim to build thriving communities. By integrate the knowledge gained through this research on occupant behaviour and how it is influenced, the design of their projects can be further improved and include occupants even more. Finally, Space&Matter works with an ecosystem of experts (e.g., energy consultants, biologists and ecologist, municipalities, etc.) to come up with sustainable and innovative projects. Hence, by sharing the gained knowledge with this ecosystem of experts, the practical value of this research can be maximised. Indeed, energy consultancy firms advising architecture offices on the right active and passive energy strategies to use for buildings can take occupant behaviour also more consciously into account to bridge the gap between expected and actual energy performance of buildings. Policy makers can integrate the results of this study into the updating of current building norms and regulations. By considering the latest knowledge on occupant behaviour and what influences it, building regulations and norms would stay up to date and could potentially work more effectively toward CO^2-emission reduction goals.

In conclusion, occupant behaviour is complex and hence often not considered accurately when modelling energy performance of buildings or designing buildings for occupants. This research advanced knowledge on how energy-consuming behaviour within residential buildings is influenced by bioclimatic conditions and psychological mechanisms. It is now better understood, and this research constitutes a first step towards the accurate integration of occupant behaviour in building energy performance modelling, but also an additional step for the appropriate consideration of occupants in architectural projects.

1. Introduction

1.1 The Building Sector and the Energy Crisis

The continuously growing energy demand, the highly volatile energy prices, and the need to save energy used in buildings from an environmental perspective call for energy efficiency measures in the building sector (Markiewicz-Zahorski et al., 2021; Zakeri et al., 2022). Indeed, energy efficiency is recognized as a cost-effective way to reduce energy demand related CO_2 emissions in all end-use sectors (Balaras et al., 2007), and improve energy security by reducing the dependence on foreign energy supply (Trotta, 2020). Additionally, a switch from fossil fuel to renewable energy while improving energy efficiency is necessary due to the current climate crisis. In that sense, the building sector offers a great opportunity to save energy and reduce the environmental impact of humanity on nature. In the European Union (EU), the building sector is considered the largest contributor to energy consumption, accounting for up to 40% of the total energy usage (Berardi, 2017; Foucquier et al., 2013) and a third of total energy-related CO_2 emissions (Balaras et al., 2007; Masseck, 2011; Pajek & Košir, 2021; Soares et al., 2017; Tzikopoulos et al., 2005). Therefore, ample attention is given to energy-saving investments in the building sector in the EU, e.g., by setting goals to reduce CO_2 levels of buildings by 90% until 2050 (compared to 1990), by introducing the Energy Performance of Buildings Directive (EPBD) or requiring new buildings to be Nearly Zero Energy Buildings (nZEB) (Berardi, 2017). The main opportunities to save energy in buildings in the short and medium term come from retrofitting the existing EU building stock, as its turnover is particularly low. Once buildings are built in the EU they stay operational from 50 to more than 100 years and are therefore only slowly replaced (Balaras et al., 2007; Berardi, 2017; Grillone et al., 2020). Further, residential buildings are important to focus on as they make up 60% of the total energy consumption of the building sector (Foucquier et al., 2013). Retrofitting of buildings changes their structure or systems after the initial construction and is estimated to save up to 33% of energy (Balaras et al., 2007).

1.2 Building Energy Performance Gap and Occupant Behaviour

Unfortunately, there tends to be a significant difference between the actual and predicted energy consumption of buildings (i.e., energy performance gap), e.g., retrofits not meeting the predicted energy savings (Galvin, 2013). This brings frustration to parties investing largely in energy efficiency measures of buildings, such as housing corporations. If investments fail to pay off due to this gap, this can lead to a decrease in energy retrofits, which poses a societal issue. The gap can be (at least partially) explained through the prebound and rebound effect. In the prebound effect, buildings predicted to consume high amounts of energy, often consume (about 30%) less than predicted, due to occupants behaving more economically than modelled. The rebound effect describes the opposite phenomenon, where low-energy dwellings, i.e., buildings with a better energy performance certificate (i.e., *energielabel* in the Netherlands), tend to consume more energy than predicted or modelled. This is due to energy savings being cancelled through increased consumption, e.g., excessive use of LED light bulbs (Sunikka-Blank & Galvin, 2012). Consequently, occupant behaviour is one of the key determinants of the energy efficiency of buildings (Masseck, 2011; Pajek & Košir, 2021; Soares et al., 2017; Tzikopoulos et al., 2005). Both *moral licensing* and *habits* can cause inefficient energy consumption. *Moral licensing* is the cognitive process in which humans justify acting morally wrong without feeling guilt by having acted morally right previously (Dütschke et al., 2018; Simbrunner & Schlegelmilch, 2017). This has been recognized as a potential cause for rebound effects (Dütschke et al., 2018). *Habits*, a type of unconscious and automated behaviour that is triggered by certain environmental cues (e.g., bioclimatic conditions) (Martin & Morich, 2011), can equally lead to inefficient behaviour (Pierce et al., 2010). Even though occupant behaviour is a crucial part of energy efficiency in buildings, its modelling is poor (Markiewicz-Zahorski et al., 2021; Sunikka-Blank & Galvin, 2012; Vázquez et al., 2011) and psychological processes behind human behaviour are typically not taken into account or well understood.

1.3 Energy Efficiency and Bioclimatic Architecture

Literature suggests taking buildings' *bioclimatic conditions* (i.e., their environmental context such as orientation, incoming solar radiation, ambient temperature, etc.) into account when constructing or retrofitting them to optimise energy efficiency. *Bioclimatic architecture* deals with improving energy efficiency by assessing the local bioclimatic conditions (Manzano-Agugliaro et al., 2015) to optimize the use of both passive (e.g., daylighting, south-facing windows for heat, natural ventilation) and active (e.g., solar panels, wind turbines, electric lights) energy strategies (Masseck, 2011; Pajek & Košir, 2021; Terrados & Moreno, 2014). Bioclimatic buildings may consume up to 10 times less heating energy than conventional buildings in the EU (Tzikopoulos et al., 2005). However, if a building's bioclimatic conditions are not carefully assessed and its energy performance is not carefully modelled, there is a risk to decrease overall energy efficiency (Masseck, 2011). As mentioned before, one component that is rarely modelled and understood is occupant behaviour (Pajek & Košir, 2021;

Tzikopoulos et al., 2005). As (inefficient) behaviour can be influenced by external factors (e.g., bioclimatic conditions) and justified through certain psychological processes (e.g., habits or moral licensing), it is necessary to better understand the link between bioclimatic conditions of buildings and occupant behaviour.

1.4 Research Question

In conclusion, bioclimatic architecture principles can guide the retrofitting of the existing building stock in the EU to achieve energy efficiency goals. For these (bioclimatic) retrofits to be successful, it is necessary to model their energy performance. Further, to have an accurate energy performance prediction, it is necessary to understand occupant behaviour which can be linked to buildings' bioclimatic conditions. Lastly, this behaviour can either be unconscious or an outcome of conscious reflections. Therefore, the research questions are:

1) *How is occupant behaviour influenced by the bioclimatic conditions of the residential building they are in?*
2) *How conscious or unconscious is occupant behaviour? And hence, to what extent can occupants be held responsible for their behaviour?*

2. Theoretical Background

2.1 The Current State of Building Energy Performance Modelling

As mentioned previously, the energy performance gap is a reason for investors (e.g., housing corporations) to stop investing in sustainable retrofits, as their return on investment is either diminished or delayed. To better understand why the energy performance gap persists, it is necessary to analyse the current state of energy performance modelling. Part of energy performance modelling is focused on the prediction of energy savings used to recommend retrofitting strategies (Grillone et al., 2020). Within this modelling category, different techniques, which are extensively reviewed by Grillone et al. (2020), are used to choose the most optimal energy efficiency measures. The methods described are either data-driven/statistical, deterministic/physics-based, or a hybrid form of the two. Behavioural changes in occupants can define the success or failure of energy efficiency measures (Lee et al., 2015). Even though it is such an important characteristic of energy performance in buildings, occupant behaviour is extremely simplified in predictive models, which adds to the energy performance gap issue (Markiewicz-Zahorski et al., 2021; Sunikka-Blank & Galvin, 2012; Vázquez et al., 2011). The only type of “behaviour” that is taken into account in such models is usually the occupancy rate, i.e., the ratio of total used space versus total available space (Grillone et al., 2020), or broad averages (Markiewicz-Zahorski et al., 2021) because of its complexity and difficulty to quantify (Soares et al., 2017). In other models, behaviour is either set as constant (Pajek & Košir, 2021) or not taken into account at all (Tzikopoulos et al., 2005), limiting the effect of behavioural changes on predicted building energy performance. In conclusion, the current state of energy performance models does not yet sufficiently understand and integrate occupant behaviour in simulations, proving the importance of this research.

2.2 Bioclimatic Architecture and Bioclimatic Conditions

As bioclimatic architecture is not a commonly known term, it is necessary to define what is meant by it, as it guides this research. *Bioclimatic architecture* refers to a sustainable way of designing buildings by taking into account the characteristics of the plot of land of the building, the characteristics of its neighbourhood, the local topography and the microclimate (Almusaed, 2011). The goal of bioclimatic architecture is to use as little energy as possible, i.e., optimizing buildings' energy efficiency (Almusaed, 2011; Bajcinovci & Jerliu, 2016) but also to guarantee human comfort conditions (Bajcinovci & Jerliu, 2016). As stated by Watson (2013), bioclimatic design tries to cover “heating, cooling and daylighting needs for comfort, health and safety when all power sources are off” (p.2). Hence, occupants are not expected to intervene to improve their comfort. Energy savings from bioclimatic design can be made during the construction phase by sourcing local materials (Tundrea & Budescu, 2013). However, most energy is saved in the operational phase of the bioclimatic building (Tzikopoulos et al., 2005). The term *bioclimatic* combines *biology* and *climate*, as this type of architecture tries to fulfil the biological needs of beings (both human and non-human) – e.g., healthy indoor environments and thermal comfort of humans, as well as environmental protection of non-human beings – but also adapts the design of buildings to their local microclimate.

There are certain *bioclimatic architecture principles* guiding the choice of design strategies. The most basic bioclimatic design principles are the following two: 1) during cold periods, heat loss through the building envelope (i.e., the building skin/shell) is limited and solar heat gain is promoted; 2) during hot periods, solar heat gain is limited and loss of heat through the building envelope is promoted. From these two basic principles, other sub-principles can be derived (see Watson, 2013). Understanding the *bioclimatic conditions* (i.e., the environmental context) of the building results in applying these principles to make choices of design strategies (Watson, 2013). Examples of bioclimatic conditions include solar radiation, wind speed and direction, temperature, vegetation, and relative humidity. The design strategies can be divided into active and passive energy strategies. Usually, bioclimatic architecture tries to optimize the use of passive energy strategies (Manzano-Agugliaro et al., 2015; Pajek & Košir, 2021). However, these are often coupled with active energy strategies to improve the overall sustainability of buildings (Masseck, 2011; Pajek & Košir, 2021; Terrados & Moreno, 2014) and their self-sufficiency (Masseck, 2011).

The terms active and passive energy strategies are generally used in the context of low-energy buildings. Buildings can be considered *low-energy* when they have an energy consumption of 150kWh/m^2y or lower (Sunikka-Blank & Galvin, 2012), i.e., an energy performance certificate equivalent to A or higher (Ministerie van Binnenlandse Zaken en Koninkrijksrelaties, 2023). *Active* strategies consist of technical devices that are either used for generating and supplying renewable energy or for converting resources more efficiently. Examples include mechanical air-conditioning, heat pumps, solar panels, electrical lighting, and wind turbines. On the other hand, *passive* technologies refer to the design of a building (e.g., its shape, envelope, and orientation) that is such that it captures, stores, and distributes both wind and solar energy. Examples include the use of natural light through strategic window placement, natural ventilation, insulation for better heat conservation, or mechanisms of natural heat-trapping (Loonen et al., 2013). Both are typically used to replace the need for fossil fuels and make buildings more sustainable. It is important to carefully assess the energy savings a bioclimatic retrofit will bring since overall energy efficiency can be decreased if the retrofit and factors influencing its success are not taken into account (Tzikopoulos et al., 2005). As occupant behaviour influences such energy savings, it is important to understand the underlying psychological mechanisms.

2.3 Occupant Behaviour

To hypothesize how bioclimatic conditions of buildings can have an influence on occupants, it is necessary to understand two relevant underlying psychological mechanisms of behaviour. First, unconscious mental processes that are relevant to this research will be discussed, in particular *habits*. Second, a cognitive psychological mechanism and its link to the rebound effect will be dived into, i.e., *moral licensing*.

2.3.1 Habits - Unconscious Mental Processes

The generally accepted theories on human behaviour stipulate that information is processed consciously, leading to the formation of attitudes, which in turn can lead to a certain decision or behaviour, e.g., the Theory of Planned Behaviour (Ajzen, 1991). However, the assumption that information is always processed consciously neglects the possible influence of factors that lie outside of the conscious awareness of people on their behaviour (Martin & Morich, 2011). In the last 10 to 15 years, the fact that human behaviour often occurs outside of their consciousness and intentions has gained acceptance outside the psychological field (Martin & Morich, 2011; Vrabel & Zeigler-Hill, 2020). These unconscious mental processes contribute to inefficient behaviour in terms of energy consumption. Research has shown that people who interact daily with technology in the home do not consciously consider the consequential energy consumption. Their behaviour is rather of habitual, unconscious and irrational nature (Pierce et al., 2010).

Unconscious behaviour can be understood through the concept of *automaticity*. *Automaticity* is the study of how environmental conditions trigger certain automatic processes that result in a certain response. These environmental cues can be either internal (e.g., thoughts, moods, feelings or changes in state that are all perceived by the mind) or external (e.g., smells, visuals, noises, time, temperature or anything else perceived by human senses) (Martin & Morich, 2011). This is relevant for this research as these environmental cues could be brought back to bioclimatic conditions. *Habits*, a form of automaticity, are unconscious behaviour that is triggered without taking any goals or intentions of a person into account (Martin & Morich, 2011) and plays an essential role in energy consumption (Pierce et al., 2010). Almost 50% of human behaviour is repeated on a day-to-day basis in a stable context, leading to a large amount of unconscious habitual behaviour over time. After a habit is formed, the brain gives environmental contexts control over human behaviour. Human behaviour is then triggered by certain environmental cues (Martin & Morich, 2011), e.g., bioclimatic conditions in the case of this research. Habits are a very challenging type of behaviour to alter due to the common heuristic: *Why change it if it works?* (Pierce et al., 2010). As this research tries to understand how occupant behaviour is influenced by the bioclimatic conditions of buildings (i.e., environmental contexts/cues), it is of utmost importance to understand the psychological mechanisms underlying this type of unconscious behaviour.

The level of automaticity of human behaviour is said to lie within a spectrum of unconsciousness to consciousness and depends on the level of familiarity with a certain context. Behaviour can either be fully automated (i.e., on “autopilot”, e.g., habits), partially automated using heuristics (i.e., simple rules) or consciously evaluated (i.e., on “pilot”).

Moreover, the more familiar a certain environmental context, the more automated behaviour is. Familiarity infers that a certain context has been experienced repeatedly and the same behaviour has been triggered as a response. On the other hand, the more novelty an environmental context brings, the more actively the brain has to evaluate and interpret the context first before deciding what the appropriate response is (Martin & Morich, 2011; Pierce et al., 2010). Hence, if occupants do not perceive any changes in the bioclimatic conditions of their building after a retrofit, their behaviour will stay on autopilot, and they will continue to inefficiently consume energy. Strong habits would therefore influence energy consumption in a stabilizing manner, neither increasing nor decreasing it. People can also become conscious of the inefficiency of their routines and try to change them. However, there are obstacles to the formation of new habits: comfort, inconvenience or lack of (awareness of) other behavioural options (Pierce et al., 2010). If habits can explain why energy consumption stays inefficient after retrofits, it does not explain why energy consumption sometimes increases. The psychological mechanism of *moral licensing* explains such rebound effects.

2.3.2 Rebound Effect and Moral Licensing

The rebound effect (R) can be defined as the relative gap between the potential energy savings (PES) and the actual energy savings (AES), i.e., $R = \frac{PES-AES}{PES}$ (Dütschke et al., 2018; Reimers et al., 2021). This effect describes the neutralization of energy savings (in total or in parts) that arises when increased consumption of goods or services (in the same or another domain) follows (energy) efficiency improvements. There are both economic (e.g., income or price) and psychological (e.g., moral licensing) causes of the rebound effect. Considering this research, the focus is on the psychological mechanism of moral licensing. A person's morals can trigger them to question and try to change some of their inefficient behaviour to try to realign it to their inner values. However, people can also continue immoral behaviour by justifying it with previous moral behaviour, e.g., driving more because a person has bought an electric car. This psychological mechanism is called *moral licensing* and can be the cause of rebound effects that contribute to the energy performance gap issue (Dütschke et al., 2018).

The psychological mechanism of moral licensing was first conceptualized by Monin and Miller (2001). It describes the cognitive process in which humans justify acting morally wrong without feeling guilt by having acted morally right previously (Dütschke et al., 2018; Simbrunner & Schlegelmilch, 2017). Monin and Miller (2001) conducted three experiments on the topics of racism and sexism which all supported their claim. These experiments also show that there does not need to be an audience that is aware of their past good behaviour for them to act immorally in the future, but rather that an internal justification suffices. Since the initial study tested the hypothesis on the topics of racism and sexism more recent studies have shown that it also applies to environmental behaviour (Burger et al., 2022; Reimers et al., 2021). Indeed, Burger et al. (2022) found that people who remembered giving up flying for two years felt less guilty about their meat consumption than those who did not. In that sense, behaving pro-environmentally first decreases the likelihood of behaving pro-environmentally in a second instance (Nilsson et al., 2017). There are two main perspectives that can lead to licensing effects: *moral credentials* and *moral credits* (Reimers et al., 2021). According to the *moral credentials* perspective, people justify immoral behaviour by having previously established credentials as moral people (Monin & Miller, 2001) (e.g., going to many climate conventions, thereby establishing pro-environmental credibility, but flying out to vacation spots). In the *moral credits* perspective, people have metaphorical moral bank accounts where moral behaviour increases the balance and immoral behaviour decreases it. These accumulated moral credits serve as a way to buy out bad behaviour and keep the moral account in balance (Miller & Effron, 2010). The more people are aware that they live in energy efficient buildings or use energy efficient devices, the less they tend to care about energy saving behaviour (Gram-Hanssen, 2014).

In conclusion, even though occupants might have core values around energy conservation, sustainability or climate change, factors such as bioclimatic conditions of buildings, habits, or moral licensing can influence their actual behaviour. How energy consuming behaviour of occupants is influenced by the bioclimatic conditions of the building they live in constitutes an important research gap. Additionally, the psychological processes of habits and moral licensing are both potential underlying explanations for their (inefficient) behaviour and are not considered when predicting energy savings from retrofits. Investigating and understanding how these factors are linked is therefore crucial to the success of future energy retrofits and can motivate further investors. Moreover, how conscious (e.g., moral licensing) or unconscious (e.g., habits) occupants are of their behaviour can indicate to what extent they can be held responsible for it and help implement the right behaviour change interventions.

3. Methodology

3.1 Research Design

To answer the research questions and hence, better understand how occupant behaviour is influenced by bioclimatic conditions of buildings and to what extent occupants can be held responsible for their behaviour, a quantitative cross-sectional research design was chosen. The dependent variable is *EnergyBehaviourScore*, a score indicating how energy-consuming the occupant's behaviour is. In terms of bioclimatic conditions, the independent variables are *Orientation*, *Shading*, *ArtificialLight*, *SolarRad*, *AmbTemp*, and *WindSpeed*. Further, in terms of underlying psychological mechanisms, the independent variables are *HabitScore*, and *MoralLicensingScore*. Additionally, control variables include basic demographics (e.g., *Age*, *Gender*, *TimeNL*, *NbWorkHours*, *Finances*) and building energy efficiency (e.g., *EnergyLabel*). More details concerning the variables used in the statistical model can be found in section 3.5 Operationalisation, as well as a complete overview in Appendix A.

3.2 Sampling Strategy

The studied population was residential building occupants and the buildings they live in. To study this population, students living in studios of housing corporations in the Netherlands were chosen as a homogenous sample. The reasons behind the sample choice are:

1) *students* due to a higher likelihood of being available for surveys, similar age, and education level,
2) *studios* as they ensure the same household size and individual measurement of the outcome variable,
3) *housing corporations* as they have various studio apartment buildings with numerous occupants, and
4) the *Netherlands* due to geographical accessibility.

Furthermore, to ensure that the results of this research have enough statistical power and show any effect of behavioural factors on the dependent variable, a target sample size of minimum 300 individuals was chosen. The size of the sample was chosen according to the medium estimated effect of behavioural factors on energy consuming behaviour (Sonderegger, 1978).

3.3 Data Collection

To quantitatively test the relationships between energy consuming behaviour of occupants, bioclimatic conditions, habits and moral licensing, a questionnaire-based data collection has been chosen for most variables (see Appendix B). The questionnaire was created on Qualtrics. In addition, some archival data was used to complement self-reported data on bioclimatic conditions and building energy efficiency that could not be reported by occupants. The following sections give more detailed insights into the distribution of the survey and the archival data collection.

3.3.1 Survey Distribution

To distribute the survey, 15,000 flyers and 250 posters were distributed in a total of 14 cities across the Netherlands, namely Amsterdam (8.76%), Breda (2.94%), Delft (9.74%), The Hague (9.47%), Eindhoven (7.20%), Groningen (12.97%), Haarlem (1.83%), Leiden (8.47%), Maastricht (9.48%), Nijmegen (1.34%), Tilburg (3.35%), Utrecht (16.07%), Wageningen (3.26%) and Zwolle (5.13%). The cities were chosen due to their different geographical locations to ensure variety in bioclimatic conditions and due to their student housing options. In total, approximately 55 studio apartment buildings from different housing corporations were visited, e.g., the SSH, DUWO, Xior, Holland2Stay, Campus Plaza, etc. All buildings were carefully chosen to fit the target sample by means of desk research before fieldtrips were executed. Moreover, to ensure an adequate response rate and good data quality, occupants were incentivised to participate by being able to enter a giveaway draw at the end of the survey. They were informed that 3 people would be drawn after the data collection phase, of which each one would win a 50€ voucher for bol.com.

3.3.2 Archival Data Collection

Firstly, location-specific climatic/meteorological data of the Netherlands was collected directly from the meteorological data portal of The Technical University of Delft. Their climate data reflects weather conditions of different locations averaged over multiple decades (TU Delft, n.d.) and is available for a total of 46 weather stations across the Netherlands. The data of this portal is calculated by using measurements from the Royal Netherlands Meteorological Institute (KNMI).

Secondly, energy labels were added manually for each participant under the variable *EnergyLabel*. To find these, multiple self-reported variables were used, i.e., *City*, *HouseCorp*, *BuildingName* and *PostCode*, as well EP-online. EP-online is the official Dutch website where energy labels are registered (see https://www.ep-online.nl/Energylabel/Search).

3.4 Participants

In total, 906 individuals participated in the survey questionnaire between the 21st of March 2023 and the 9th of May 2023. These 906 responses were filtered using 4 conditions in SPSS[1] syntax. To be considered in the statistical analysis of this research, participants had to have responded *"Yes"* to the following 3 questions:

- *Are you a student?*
- *Do you live by yourself? (meaning without any other housemates)*
- *Do you live in the Netherlands in a building of a housing corporation (e.g., the SSH, DUWO, Xior, etc.)?*

Further, the variable *Progress* had to be equal to 100.00, which was created by Qualtrics and translates to participants having completed the survey. After filtering, the sample size was 545 participants, thereby exceeding the intended size of 300 participants. All participants signed an informed consent form at the start of the survey. With this form, they consented to their responses being used in this research. Participants are also informed of their rights and how their data is handled.

Participants were on average 23.21 years old (SD = 3.07; see also Figure F4[2]). Further, 55.3% of the participants identify as "Female", 41.1% as "Male", 2.3% as "Other" and 1.3% preferred not to answer the question (Table E1). Moreover, the sample was split rather equally between Dutch citizens and internationals, indicated by the time they have been living in the Netherlands (see Figure F5). On average, participants have been living for 13.18 years in the Netherlands (SD = 11.08).

3.5 Operationalization

For the operationalization of the research, the relevant concepts were translated into variables based on different scientific literature. In case certain variables could not be measured in the same way as in previous studies, the operationalization of such variables was adjusted to better fit the data that could be collected. For example, the orientation of a building is typically measured through the azimuth, which cannot be measured by occupants. Instead, occupants were asked to use a compass on their phones to determine the orientation of their building,

---

[1] SPSS is the statistical software used for the data analysis.

[2] All figures or tables that are numbered by a letter (and a number) are found in the appendix of the corresponding letter. E.g., Figure F4 is the 4th figure in Appendix F.

making the variable categorical instead of continuous. The different variables are presented in the following sections. An overview of all variables can also be found in Appendix A.

3.5.1 Dependent Variable

EnergyBehaviourScore was used as the outcome variable. It measures how energy-consuming an occupant's behaviour is on a continuous scale from 1 to 5. It is calculated using self-reported data from the questionnaire. Participants were asked to take the last 4-8 weeks into account when answering questions about their energy-consuming behaviour inside their homes, i.e., corresponding to the months of March and April 2023. In total, 19 questions were asked (see Appendix B) and were inspired by or adopted directly from previous surveys on energy-consuming behaviour (Chen et al., 2013; Gram-Hanssen, 2003)[3].

Each of the questions represents a variable that can take discrete values from 1 to 5, with 1 being the least energy consuming and 5 the most energy-consuming behaviour, e.g.:

EB_Dryer How often do you use the dryer per week approx.?

If you do not own said appliance, you can check the box "Never".

○ Never (1)

○ On 1-2 days (2)

○ On 3-4 days (3)

○ On 5-6 days (4)

○ Every day (5)

The 19 variables are *EB_Oven*, *EB_Microwave*, *EB_Dishwasher*, *EB_Laundry*, *EB_Dryer*, *EB_Hairdryer*, *EB_KettleCoffee*, *EB_TV*, *EB_LightDay*, *EB_LightNight*, *EB_Standby*, *EB_Clothes*, *EB_Heater*, *EB_Curtains*, *EB_Doors*, *EB_Windows*, *EB_LightsForgotten*, *EB_BackgroundNoise*, and *EB_HomeWeekTOT*[4]. *EnergyBehaviourScore* was then calculated by taking the average of these 19 variables to give a final score indicating how

[3]For a comment on the reliability and a factor analysis of the dependent variable, see Appendix G.

[4]*EB_HomeWeekTOT* is a variable that reflects how much time participants spend at home in an average week. It is calculated using multiple variables. For more details on its calculation, see Appendix C.

energy-consuming the occupant's behaviour is. The complete formula to calculate *EnergyBehaviourScore* can be found in Appendix C, whereas the overview of all variables can be found in Appendix A.

3.5.2 Independent Variables

3.5.2.1 Bioclimatic Conditions

In terms of bioclimatic conditions, six variables[5] were defined after assessing which ones were the most mentioned in scientific literature in the domain of bioclimatic architecture. The six variables are:

1) ***Orientation**,* i.e., the orientation of the main windows of the participant's studio/apartment (e.g., North, North-East, East, etc.) (Fumo & Rafe Biswas, 2015; Tzikopoulos et al., 2005; Wilson, 2013). This variable was divided into the following dummy variables: *BC_OrN, BC_OrNE, BC_OrE, BC_OrSE, BC_OrS, BC_OrSW, BC_OrW* and *BC_OrNW*. Each of these represents a value of the variable Orientation (e.g., *BC_OrN* for "Bioclimatic condition Orientation North") which takes the value 1 when it is chosen and 0 when it is not. Multiple orientations can be chosen simultaneously.
2) ***Shading***, i.e., the degree of shade through vegetation and other elements on the façade or windows of the participant's home (from 1 = "not shaded at all" to 5 "completely shaded") for the months of March and April (Tzikopoulos et al., 2005; Watson, 2013; Wilson, 2013).
3) ***ArtificialLight***, i.e., the extent to which extra artificial light is needed in living spaces due to lack of natural light (from 1 = "only need artificial light when it is dark out", to 5 = "need artificial light at all times") for the months of March and April (Tzikopoulos et al., 2005).

[5] Two more bioclimatic conditions, i.e., wind direction and relative humidity, could have been added to these variables. However, data for these had to be downloaded directly from the KNMI website (a total of 8640 files for the months of March and April 2023), extracted using R Studio, exported to an Excel file, and finally, averaged per city. Due to time constraints, wind direction and relative humidity were, hence, not considered. They should, however, be integrated in future research since they are also part of the most mentioned bioclimatic conditions in scientific literature (see 5. Discussion).

4) ***SolarRad***, i.e., the average local incoming solar radiation on a participant's building measured in Watts per square meter (W/m^2) for the months of March and April (Fumo & Rafe Biswas, 2015; Tzikopoulos et al., 2005; Watson, 2013).
5) ***AmbTemp**,* i.e., the average local ambient temperature outside a participant's building measured in degrees Celsius (C°) for the months of March and April (Fumo & Rafe Biswas, 2015; Tzikopoulos et al., 2005; Watson, 2013).
6) ***WindSpeed**,* i.e., the average local wind speed around a participant's building measured in meters per second (m/s) for the months of March and April (Fumo & Rafe Biswas, 2015; Tzikopoulos et al., 2005; Watson, 2013).

The first three, i.e., *Orientation*, *Shading* and *ArtificialLight,* were self-reported by participants through the survey and were specific to their own studio/apartment within a building. The following three variables, i.e., *SolarRad*, *AmbTemp*, and *WindSpeed*, were part of the archival data collection as described in section 3.3.2 Archival data collection. Each of these 3 variables was measured by averaging climatic data from March and April for the different values of the variable *City* (e.g., Amsterdam, Breda, Delft, the Hague, etc.). Then, the data is matched with each participant using the variable *City*.

3.5.2.2 Habits

HabitScore is the independent variable that was used to measure how habitual a participant's behaviour is. The survey questions used to calculate this variable were based on a shortened version of the Self-Report Habit Index (SRHI) that accounts for the three features of habits, i.e., repetition/frequency, automaticity, and expressing identity (Verplanken & Orbell, 2003). These three features were investigated in the questionnaire through four statements on different habitual behaviours (see Appendix B) that were estimated to influence energy consumption (Eurostat, 2020). For each statement, the participant agreed/disagreed (on a 5-point Likert scale) with the three features of the habit mentioned in the statement. E.g., the participant was given the following statement in the survey:

"Taking a warm shower before starting the day or at the end of the day is something..."

Indicate to what extent you agree/disagree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do frequently (*HabitShower_Fr*)	○	○	○	○	○
I do automatically (*HabitShower_Auto*)	○	○	○	○	○
That makes me feel weird if I do not do it. (*HabitShower_ID*)	○	○	○	○	○

The habit mentioned in the statement was "taking a warm shower" either at the start or end of the day. Per statement, three variables were defined, one for each feature of habits (e.g., *HabitShower_Fr* for frequency, *HabitShower_Auto* for automaticity and *HabitShower_ID* for identity). Hence, in total 12 variables relate to habits. *HabitScore* was then calculated by taking the average of these 12 variables and its values therefore lie on a continuous scale from 1 to 5. The more a participant agrees, the higher their *HabitScore* becomes and, hence, the more habitual their behaviour is. The complete formula to calculate *HabitScore* can be found in Appendix C, whereas the overview of all variables can be found in Appendix A.

HabitScore has high internal consistency[6] ($\alpha = 0.75$). Hence, *HabitScore* reliably measures how habitual behaviour is. This was expected, as the variable is measured through a shortened version of the Self-Report Habit Index (SRHI), a tested scale (Verplanken & Orbell, 2003).

3.5.2.3 Moral Licensing

MoralLicensingScore is the variable that measured to what extent participants use the psychological mechanism of moral licensing. In the survey, participants were first presented with seven statements about their previous pro-environmental behaviour to which they were asked to react with Yes/No, e.g., *"I have stopped or decreased my meat consumption"*. By having to indicate whether these statements apply to themselves, participants were reminded of their previous pro-environmental behaviour which acted as a trigger to the moral licensing measured in the next part of the survey. The same logic was used in a survey conducted by

[6] Internal consistency is measured through Cronbach's Alpha α.

Burger et al. (2022) that investigated moral licensing within climate-related behaviour (see Appendix B).

After these seven questions, participants were asked to agree/disagree (on a 5-point Likert scale) with different statements that measured to what extent they use licensing. E.g., participants were presented with the following question in the survey:

ML_NoDishwasher "Not using a dishwasher can make up for longer showers."

- ○ Strongly disagree (1)
- ○ Somewhat disagree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat agree (4)
- ○ Strongly agree (5)

These statements were adopted from the survey conducted by Burger et al. (2022) mentioned previously (see Appendix B). The more participants agreed with these statements, the more moral licensing was present. Each statement is represented by a variable, i.e., *ML_Indulge*, *ML_Strictness*, *ML_Offset*, *ML_Standby*, *ML_NoDishwasher* and *ML_Vegetarian*. *MoralLicensingScore* was then calculated by taking the average of these six variables and is hence measured on a continuous scale from 1 to 5. The smaller the value, the less moral licensing was used by the occupant. The complete formula to calculate *MoralLicensingScore* can be found in Appendix C, whereas the overview of all variables can be found in Appendix A.

Internal consistency[7] of *MoralLicensingScore* is on the lower side ($\alpha = 0.65$). However, it is still acceptable and *MoralLicensingScore* is used in the regression analysis.

3.5.3 Control Variables

To account for different factors that might influence the relationship between the dependent variable and the independent variables, several control variables were chosen. These control

[7] Internal consistency is measured through Cronbach's Alpha α.

variables are either basic demographics or represent the building's energy efficiency. The following control variables were defined:

1) ***Age***, i.e., the age of the participant in years.
2) ***Gender***, i.e., the Gender of the participant with a choice between "Male" (1), "Female" (2), "Other" (3) or "Prefer not to say" (4).
3) ***TimeNL***, i.e., the total time (years and months) the participant has lived in the Netherlands on a continuous scale[8].
4) ***NbWorkHours***, i.e., the average number of hours worked per month next to the studies of a participant.
5) ***Finances***, i.e., the financial situation of the participant with a choice between "Saved money" (1), "Just got by" (2), "Spent some savings" (3), "Spent savings and borrowed money" (4) and "Prefer not to say" (5).
6) ***EnergyLabel***, i.e., the energy label of the home of the participant (taking values from A to G and re-coded as a discrete numeric variable from 1 to 7 respectively)[9].

The first five variables were self-reported in the survey, whereas energy labels were part of the archival data collection as mentioned in section 3.3.2 Archival data collection.

3.5.4 Other Variables

To find energy labels of their homes, participants were asked to provide their postcode and house number under the variable *PostCode* but were also given the alternative to give the building name under *BuildingName* and the name of their housing corporation under *HouseCorp* if they felt uncomfortable sharing their full address. As expected, most people only filled in either the postcode without the house number or the building name with the housing corporation. To find the registration of an energy label in the Netherlands, both the postcode and house number are, however, necessary. Whenever a participant did not give their full address, estimations about the energy label had to be made. Hence, an additional variable, i.e., *EL_Qual*, was created to reflect the quality of the data in *EnergyLabel*. *EL_Qual* was coded with discrete values from 1 to 8 (see Table 1).

[8] *TimeNL* is calculated by using *TimeNL_YR* and *TimeNL_MO* (see Appendix C).

[9] Interpretation: Higher values of *EnergyLabel* translate to worse energy labels (e.g., 7 = G). This needs to be taken into account when interpreting the results.

Table 1 *Coding, Interpretation, Frequencies, and Percentages of EL_Qual*

Code	Label	Interpretation	*f*	%
1	**Excellent**	People who have provided their exact address → 1 result in EP-online	57	10.8
2	**Very Good**	People who have provided the postcode (with the house number of their building) and every studio for that postcode or building number having the same energy label. → All results in EP-online have the same energy label (100%)	223	42.1
3	**Good**	People who have provided the postcode (with the house number of their building), but the postcode/building has different energy labels. → Multiple results in EP-online with different energy labels but one clearly prevalent one (90-99%).	54	10.2
4	**Okay**	People who have provided the postcode (with the house number of their building), but the postcode/building has different energy labels. → Multiple results in EP-online with different energy labels but one clearly prevalent one (≥75%).	29	5.5
5	**Bad**	People who have provided the postcode (with the house number of their building), but the postcode/building has different energy labels. → Multiple results in EP-online with different energy labels, one prevalent one (50-74%).	32	6.0
6	**Insufficient A**	The postcode or building having a wide variety of energy labels or no clear prevalent one.	46	8.7

7	**Insufficient B**	People not having filled out the survey question or the energy label not being registered in EP-online for the given address.	31	5.8
8	**Insufficient C**	The participant not having provided enough information on their location and hence no estimation being possible.	58	10.9

The variable was coded as such to be able to give more information in the descriptive analysis of *EnergyLabel* (see Appendix H).

3.6 Data Analysis

The data analysis proceeded in multiple steps explained in the following paragraphs. The different steps included doing a first variable check, matching archival data to participants, identifying, and handling outliers, checking and managing missing values, and finally, conducting the statistical analysis.

Variable check. The data was exported from Qualtrics to a .sav file that is compatible with SPSS, i.e., the program chosen to conduct the statistical analysis. Before starting the analysis, all variables and the data were thoroughly checked in SPSS. Each variable was checked to fit the correct type (i.e., numeric or string) and measurement level (i.e., scale, ordinal or nominal). E.g., *NbWorkHours* was imported as a nominal string variable and, hence, had to be re-coded into a numeric variable measured on a continuous scale. All values of the variables were also checked and re-coded if necessary. E.g., in the initial data import, *Finances* was coded from 2 to 6 instead of from 1 to 5. Finally, score variables were computed, e.g., *EnergyBehaviourScore*, *HabitScore* and *MoralLicensingScore*.

Matching. Archival data on solar radiation (*SolarRad*), ambient temperature (*AmbTemp*) and wind speed (*WindSpeed*) was downloaded from the TU Delft Meteorological Data Portal for each of the 14 cities where survey data was collected from. The data concerning the months of March and April were then averaged per city. This data set was then imported into SPSS and matched with the initial questionnaire data set using the key variable *City*. For *EnergyLabel*, archival data was added manually for each participant as described in section 3.3.2 Archival data collection.

Outliers. After that, multiple outliers were identified using boxplots and the Tukey method[10]. Some were filtered out (from N= 545 to N = 530) to avoid the distortion of results. More precisely:

1) *HabitScore:* The extreme outlier with a *HabitScore* of 5 (the maximum) was filtered out, since it was probably due to the participant arbitrarily choosing the same option every time when answering questions regarding habitual behaviour.
2) *SolarRad*, *AmbTemp* and *WindSpeed* (bioclimatic conditions): Even though multiple outliers were identified for these variables, none were filtered out initially. This choice is justified by the data reflecting actual measurements from weather stations across the Netherlands. The data is considered reliable since it is based on measurements registered by the Royal Netherlands Meteorological Institute (KNMI) and was checked for errors in the calculation of averages for March and April.
3) *Shading* (bioclimatic condition): SPSS identified all responses with a value of 4 or 5 as outliers for the variable *Shading*. These were, however, not filtered out, since the identified participants did not show any answering pattern that would indicate incorrect measurements. They are therefore considered real measures and are included in the analysis.
4) *Age*: Multiple extreme outliers were identified for *Age*. Responses, where *Age* was higher than or equal to 39, were filtered out. These likely correspond to people that participated in the survey even though they were no students. The decision to filter out people that were 39 years or older is further supported by the very low number of students aged 39 years and older in the Netherlands (OECD, 2019).
5) *NbWorkHours*: SPSS identified extreme outliers as those where *NbWorkHours* is equal to 128 or higher. These likely correspond to participants who work full-time jobs and are likely no students anymore (e.g., 150 hours). Hence, these were filtered out.
6) *EnergyLabel*: In total, 11 outliers were identified for *EnergyLabel*, four extreme ones (i.e., one F and three G energy labels) and seven mild ones (i.e., three D and four E energy labels). The quality of these energy labels (i.e., *EL_Qual*) was excellent (1) except in two cases. Therefore, they were not filtered out at first.

---

[10] In the Tukey method, mild outliers are defined as values that lie further than 1.5 times the interquartile range (IQR) from the quartiles, i.e., below Q1 – 1.5*IQR or above Q3 + 1.5*IQR. Extreme outliers are defined as values that lie further than 3 times the interquartile range from the quartiles, i.e., below Q1 – 3*IQR or above Q3 + 3*IQR.

Missing values. The last step before conducting the analysis was to check for missing data.

1) *EnergyBehaviourScore*: In total, there were only three missing values in the 19 variables used to calculate *EnergyBehaviourScore*. These are simply not considered when calculating the mean of the 19 variables and, hence, *EnergyBehaviourScore* has no missing values.
2) *HabitScore*: Out of the 12 variables that are used to calculate *HabitScore*, only 2 values were missing for 2 participants. These are, again, simply not considered when calculating the mean of the 12 variables and, hence, *HabitScore* has no missing values.
3) *Gender*: Seven people (1.3%) preferred not to answer the question regarding their gender identity in the questionnaire and are, hence, coded as missing values.
4) *TimeNL*: Only 2 missing values were reported in the two variables used to calculate *TimeNL*, i.e., *TimeNL_YR* and *TimeNL_MO*.
5) *Finances*: 22 people (4.2%) preferred not to answer the question regarding their financial situation and are, hence, coded as missing values.
6) *EnergyLabel:* After the estimation of energy labels where the full address was not provided, 135 values are missing (25.5%), i.e., values of *EnergyLabel* that were coded as "Insufficient" (6, 7 or 8) in *EL_Qual*. Without the estimation, the number of missing values would be at 473 (89.2%), i.e., values of *EnergyLabel* that were coded from "Very Good" (2) to "Bad" (5) in *EL_Qual*.

For *EnergyBehaviourScore*, *HabitScore*, *Gender*, *TimeNL* and *Finances*, the number of missing values is very low (<5%). For *EnergyLabel*, the number of missing values has been decreased through estimations.

Statistical analyses. To answer the research questions, three main analyses were conducted (i.e., Analysis 1, Analysis 2, and Analysis 3). Each of these main analyses used multiple linear regression modelling to investigate the relationship between energy consuming behaviour (i.e., *EnergyBehaviourScore*) and different sets of predictor variables. **Analysis 1** analysed the relationship between bioclimatic conditions of participant's buildings (i.e., *Orientation*, *Shading*, *ArtificialLight*, *SolarRad*, *AmbTemp* and *WindSpeed*) and energy-consuming behaviour (i.e., *EnergyBehaviourScore*). **Analysis 2** analysed the relation between psychological mechanisms (i.e., *HabitScore* and *MoralLicensingScore*) and energy-consuming behaviour (i.e., *EnergyBehaviourScore*). In both, basic demographics (i.e., Age, Gender, Finances, City) and building energy efficiency (i.e., *EnergyLabel*) were used as control variables to account for potential confounding effects. Means, standard deviations and correlation coefficients were also reported and interpreted for Analysis 1 and Analysis 2. The optimal regression model for both analyses was found through backward variable elimination.

Backward elimination of variables is an iterative process in which insignificant variables are removed from the model to find the optimal one. **Analysis 3** combined the optimised models of Analysis 1 and Analysis 2 to determine which predictors have a stronger impact on *EnergyBehaviourScore*.

If assumptions of multiple linear regression were not met (i.e., normality, linearity, homoscedasticity, absence of outliers), bootstrapping was used. Bootstrapping is a resampling method that can be used in combination with statistical analyses, such as multiple linear regression, when assumptions are not fulfilled. Indeed, bootstrapping does not make assumptions about the distributions of variables. Additionally, if the optimal models of Analysis 1 or 2 included variables with extreme outliers, a sensitivity analysis was conducted by removing these, one variable at a time. The sensitivity analysis was conducted to investigate the influence of extreme outliers on the overall findings and the robustness of the results.

3.7 Research quality indicators

The methodology of this research was checked on reliability, replicability and validity are the 3 most used quality indicators of research (Bryman, 2012). Firstly, the reliability of the research was expected not pose a problem given that the research was based on tested theory and methods which assures consistency. Secondly, since the procedures used for the research were described extensively, replicability should be highly probable. Thirdly, validity of a study can be categorised into: measurement validity, internal validity and external validity (Bryman, 2012). Measurement validity was assured by using tested frameworks, e.g., the Self-Report Habit Index (Verplanken & Orbell, 2003), and using scientific articles that measure similar concepts as a foundation to measure the different variables (see Appendix 2). Internal validity was assured by using linear regression as a data analysis strategy, since it is recognized to accurately predict energy consumption for residential buildings (Fumo & Rafe Biswas, 2015). Moreover, control variables are introduced. Lastly, the research was expected to have external validity as a homogenous sample was chosen to draw generalizable conclusion from the results.

3.8 Ethical Considerations

Since this research collects personal information of survey participants, ethical issues are touched upon. Firstly, survey participants are asked to sign an informed consent form at the start of the questionnaire. They agreed to having filled out the survey voluntarily and to their data being collected and used for the purpose of this research. Participants were also informed that they had the right to stop the survey at any moment and were never obligated to answer questions if they did not feel comfortable doing so. Secondly, participants were informed that all data is handled according to the General Data Protection Regulation (GDPR). Additionally, all data is used anonymously, and participants have been informed of their rights to withdraw their data. Data collected on participant's home addresses and Email addresses is saved in a secured SPSS file that will only be shared with Utrecht University to secure confidentiality. Email addresses were only collected for the giveaway at the end of the survey, for which an additional consent was asked from participants.

4. Results

Three main analyses were conducted to answer the research questions, and hence, the results are divided into three parts, i.e., Analysis 1, Analysis 2, and Analysis 3. **Analysis 1** investigates how bioclimatic conditions of residential buildings influence occupant behaviour. **Analysis 2** investigates how occupant behaviour is influenced by two psychological mechanisms, i.e., habits and moral licensing. It also gives insights into how conscious (moral licensing), or unconscious (habits) occupant behaviour is. Finally, **Analysis 3** investigates which of the two has a stronger impact on occupant behaviour: bioclimatic conditions or psychological mechanisms. Before reporting results that are more specific to each analysis, some general results are presented:

1) ***EnergyBehaviourScore* (*N* = 530).** On average, participants scored 2.28 for *EnergyBehaviourScore* (*SD* = 0.31). The variable follows a normal distribution (see Figure F1). For more descriptive statistics of *EnergyBehaviourScore* see Table D1.
2) ***HabitScore* (*N* = 530).** On average, participants scored 2.90 for *HabitScore* (*SD* = 0.70). Further, the variable follows a rather normal distribution (see Figure F2). For more descriptive statistics of *HabitScore* see Table D2.
3) ***MoralLicensingScore* (*N* = 530).** The average score was at 2.79 for *MoralLicensingScore* and the variable follows a rather normal distribution (see Figure F3). For more descriptive statistics of *MoralLicensingScore* see Table D2.
4) ***Orientation* (*N* = 528).** For all the dichotomous variables *BC_OrN* to *BC_OrNW* designating all the possible orientations of a building (i.e., North, North-East, East, South-East, South, South-West, West and North-West), responses for each variable took the value 1 between 10% and 17.2% of the time. A more detailed overview can be found in Table E5.

5) ***Shading* (*N* = 530).** Most participants indicated that their homes were not shaded at all (65.7%), and the least participants had completely shaded homes (2.6%). On average, participants scored 1.65 (*SD* = 1.06) for the level of shade on their homes (Table D4). See also Figure F10 for the distribution of *Shading*.
6) ***ArtificialLight* (*N* = 530).** When it comes to the amount of artificial light needed in their homes, 37.5% indicate needing artificial light only when it is dark out, whereas only 3.8% always need artificial light. On average, participants scored 2.09 (*SD* = 1.11) for artificial light needed throughout the day in their homes (Table D4). See also Figure F11 for the distribution of *ArtificialLight.*
7) ***SolarRad* (*N* = 530).** On average, solar radiation was at 136.08 W/m^2 (*Mdn* = 134.53; *Mode* = 135.38; *SD* = 6.43) for the sample (Table D4). The distribution is non-normal (Figure F12).
8) ***AmbTemp* (*N* = 530)**. On average, the ambient temperature outside participant's homes is at 7.92°C (*Mdn* = 8.07; *Mode* = 8.10; *SD* = 0.32) (Table D4). The distribution is non-normal (Figure F13).
9) ***WindSpeed* (*N* = 530).** On average, wind speed around participant's homes was at 4.32 m/s (*Mdn* = 4.46; *Mode* = 4.53; *SD* = 0.53) (Table D4). The distribution is non-normal (Figure F14).
10) ***NbWorkHours.*** 45.8% of participants did not work next to their studies (*N* = 530). Participants that worked next to their studies, worked an average of 34 hours per month (*N* = 287; *SD* = 24.75). Further, *NbWorkHours* is not normally distributed (see Figure F6 and F7).
11) ***Finances* (*N* = 508)*.*** All categories of the variable were relatively equal in frequency: 24% "Saved money", 27.8% "Just got by", 26.4% "Spent some savings" and 21.9% "Spent savings and borrowed money" (see Table E2).
12) ***City* (*N* = 530).** The highest proportion of participants comes from Delft with 19.8%. Utrecht comes in second with 14.2%. For the rest, 10.8% come from Maastricht, 9.8% from The Hague, 9.2% from Groningen, 9.1% from Leiden, 8.7% from Wageningen, 4.7% from Amsterdam, 4.3% from Eindhoven, 4.2% from Zwolle, 2.6% from Tilburg, 1.5% from Breda and 1.1% from Haarlem (see Table E4). Overall, the sample is very diverse in terms of locations (see Figure F8).
13) ***EnergyLabel* (*N* = 395).** A large majority of participants had an A energy label (71.1%). The second and third most prevalent energy labels were C (14.9%) and B (6.8%) (Table E3). Other categories were present but only very rarely (see Figure F9).
14) ***EL_Qual* (*N* = 530).** Some comments can be made in terms of the quality of the data in *EnergyLabel*. In 52,9% of cases, the label recorded under *EnergyLabel* is the actual label of the participant's home registered in EP-online (i.e., *EL_Qual* = 1 or 2). In 25.4% of

cases, the quality is deemed insufficient and hence, no energy label was recorded in *EnergyLabel* (i.e., *EL_Qual* = 6, 7 or 8). For the last 21.7% of cases, estimations on energy labels could be made and were recorded in *EnergyLabel* (*EL_Qual* = 3, 4 or 5). This explains why N = 395 for *EnergyLabel*. See also Appendix H for a more detailed comment.

In the following sections, each analysis will be commented on in detail.

4.1 Analysis 1: Bioclimatic Conditions and Energy Consumption

As mentioned previously, Analysis 1 investigated the influence of bioclimatic conditions (i.e., *Orientation*, *Shading*, *ArtificialLight*, *SolarRad*, *AmbTemp* and *WindSpeed*) on energy consuming behaviour (i.e., *EnergyBehaviourScore*), through a multiple linear regression analysis. Basic demographics and energy efficiency of the building were used to control for other effects (i.e., *Age*, *Gender*, *Finances*, *City* and *EnergyLabel*). The assumption of normality was not met by either *SolarRad*, *AmbTemp* or *WindSpeed*, all of which are part of the independent variables. Further, outliers were identified for *Shading*, *SolarRad*, *AmbTemp* and *WindSpeed*, which were not filtered out after sound reasoning (see 3.6 Data analysis). Overall, bootstrapping was used for Analysis 1 to account for the issue of non-normality of the independent variables and the presence of outliers. Bootstrapping is a resampling method that increases the robustness of the findings for non-normal distributions among others. The number of samples was set to 1000 for the bootstrapping and bias corrected accelerated (BCa) confidence intervals are computed at a level of 95%.

The following section first reports some descriptive statistics of the variables used in Analysis 1 as well as their correlations. After, the multiple regression analysis is conducted as described in section 3.6 Data analysis. The optimal regression model was found through backward elimination of variables. The significance level (i.e., the p-value) for the inclusion of variables was set at $p \leq 0.10$. Hence, if the effect of a variable in the model had a p-value greater than 0.10, it was eliminated from the model iteratively, starting with the highest p-value. The first model started with all variables being included. Finally, a sensitivity analysis was conducted by removing outliers to investigate the effect of extreme values on the overall findings.

4.1.1 Means, Standard Deviations, and Correlations

First, bivariate correlations were calculated for all variables considered in Analysis 1 (see Table 2). None of the absolute correlations exceeded 0.8, which could have caused issues in terms of multicollinearity.

Table 2 *Means, Standard Deviations, and Pearson's Correlations (Analysis 1)*

	Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	***EnergyBehaviourScore***	2.28	0.31																		
2	***BC_OrN***[a]			.04																	
3	***BC_OrNE***[a]			-.03	-.12*																
4	***BC_OrE***[a]			.15**	-.16**	-.10															
5	***BC_OrSE***[a]			.07	-.18**	-.12*	-.10														
6	***BC_OrS***[a]			-.07	-.16**	-.17**	-.15**	.01													
7	***BC_OrSW***[a]			-.10	-.19**	-.15**	-.13*	-.05	-.03												
8	***BC_OrW***[a]			.06	-.16**	-.17**	-.10	-.13*	-.05	-.03											
9	***BC_OrNW***[a]			-.09	-.07	-.12*	-.13*	-.11*	-.13*	-.12*	-.10										
10	***Shading***	1.65	1.06	.04	.07	.02	-.07	-.04	-.09	-.10	.06	.13*									
11	***ArtificialLight***	2.12	1.12	.08	.17**	.17**	-.03	-.08	-.21**	-.13*	-.05	-.02	.30**								
12	***SolarRad***	134.99	5.64	-.15**	-.01	.02	-.10	.14*	.11	-.02	-.10	-.04	.09	.08							
13	***AmbTemp***	7.90	0.33	.06	.07	-.02	.06	-.01	.02	-.08	-.08	.04	-.04	.04	.15**						
14	***WindSpeed***	4.25	0.57	-.11*	-.06	.03	-.03	-.01	.06	.01	.04	-.07	.08	.12*	.56**	-.04					
15	***Age***	23.30	2.78	-.02	-.02	.07	.11	-.04	-.01	.03	.00	-.02	-.06	.05	-.07	-.04	-.12*				
16	***Gender***[b]			.02	-.06	.07	.06	.01	-.09	.89	-.04	-.08	.00	-.06	-.10	-.13*	.01	.01			
17	***Finances***[b]			.03	-.01	.00	-.05	.05	.09	.00	-.03	-.43	-.08	-.05	.03	.13*	-.08	.04	.00		
18	***City***[b]			.01	.07	-.05	.03	.02	-.04	.00	-.05	.02	-.07	-.16**	-.54**	-.30**	-.72**	.19**	.09	.08	
19	***EnergyLabel***[b]			-.03	.00	-.10	.08	-.10	-.06	-.03	.14*	.02	-.02	-.01	-.20**	.00	-.02	.00	.01	-.05	-.10

[a]Point-biseral correlation coefficients (r_{pb}) are reported for the dichotomous variables *BC_OrN* to *BC_OrNW*.

[b]Spearman's correlation coefficients (ρ) are reported for the categorical variables *Gender*, *Finances, City* and *EnergyLabel*.

Numbers in red had BCa confidence intervals (95%) that included 0, i.e., there is a lack of evidence for a significant correlation.

**p* < 0.05.

***p* < 0.01.

Firstly, studios that are oriented to the East (*BC_OrE*) are positively correlated to energy consumption behaviour (r_{pb} = .15; p = .006; BCa 95% CI = [0.059; 0.251]), i.e., occupant behaviour in eastern-oriented homes was more energy-consuming. This correlation is statistically significant. Similarly, the negative correlation of incoming solar radiation (*SolarRad*) and energy consumption behaviour is statistically significant (*r* = -.15; p = .008; BCa 95% CI = [-0.247; -0.033]), i.e., the more solar radiation there was in the local environment of the occupant's home, the less energy-consuming they were.

One can also recognize that correlations between the different orientations of occupants' homes are usually negative (and significant; p < .01). These negative correlations reflect the fact that occupants' homes are usually oriented towards one direction instead of multiple.

Further, *Shading* is positively correlated with *BC_OrNW* (r = .13; p = .016; BCa 95% CI = [0.015; 0.260]), i.e., a North-West orientation of the building is associated with higher levels of shade. Similarly, *ArtificialLight* is positively correlated with *BC_OrN* (r = .17; p = .002; BCa 95% CI = [0.069; 0.275]) and *BC_OrNE* (r = .17; p = .002; BCa 95% CI = [0.056; 0.280]), while it is negatively correlated with *BC_OrS* (r = -.21; p < .001; BCa 95% CI = [-0.298; -0.112]) and *BC_OrSW* (r = -.13; p = .025; BCa 95% CI = [-0.213; -0.032]). Since higher values of *ArtificialLight* translate to needing more artificial light, the previous correlations can be interpreted as the following: A northern or north-eastern orientation of the building is associated with a higher need for artificial light in the home, while a southern or south-western orientation is associated with a lower need for artificial light. Additionally, *ArtificialLight* and *Shading* are positively correlated (r = .30; p < .001; BCa 95% CI = [0.195; 0.406]), i.e., the more the façades and windows of the participant's home are shaded, the more artificial light is needed.

Further, locations that have higher ambient temperatures tend to have more incoming solar radiation. And places that have higher average wind speeds tend to be places with higher average temperatures and incoming solar radiation. Indeed, *AmbTemp* is positively correlated with *SolarRad* (r = .15; p = .006; BCa 95% CI = [0.063; 0.222]). And *WindSpeed* is also positively correlated to *AmbTemp* (r = .12; p = .025; BCa 95% CI = [0.027; 0.225]) and *SolarRad* (r = .56; p < .001; BCa 95% CI = [0.514; 0.596]).

Lastly, *EnergyLabel* is positively correlated to *BC_OrW* (ρ = .14; p = .013; BCa 95% CI = [0.023; 0.248]), while it is negatively correlated to *ArtificialLight* (ρ = -.20; p < .001; BCa 95% CI = [-0.290; -0.099]). Given that increasing values of *EnergyLabel* translate to a decrease in energy efficiency, a western orientation of the building is associated with worse energy labels. On the other hand, worse energy labels are associated with a lower need for artificial light.

4.1.2 Regression

In total, 14 iterations led to the model where the p-values for all regression coefficients were smaller than or equal to 0.10 and where all BCa confidence intervals did not include 0. However, the 13th iteration is considered the optimal regression model rather than the 14th iteration. The two models are compared in Table 3. One can see that R^2 drastically decreases by taking out the variable *BC_OrSE* in Iteration 14. Iteration 14 only explains 6% (R^2 = .06) of variation in *EnergyBehaviourScore*, whereas Iteration 13 explains 7% (R^2 = .07). Since the p-value for the regression coefficient of *BC_OrSE* is at the threshold of inclusion (i.e., p = 0.10) Iteration 13 is chosen as the optimal model.

Table 3 *Comparison of Iteration 13 and Iteration 14 (Analysis 1)*

	Iteration 13 (Optimal model)	**Iteration 14**
Variables	*EnergyBehaviourScore*	*EnergyBehaviourScore*
	BC_OrE	*BC_OrE*
	BC_OrSE **(B = 0.088; p = 0.100)**	
	BC_OrW	*BC_OrW*
	ArtificialLight	*ArtificialLight*
	WindSpeed	*WindSpeed*
	EnergyLabel	*EnergyLabel*
R^2	.07	.06
Model ANOVA	$p < 0.001$ $F = 5.06$	$p < 0.001$ $F = 5.31$

The optimal model is composed of 7 variables, of which the unstandardized regression coefficients (B), the coefficients standard errors (Std. Error), the standardised regression coefficients (β), the p-values and the BCa 95% confidence intervals are given in Table 4. The p-values and BCa confidence intervals are taken from the “Bootstrap for Coefficients” table in SPSS. Moreover, no collinearity has been found (Tolerance > 0.10 and VIF < 10 for all variables). The optimal model significantly explains the relationship between *EnergyBehaviourScore* and the predictor variables ($F = 5.06$; $p < 0.001$).

Table 4 *Optimized Regression Model for the Prediction of Energy-Consuming Behaviour Through Bioclimatic Conditions (Analysis 1)*

Variable	B	Std. Error	β	p	BCa 95% CI
***EnergyBehaviourScore* (Constant)**	2.48	.12		<.001	[2.227; 2.757]
BC_OrE	.18	.04	.20	<.001	[0.092; 0.269]
BC_OrSE	.09	.05	.10	.100	[-0.026; 0.211]
BC_OrW	.08	.04	.10	.058	[0.001; 0.174]
ArtificialLight	.03	.01	.10	.032	[0.002;0.054]
WindSpeed	-.06	.03	-.11	.039	[-0.116; -0.009]
EnergyLabel	-.02	.01	-.10	.057	[-0.048; -1.009E-5]

The regression equation for the optimized model is therefore the following:

$$
\begin{aligned}
EnergyBehaviourScore \\
&= 2.48 + 0.18BC\_OrE + 0.09BC\_OrSE + 0.08BC\_OrW \\
&+ 0.03NaturalLight - 0.06WindSpeed - 0.02EnergyLabel
\end{aligned}
$$

Table 2 showed only *BC_OrE* and *SolarRad* to be significant correlators of *EnergyBehaviourScore*. The optimized regression model, however, identifies six variables to be significant predictors of *EnergyBehaviourScore*, i.e., *BC_OrE*, *BC_OrSE*, *BC_OrW*, *ArtificialLight*, *WindSpeed* and *EnergyLabel* (see Table 4). *EnergyLabel* is the only control variable that has a significant effect on *EnergyBehaviourScore*. This shows that the energy performance/efficiency of a building predicts to a certain extent how occupants behave in terms of energy consumption.

The regression equation shows that an eastern, south-eastern, or western orientation of the occupant's home is associated with increased energy-consuming behaviour. Additionally, the need for artificial light due to the lack of natural daylight is linked positively to occupants' energy-consuming behaviour. I.e., for higher values of *ArtificialLight*, *EnergyBehaviourScore* increases. On the other hand, increased average wind speeds are negatively associated with energy-consuming behaviour. Lastly, energy labels are negatively related to energy-consuming behaviour. This should be interpreted with caution since energy labels A to G are coded respectively from 1 to 7. Hence, lower numbers of *EnergyLabel* represent better energy performance. In the regression model, when *EnergyLabel* increases, i.e., energy efficiency decreases, energy-consuming behaviour decreases. In other words, the worse the energy label, the less energy-consuming the occupant's behaviour is.

In terms of the relative strength of the predictors, one has to look at the standardized regression coefficients *β*. *BC_OrE* is the strongest predictor (β = .20) and *WindSpeed* comes in second (β = -.11). *BC_OrSE*, *BC_OrW*, *ArtificialLight* and *EnergyLabel* have the same relative predictive strength in absolute terms (β = .10 for *BC_OrSE*, *BC_OrW*, *ArtificialLight*; β = -.10 for *EnergyLabel*).

Solar radiation is not recognized as a significant predictor of energy-consuming behaviour in the optimal model, although it had a significant negative correlation with it. Instead, wind speed is part of the predictors in the optimal model. This could be due to bootstrapping combined with backward elimination. Indeed, bootstrapping produces bootstrapped p-values and bias-accelerated and corrected confidence intervals. These can slightly change each time the regression model is run with bootstrapping. In terms of backward elimination, this could mean that a variable could have been eliminated before another one due to the variation in p-values. Hence, it does not necessarily mean that solar radiation does not have a certain predictive power on energy-consuming behaviour (see Limitations).

4.1.3 Sensitivity Analysis

In the optimised regression model, outliers are still present in *EnergyLabel* and *WindSpeed*. Three sensitivity analyses are conducted to investigate the influence of these outliers on the previous findings. The first sensitivity analysis investigates the effect of extreme outliers of *EnergyLabel*. The second sensitivity analysis investigates the effect of extreme outliers of *WindSpeed*. The third sensitivity analysis investigates the effect of all extreme outliers, i.e., *EnergyLabel* and *WindSpeed* combined.

Sensitivity analysis 1. First, energy labels F and G were identified as extreme outliers and, hence, defined as missing values to remove them. Next, the optimised model was run again (using bootstrapping) without these extreme outliers. The model fit has slightly decreased (R^2 = .07, F = 4.86, p < .001), since the F-statistic is lower than in the optimised model including *EnergyLabel* outliers. Further, the regression coefficients, p-values and BCa confidence intervals are presented in Table 5. By removing the extreme outliers of *EnergyLabel*, the variable became an insignificant predictor of *EnergyBehaviourScore* with a weaker standardized coefficient (β = -.07; p = .136; BCa 95% CI = [-0.051; 0.007]). This suggests that the outliers were driving the relationship between *EnergyLabel* and *EnergyBehaviourScore*. Additionally, *BC_OrSE* (i.e., a south-easter orientation of the participant's home) also became an insignificant predictor of the outcome variable, suggesting that *EnergyLabel* had an influence on its relationship with *EnergyBehaviourScore*.

Table 5 *Optimized regression model without extreme outliers of EnergyLabel*

Variable	B	Std. Error	β	p	BCa 95% CI
***EnergyBehaviourScore* (Constant)**	2.49	.12		<.001	[2.248; 2.723]
BC_OrE	.18	.04	.21	<.001	[0.096; 0.271]
BC_OrSE	.08	.05	.09	.128	[-0.023; 0.196]
BC_OrW	.10	.04	.11	.037	[0.007; 0.189]
ArtificialLight	.03	.01	.10	.041	[0.002;0.054]
WindSpeed	-.06	.03	-.11	.029	[-0.118; -0.005]
EnergyLabel	-.02	.02	-.07	.136	[-0.051; 0.007]

Sensitivity analysis 2. First, values for *WindSpeed* higher or equal to 7.08 were set as missing, as these were identified as extreme outliers. Next, the optimised model was run again (using bootstrapping) without these extreme outliers. *EnergyLabel* was left unchanged (i.e., including its extreme outliers), to analyse the singular effect of removing the outliers of *WindSpeed*. The model fit has slightly improved, it explains slightly more variation in *EnergyBehaviourScore* and has a slightly higher F-statistic than the optimized model including outliers (R^2 = 0.08; F = 5.12; p < .001). However, three variables become insignificant predictors of *EnergyBehaviourScore* by removing extreme outliers of *WindSpeed*, i.e., *BC_OrSE*, *BC_OrW* and *EnergyLabel* (see Table 6). Indeed, their confidence intervals include zero, indicating statistical insignificance[11]. This suggests that the relationship between these three variables and *EnergyBehaviourScore* was magnified by the outliers of *WindSpeed*.

[11] When bootstrapping is used, the bias-corrected and accelerated bootstrap intervals (BCa CI) give a more accurate view on the statistical significance than the p-values alone.

Table 6 *Optimized regression model without extreme outliers of WindSpeed*

Variable	B	Std. Error	β	p	BCa 95% CI
***EnergyBehaviourScore* (Constant)**	2.53	.14		<.001	[2.244; 2.818]
BC_OrE	.18	.05	.20	<.001	[0.083; 0.265]
BC_OrSE	.10	.05	.10	.092	[-0.013; 0.209]
BC_OrW	.08	.04	.10	.077	[-0.008; 0.172]
ArtificialLight	.03	.01	.11	.035	[0.002;0.057]
WindSpeed	-.07	.03	-.11	.046	[-0.144; -0.002]
EnergyLabel	-.02	.01	-.10	.063	[-0.049; 0.002]

Sensitivity analysis 3. In this analysis, both the extreme outliers of *EnergyLabel* and *WindSpeed* are defined as missing values and hence removed from the regression model. The optimised model is then re-run (using bootstrapping) without any extreme outliers to assess their combined effect. The optimised model without any extreme outliers (R^2 = 0.07; F = 4.91; p < .001) explains 7% of the variation in *EnergyBehaviourScore*, i.e., the same as the optimised model including extreme outliers from both *EnergyLabel* and *WindSpeed* (R^2 = 0.07; F = 5.06; p < .001). However, the F-statistic is slightly lower for the optimised model that excludes outliers. Hence, the overall significance of the model is lowered. Table 7 shows which variables become statistically insignificant predictors of EnergyBehaviourScore when all extreme outliers are removed.

Table 7 *Optimized regression model without extreme outliers of EnergyLabel and WindSpeed*

Variable	B	Std. Error	β	p	BCa 95% CI
***EnergyBehaviourScore* (Constant)**	2.53	.14		<.001	[2.216; 2.814]
BC_OrE	.18	.05	.20	<.001	[0.091; 0.263]
BC_OrSE	.09	.05	.10	.107	[-0.014; 0.202]
BC_OrW	.09	.04	.11	.048	[0.004; 0.189]
ArtificialLight	.03	.01	.11	.035	[0.003;0.058]
WindSpeed	-.07	.03	-.11	.044	[-0.141; 0.000]
EnergyLabel	-.02	.02	-.07	.101	[-0.053; 0.006]

Overall, the sensitivity analyses show that *BC_OrSE* and *EnergyLabel* become statistically insignificant predictors of *EnergyBehaviourScore*, regardless of which extreme outliers are removed, i.e., from *EnergyLabel*, *WindSpeed* or both. *BC_OrW* becomes an insignificant predictor when extreme outliers of *WindSpeed* are excluded. And *WindSpeed* becomes an insignificant predictor when extreme outliers of both *EnergyLabel* and *WindSpeed* are removed simultaneously. Hence, outliers do have a considerable effect on the optimal regression model.

4.2 Analysis 2: Psychological Mechanisms and Energy Consumption

Analysis 2 investigated the influence of psychological mechanisms (i.e., *HabitScore* and *MoralLicensingScore*) on energy-consuming behaviour (i.e., *EnergyBehaviourScore*), through a multiple linear regression analysis. Basic demographics and energy efficiency of the building were used to control for other effects (i.e., *Age*, *Gender*, *Finances*, *City* and *EnergyLabel*). The assumptions of multiple linear regression were checked and fulfilled by all variables included in the regression modelling (i.e., linearity, normality, and homoscedasticity).

The following sections first review some descriptive statistics of the variables used in Analysis 2 as well as their correlations. After, the multiple regression analysis is conducted as described in section 3.6 Data analysis. The optimal regression model was found through the backward elimination of variables. The significance level (i.e., the p-value) for the inclusion of variables is set at $p \leq 0.10$. Hence, if the effect of a variable in the model has a p-value greater than 0.10, it is eliminated from the model iteratively, starting with the highest p-value. The first model starts with all variables being included.

4.2.1 Means, Standard Deviations, and Correlations

First, bivariate correlations were calculated for all variables considered in Analysis 1 (see Table 8). None of the absolute correlations exceeded 0.8, which could have caused issues in terms of multicollinearity.

Table 8 *Means, Standard Deviations, and Pearson's Correlations (Analysis 2)*

Variable	*M*	*SD*	1	2	3	4	5	6	7
1 ***EnergyBehaviourScore***	2.28	0.31							
2 ***HabitScore***	2.90	0.70	.43**						
3 ***MoralLicensingScore***	2.79	0.66	.26**	.21**					
4 ***Age***	23.21	3.07	.01	-.03	-.04				
5 ***Gender*** [a]	-	-	.06	.01	.02	-.01			
6 ***Finances*** [a]	-	-	.00	-.08	-.01	.09	-.04		
7 City [a]	-	-	.03	-.05	-.00	-.16**	.10*	.07	
8 EnergyLabel [a]	-	-	-.04	-.02	-.14**	-.01	-.01	-.04	-.12*

[a]Spearman's correlations are reported for correlations with the categorical variables *Gender*, *Finances* and *EnergyLabel*.

**p* < 0.05.

***p* < 0.01.

Table 8 suggests that *HabitScore* has a significant positive correlation with *EnergyBehaviourScore* (r = .43; p < .001). *MoralLicensingScore* has a significant positive correlation with both *EnergyBehaviourScore* (r = .26; p < .001) and *HabitScore* (r = .21; p < .001). In other words, both habitual behaviour and increased moral licensing are associated with more energy-consuming behaviour. Increased use of moral licensing is also positively linked to more habitual behaviour, i.e., there is an overlap of the two psychological mechanisms. Finally, lower energy labels (e.g., energy labels F or G) are related to lower levels of moral licensing. Indeed, the negative correlation of *EnergyLabel* and *MoralLicensingScore* (ρ = -.14; p = .005) has to be interpreted with caution. The different energy labels A to G are respectively coded 1 to 7, i.e., higher values of *EnergyLabel* correspond to lower energy labels, i.e., lower energy efficiency. The correlation shows that when *EnergyLabel* increases, i.e., when energy efficiency becomes worse, *MoralLicensingScore* decreases, i.e., moral licensing is used less. On the other hand, improvements in energy labels are associated with an increase in the use of moral licensing.

4.2.2 Regression

In total, six iterations led to the optimal model where the p-values for all regression coefficients were smaller than or equal to 0.10. The optimized model (Iteration 6) is composed of 3 variables, of which the unstandardized regression coefficients (B), the coefficients standard errors (Std. Error), the standardised regression coefficients (β), the p-values, the part correlations and the 95% confidence intervals are given in Table 9. Moreover, there is no collinearity issue since the tolerance for all included variables is 0.97 (> 0.10) and the VIF is 1.03 (< 10). Overall, the optimized model explains 17% of the variation in *EnergyBehaviourScore* (R^2 = .17) and is considered significant (F = 33.67; p < .001).

Table 9 *Optimized Regression Model for the Prediction of Energy-Consuming Behaviour Through Psychological Mechanisms (Analysis 2)*

Variable	B	Std. Error	β	p	Part Correlations	95% CI
***EnergyBehaviourScore* (Constant)**	1.58	.09		<.001		[1.404; 1.755]
HabitScore	.16	.02	.34	<.001	.34	[0.110; 0.202]
MoralLicensingScore	.09	.03	.19	<.001	.19	[0.042; 0.139]

The optimized model includes the dependent variable *EnergyBehaviourScore* and the two independent variables *HabitScore* (B = .16; β = .34; p < .001) and *MoralLicensingScore* (B = .09; β = .19; p < .001). For both independent variables, the effect is significant and, hence, moral licensing and habits can significantly explain energy-consuming behaviour. The effects of all control variables were insignificant and, hence, all of them were left out of the model.

This leads to the following regression equation:

$$EnergyBehaviourScore = 1.58 + 0.16HabitScore + 0.09MoralLicensingScore$$

Both *HabitScore* and *MoralLicensingScore* are positively related to *EnergyBehaviourScore*, confirming the significant positive correlation between the variables (see section 4.2.1 Means, Standard Deviations and Correlations). This confirms that the more habitual the behaviour is, the more energy-consuming the occupant's behaviour will be. Equally, the more moral licensing is used to justify immoral behaviour, the more energy-consuming the behaviour will be.

When it comes to the relative strength of the predictors, *HabitScore* (β = .34) has a more important impact on the dependent variable than *MoralLicensingScore* (β = .19). Moreover, the part correlations give the unique variance of the dependent variable explained by each independent variable. *HabitScore* uniquely explains 34% and *MoralLicensingScore* uniquely explains 19% of the variation in *EnergyBehaviourScore*. However, together the variables explain only 17% of the variation in the dependent variable (R^2 = .17). This is due to the overlap of variance from the independent variables, which was also shown through the significant correlation between *MoralLicensingScore* and *HabitScore* in the previous section.

4.3 Analysis 3: Combination of Optimized Regression Models

In Analysis 3, the optimised models of Analysis 1 and 2 are combined. A multiple regression analysis using bootstrapping is run with the following variables: *EnergyBehaviourScore* as the dependent variable, and *HabitScore*, *MoralLicensingScore*, *BC_OrE*, *BC_OrSE*, *BC_OrW*, *ArtificialLight*, *WindSpeed*, and *EnergyLabel* as the predictor variables. Hence, the combined model (R^2 = .23, F = 14.22, p < .001) is composed of 9 variables, of which the unstandardized regression coefficients (B), the coefficients standard errors (Std. Error), the standardised regression coefficients (β), the p-values, and the bias-corrected and accelerated confidence intervals (at the 95% level) are given in Table 10. In total, 23% of the variation in *EnergyBehaviourScore* is explained by the model, i.e., more than the two optimised models from Analysis 1 or 2 individually. Although the combined model explains more variation in the dependent variable, the significance of the combined model is lower than the significance of the optimised model from Analysis 1, i.e., the F-statistic is lower. Further, the model does not present any collinearity issues since the tolerance for all included variables is higher than 0.10 and the VIF is lower than 10.

Table 10 *Combined Optimized Regression Models Using Bioclimatic Conditions and Psychological Mechanisms as Predictors of Energy-Consuming Behaviour (Analysis 3)*

Variable	B	Std. Error	β	p	BCa 95% CI
***EnergyBehaviourScore* (Constant)**	1.87	.13		<.001	[1.611; 2.120]
HabitScore	.14	.02	.31	<.001	[0.096; 0.180]
MoralLicensingScore	.10	.02	.22	<.001	[0.057; 0.144]
BC_OrE	.12	.04	.13	.006	[0.036; 0.207]
BC_OrSE	.06	.05	.07	.215	[-0.035; 0.160]
BC_OrW	.10	.04	.11	.010	[0.021; 0.184]
ArtificialLight	.01	.01	.04	.355	[-0.014; 0.040]
WindSpeed	-.07	.03	-.13	.011	[-0.125; -0.019]
EnergyLabel	-.01	.01	-.05	.247	[-0.034; 0.007]

By combining the optimised models of Analysis 1 and 2, *BC_OrSE*, *ArtificialLight* and *EnergyLabel* all become insignificant predictors of *EnergyBehaviourScore* (i.e., p-values > 0.10 and BCa 95% CI include zero). A potential explanation for this is that the effects of *HabitScore* and *MoralLicensingScore* overshadow the effects of *BC_OrSE*, *ArtificialLight* and *EnergyLabel*. Additionally, when analysing the standardized regression coefficients (β), one can see that psychological mechanisms (i.e., habits and moral licensing) have a stronger influence on energy-consuming behaviour than bioclimatic conditions (i.e., Eastern/Western orientation or wind speed).

5. Discussion

5.1 Theoretical Implications

Knowledge contribution. The findings of this research have several theoretical implications. First, both bioclimatic conditions and psychological mechanisms are shown to predict occupant behaviour to a certain extent, thereby improving the simplistic representation of occupant behaviour in predictive models of energy efficiency such as shown in Markiewicz-Zahorski et al.(2021), Sunikka-Blank & Galvin (2012) or Vázquez et al. (2011). Second, the optimized model of Analysis 1 showed that energy labels are negatively related to energy-consuming behaviour, which needed to be interpreted with caution due to non-intuitive coding of the variable. Indeed, when values of *EnergyLabel* increase, i.e., energy efficiency decreases, energy-consuming behaviour decreases. In other words, the worse the energy label, the less energy-consuming the occupant's behaviour is. This is in line with the prebound effect explained by Sunikka-Blank & Galvin (2012). Third, the results of Analysis 1 showed that 7% of energy-consuming behaviour can be robustly explained by two building orientations (i.e., East and West), as well as the need for artificial light and the average wind speed around an occupant's home (see 4.1.3 Sensitivity Analysis). This shows that external cues (here bioclimatic conditions) have an influence on behaviour such as proposed by Martin & Morich (2011). Fourth, the results of Analysis 2 showed that 17% of energy-consuming behaviour can be robustly explained by habits and moral licensing (i.e., the two psychological mechanisms that were considered). The positive relation between moral licensing and more energy-consuming behaviour supports the work of Dütschke et al. (2018). Additionally, the unconscious psychological mechanism (i.e., habits) is a stronger underlying explanation of occupant behaviour than the conscious psychological mechanism (i.e., moral licensing). This shows that energy-consuming behaviour happens on a more unconscious basis, which is in line with Martin & Morich (2011). Last, 23% of energy-consuming behaviour can be explained by combining bioclimatic conditions and psychological mechanisms, supporting the importance of occupant behaviour as a key determinant of energy efficiency in buildings (Masseck, 2011; Pajek & Košir, 2021; Soares et al., 2017; Tzikopoulos et al., 2005). Analysis 3 also shows that psychological mechanisms have a much larger influence on energy-consuming behaviour than bioclimatic conditions, a new finding that adds to the existing knowledge of occupant behaviour.

Alternative explanations. Bioclimatic conditions were expected to have a more important and clear effect on occupant behaviour (Tzikopoulos et al., 2005). There are multiple potential explanations for the weak effect of bioclimatic conditions on energy-consuming behaviour. Firstly, measures of solar radiation, ambient temperature, and wind speed did not differ within cities. The measures of these bioclimatic conditions are taken from different weather stations in the Netherlands, one per city the data was collected from. Secondly, the Netherlands is a small country with a rather stable climate, which means solar radiation, ambient temperature and wind speed vary only slightly within the country. The effect of bioclimatic conditions on occupant behaviour is therefore more difficult to detect. Thirdly, the orientation of the occupant's building, the level of shade on their home and the need for artificial light were all self-reported bioclimatic conditions. The weak effect of bioclimatic conditions could also be linked to the self-report bias, where survey participants tend to answer always in the middle or on the extremes of Likert-scales (Bauhoff, 2014).

Moreover, the energy efficiency of a building and occupant behaviour were also expected to be correlated more strongly (Sunikka-Blank & Galvin, 2012). Energy labels, indicating the energy efficiency of a building, were first identified to be a significant predictor of energy-consuming behaviour in the optimized model of Analysis 1. However, when removing extreme outliers, energy labels became insignificant in the prediction of occupant behaviour. In Analysis 2, energy labels were never considered to be a significant predictor of occupant behaviour. This can potentially be explained by the 25.4% of missing energy labels and the estimations about energy labels that had to be made. Most homes of participants had an A energy label and only a very small number of homes had F or G energy labels, which could explain why F and G energy labels were defined as outliers. The distribution of the energy labels was very skewed, i.e., many A energy labels and very little F or G energy labels. This could also explain why energy labels are considered significant in predicting occupant behaviour in the optimized model of Analysis 1 but not in the optimised model of Analysis 2. In Analysis 1, bootstrapping was used, which accounts for issues of non-normality (e.g., skewed distributions of variables). Hence, the distribution of the energy labels was "corrected" in Analysis 1 but not in Analysis 2.

Research quality. Overall, this research presents the first attempt at predicting energy consuming behaviour through bioclimatic conditions of residential buildings and psychological mechanisms. A substantial dataset (i.e., 545 data points) was created which groups data on energy-consuming behaviour, bioclimatic conditions of residential buildings, habitual behaviour, and the use of moral licensing. The sample was representative of the student demographic in the Netherlands. E.g., the presence of 55.3% of females in our sample is in line with the national average, i.e., 54% of female students at university and 53% in higher professional education enrolments (CBS Statistics Netherlands, 2023). Also, the rather equal split between Dutch citizens and internationals reflects the reality of the student population in the Netherlands. Additionally, data was gathered from diverse locations across the

Netherlands. Therefore, results are generalizable to the population of residential occupants in the Netherlands, and hence, external validity is high.

The identified research gap was the lack of understanding and integration of occupant behaviour in building energy performance modelling/prediction. This gap was bridged by this research since understanding of occupant behaviour was advanced. How energy-consuming behaviour within residential buildings is influenced is now better understood and this research constitutes a first step towards the accurate integration of occupant behaviour in building energy performance modelling. Indeed, the optimized multiple regression models of this research could be combined with other regression models that aim to predict energy efficiency of buildings, e.g., the regression model found in Tzikopoulos et al. (2005).

5.2 Limitations

Despite the valuable scientific and practical insights of this research, some limitations that impact both the interpretation and generalizability of results should be acknowledged. First, wind direction and relative humidity are two bioclimatic conditions that could not be integrated as the data collection of these was hindered due to the time constraint, impacting the content validity of bioclimatic conditions negatively. However, even though they were not integrated in this research, results still showed that bioclimatic conditions influence occupant behaviour to a certain extent. Second, the quality of the energy labels poses a limitation to this research, as they are partly based on estimations. However, the results still gave useful insights of the relationship between energy labels and energy-consuming behaviour. Third, the self-report bias (as mentioned above) could have impacted the measurement of self-reported data. This can be improved in future research by using more objective measurements (see 5.3 Future Research). Lastly, the results of the optimised model in Analysis 1 are not completely robust. The model was already improved by bootstrapping to tackle the issue of non-normal distributions. However, the extreme outliers in *WindSpeed* and *EnergyLabel* decreased the robustness of the results. Therefore, a sensitivity analysis was conducted (see 4.1.3 Sensitivity Analysis).

5.3 Future Research

In terms of avenues for future research, some recommendations can be given. First, future research should further investigate the influence of bioclimatic conditions on occupant behaviour by expanding the climatic scope of the study, i.e., by having more variation in terms of bioclimatic conditions. This could be done by including larger countries with more diverse climate or different countries from different climatic zones in the data collection. Second, wind direction and relative humidity are two bioclimatic conditions that should be added in future research, as they were not included in this research but are often mentioned in scientific literature. Third, in order to avoid the self-report bias (Bauhoff, 2014), future research should include objective observations of occupant behaviour, bioclimatic conditions and energy efficiency of their residential buildings. This would also solve the issue of quality of energy labels. Lastly, building standards and norms, as well as municipalities and energy consultancy firms, are usually the different parties that define how buildings are oriented, the minimum sizes of windows, airflow, etc. Hence, future research should also focus on how well occupant behaviour is integrated into such standards, norms, and municipality regulations. It should also investigate to what extent energy consultancy firms take occupant behaviour into account when advising architecture offices.

6. Conclusion

The aim of this research was to gain a more profound understanding of occupant behaviour within residential buildings. More precisely the influence of bioclimatic conditions and two psychological mechanisms (i.e., habits and moral licensing) on energy consuming behaviour within homes was investigated. To achieve the aim of this research, a quantitative cross-sectional study was conducted on a sample of 545 participants. Data was collected both through a survey questionnaire and through archival data collection. Data was analysed mainly by conducting multiple linear regression analyses to answer the two research questions:

1) *How is occupant behaviour influenced by the bioclimatic conditions of the residential building they are in?*
2) *How conscious or unconscious is occupant behaviour? And hence, to what extent can occupants be held responsible for their behaviour?*

The research showed that occupant behaviour is influenced to a small extent by bioclimatic conditions. However, the small effect of bioclimatic conditions on occupant behaviour could be due to the Netherlands being a small country with little variation in bioclimatic data. According to Space&Matter, architects designing buildings in the Netherlands usually apply the same sets of rules to take bioclimatic conditions into account wherever in the Netherlands the building is being constructed. Hence, the rules do not have to be adapted depending on the city within the Netherlands. However, this might not hold when buildings are being designed in areas where bioclimatic conditions differ more. Hence, it is imperative to investigate the influence of bioclimatic conditions on occupant behaviour further as a small but statistically significant effect was detected in this study.

The research also showed that occupant behaviour is significantly influenced by psychological mechanisms. More precisely, unconscious habitual behaviour was shown to have a larger effect on energy consuming behaviour than moral licensing (conscious). Since more than half of human behaviour is unconscious, this shows the importance of taking habits into account when designing buildings or predicting their energy performance. Not taking habits into account can result in inefficient energy-consuming behaviour or decreased return on investments when buildings do not meet predicted energy performances. Combining the optimised regression models showed that psychological mechanisms have a larger influence on energy-consuming behaviour than bioclimatic conditions.

Overall, the results of this research can be used to formulate practical recommendations for different parties. For architects and designers, the results imply that bioclimatic conditions and underlying psychological mechanisms can be consciously considered when designing buildings. In terms of habits, they should consider that familiar environments trigger learned habits, which can be inefficient. By considering these points, buildings could be designed such as to optimise energy-consuming behaviour. Energy consultancy firms advising architecture offices on the right active and passive energy strategies to use within buildings can take occupant behaviour also more consciously into account to bridge the gap between expected and actual energy performance of buildings. Policy makers can integrate the results of this study into the updating of current building norms and regulations. By considering the latest knowledge on occupant behaviour and what influences it, building regulations and norms would stay up to date and could potentially work more effectively toward CO^2-emission reduction goals. Finally, since occupant behaviour was shown to be more unconscious, the occupants cannot be held fully responsible of their energy-consuming behaviour. Hence, behaviour change interventions would potentially only work to a limited extent on occupant behaviour.

Finally, this thesis presents the first successful attempt at predicting energy-consuming behaviour through bioclimatic conditions of residential buildings and psychological mechanisms underlying occupant behaviour (i.e., habits and moral licensing). This research can support future predictive building energy performance modelling by providing a first quantitative model of energy-consuming behaviour explained through the lens of bioclimatic conditions, habits, and moral licensing.

References

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behaviour and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Almusaed, A. (2011). *Biophilic and Bioclimatic Architecture—Analytical Therapy for the Next Generation of Passive Sustainable Architecture*. Springer. https://link.springer.com/book/10.1007/978-1-84996-534-7

Bajcinovci, B., & Jerliu, F. (2016). Achieving Energy Efficiency in Accordance with Bioclimatic Architecture Principles. *Environmental and Climate Technologies*, *18*(1), 54–63. https://doi.org/10.1515/rtuect-2016-0013

Balaras, C. A., Gaglia, A. G., Georgopoulou, E., Mirasgedis, S., Sarafidis, Y., & Lalas, D. P. (2007). European residential buildings and empirical assessment of the Hellenic building stock, energy consumption, emissions, and potential energy savings. *Building and Environment*, *42*(3), 1298–1314. https://doi.org/10.1016/j.buildenv.2005.11.001

Bauhoff, S. (2014). Self-Report Bias in Estimating Cross-Sectional and Treatment Effects. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (pp. 5798–5800). Springer Netherlands. https://doi.org/10.1007/978-94-007-0753-5_4046

Berardi, U. (2017). A cross-country comparison of the building energy consumptions and their trends. *Resources, Conservation and Recycling*, *123*, 230–241. https://doi.org/10.1016/j.resconrec.2016.03.014

Bryman, A. (2012). *Social Research Methods*. Oxford University Press.

Burger, A. M., Schuler, J., & Eberling, E. (2022). Guilty pleasures: Moral licensing in climate-related behaviour. *Global Environmental Change*, *72*, 102415. https://doi.org/10.1016/j.gloenvcha.2021.102415

CBS Statistics Netherlands. (2023, March 8). *More women than men in higher education for 23 consecutive years* [Webpagina]. CBS Statistics Netherlands.

https://doi.org/10/more-women-than-men-in-higher-education-for-23-consecutive-years

Chen, J., Wang, X., & Steemers, K. (2013). A statistical analysis of a residential energy consumption survey study in Hangzhou, China. *Energy and Buildings*, *66*, 193–202. https://doi.org/10.1016/j.enbuild.2013.07.045

Dütschke, E., Frondel, M., Schleich, J., & Vance, C. (2018). Moral Licensing—Another Source of Rebound? *Frontiers in Energy Research*, *6*. https://www.frontiersin.org/articles/10.3389/fenrg.2018.00038

Eurostat. (2020). *Energy consumption and use by households*. Eurostat. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20200626-1

Foucquier, A., Robert, S., Suard, F., Stéphan, L., & Jay, A. (2013). State of the art in building modelling and energy performances prediction: A review. *Renewable and Sustainable Energy Reviews*, *23*, 272–288. Scopus. https://doi.org/10.1016/j.rser.2013.03.004

Fumo, N., & Rafe Biswas, M. A. (2015). Regression analysis for prediction of residential energy consumption. *Renewable and Sustainable Energy Reviews*, *47*, 332–343. https://doi.org/10.1016/j.rser.2015.03.035

Galvin, R. (2013). *Making the 'rebound effect' more useful for performance evaluation of thermal retrofits of existing homes: Defining the 'energy savings deficit' and the 'energy performance gap'*. https://doi.org/10.1016/j.enbuild.2013.11.004

Gram-Hanssen, K. (2003). Boligers energiforbrug—Sociale og tekniske forklaringer på forskelle. In *Boligers energiforbrug—Sociale og tekniske forklaringer på forskelle* (Rapport No. 87-563-1170–2). SBI forlag.

Gram-Hanssen, K. (2014). New needs for better understanding of household's energy consumption—Behaviour, lifestyle, or practices? *Architectural Engineering and Design Management*, *10*(1–2), 91–107. Scopus. https://doi.org/10.1080/17452007.2013.837251

Grillone, B., Danov, S., Sumper, A., Cipriano, J., & Mor, G. (2020). A review of deterministic and data-driven methods to quantify energy efficiency savings and to predict retrofitting scenarios in buildings. *Renewable and Sustainable Energy Reviews*, *131*. Scopus. https://doi.org/10.1016/j.rser.2020.110027

Lee, S. H., Hong, T., Piette, M. A., & Taylor-Lange, S. C. (2015). Energy retrofit analysis toolkits for commercial buildings: A review. *Energy*, *89*, 1087–1100. https://doi.org/10.1016/j.energy.2015.06.112

Loonen, R. C. G. M., Trčka, M., Cóstola, D., & Hensen, J. L. M. (2013). Climate adaptive building shells: State-of-the-art and future challenges. *Renewable and Sustainable Energy Reviews*, *25*, 483–493. https://doi.org/10.1016/j.rser.2013.04.016

Manzano-Agugliaro, F., Montoya, F., Sabio-Ortega, A., & García-Cruz, A. (2015). Review of bioclimatic architecture strategies for achieving thermal comfort. *Renewable and Sustainable Energy Reviews*, *49*, 736–755. https://doi.org/10.1016/j.rser.2015.04.095

Markiewicz-Zahorski, P., Rucińska, J., Fedorczak-Cisak, M., & Zielina, M. (2021). Building Energy Performance Analysis after Changing Its Form of Use from an Office to a Residential Building. *Energies*, *14*(3), 564. https://doi.org/10.3390/en14030564

Martin, N., & Morich, K. (2011). Unconscious mental processes in consumer choice: Toward a new model of consumer behavior. *Journal of Brand Management*, *18*(7), 483–505. Scopus. https://doi.org/10.1057/bm.2011.10

Masseck, T. (2011). LOW3—A Mediterranean Net Zero Energy Building. *Proceedings of the ISES Solar World Congress 2011*, 1–11. https://doi.org/10.18086/swc.2011.13.09

Miller, D. T., & Effron, D. A. (2010). Psychological License: When it is Needed and How it Functions. In M. P. Zanna & J. M. Olson (Eds.), *Advances in Experimental Social Psychology* (Vol. 43, pp. 115–155). Academic Press. https://doi.org/10.1016/S0065-2601(10)43003-8

Ministerie van Binnenlandse Zaken en Koninkrijksrelaties. (2023, January 16). *Regeling energieprestatie gebouwen* [Wettenbank]. Overheid.nl. https://wetten.overheid.nl/BWBR0020921/2021-01-01/#BijlageI

Monin, B., & Miller, D. T. (2001). Moral Credentials and the Expression of Prejudice. *Journal of Personality and Social Psychology*, *81 (1)*, 33–43. https://doi.org/doi: 10.1037/0022-3514.81.1.33

Nilsson, A., Bergquist, M., & Schultz, W. P. (2017). Spillover effects in environmental behaviors, across time and context: A review and research agenda. *Environmental Education Research*, *23*(4), 573–589. https://doi.org/10.1080/13504622.2016.1250148

OECD. (2019). *Education at a Glance: OECD Indicators—The Netherlands*. OECD. https://doi.org/10.1787/f8d7880d-en

Pajek, L., & Košir, M. (2021). Strategy for achieving long-term energy efficiency of European single-family buildings through passive climate adaptation. *Applied Energy*, *297*, 117116. https://doi.org/10.1016/j.apenergy.2021.117116

Pierce, J., Schiano, D. J., & Paulos, E. (2010). *Home, habits, and energy: Examining domestic interactions and energy consumption*. *3*, 1985–1994. Scopus. https://doi.org/10.1145/1753326.1753627

Reimers, H., Jacksohn, A., Appenfeller, D., Lasarov, W., Hüttel, A., Rehdanz, K., Balderjahn, I., & Hoffmann, S. (2021). Indirect rebound effects on the consumer level: A state-of-the-art literature review. *Cleaner and Responsible Consumption*, *3*, 100032. https://doi.org/10.1016/j.clrc.2021.100032

Simbrunner, P., & Schlegelmilch, B. B. (2017). Moral licensing: A culture-moderated meta-analysis. *Management Review Quarterly*, *67*(4), 201–225. https://doi.org/10.1007/s11301-017-0128-0

Soares, N., Bastos, J., Pereira, L. D., Soares, A., Amaral, A. R., Asadi, E., Rodrigues, E., Lamas, F. B., Monteiro, H., Lopes, M. A. R., & Gaspar, A. R. (2017). A review on current advances in the energy and environmental performance of buildings towards a more sustainable built environment. *Renewable and Sustainable Energy Reviews*, *77*, 845–860. https://doi.org/10.1016/j.rser.2017.04.027

Sonderegger, R. C. (1978). Movers and stayers: The resident's contribution to variation across houses in energy consumption for space heating. *Energy and Buildings*, *1*(3), 313–324. https://doi.org/10.1016/0378-7788(78)90011-7

Space&Matter. (n.d.). *Object One—Space&Matter*. Retrieved 1 July 2023, from https://www.spaceandmatter.nl/work/object-one

Sunikka-Blank, M., & Galvin, R. (2012). Introducing the prebound effect: The gap between performance and actual energy consumption. *Building Research & Information*, *40*(3), 260–273. https://doi.org/10.1080/09613218.2012.690952

Terrados, F. J., & Moreno, D. (2014). "Patio" and "Botijo": Energetic strategies' architectural integration in "Patio 2.12" prototype. *Energy and Buildings*, *83*, 70–88. https://doi.org/10.1016/j.enbuild.2014.03.081

Trotta, G. (2020). Assessing energy efficiency improvements and related energy security and climate benefits in Finland: An ex post multi-sectoral decomposition analysis. *Energy Economics*, *86*. Scopus. https://doi.org/10.1016/j.eneco.2019.104640

TU Delft. (n.d.). *Meteorological data portal*. TU Delft. Retrieved 23 June 2023, from https://www.tudelft.nl/en/ewi/over-de-faculteit/afdelingen/electrical-sustainable-energy/photovoltaic-materials-and-devices/dutch-pv-portal/meteorological-data

Tundrea, H., & Budescu, M. (2013). *Bioclimatic Architecture, A Sensible And Local Approach Towards The Future Of Building Development*. Gheorghe Asachi Technical University of Iaşi.

Tzikopoulos, A. F., Karatza, M. C., & Paravantis, J. A. (2005). Modeling energy efficiency of bioclimatic buildings. *Energy and Buildings*, *37*(5), 529–544. https://doi.org/10.1016/j.enbuild.2004.09.002

Vázquez, F. I., Gaceo, S. C., Kastner, W., & Morales, J. A. M. (2011). Behavioral Profiles for Building Energy Performance Using eXclusive SOM. In L. Iliadis & C. Jayne (Eds.), *Engineering Applications of Neural Networks* (pp. 31–40). Springer. https://doi.org/10.1007/978-3-642-23957-1_4

Verplanken, B., & Orbell, S. (2003). Reflections on Past Behavior: A Self-Report Index of Habit Strength1. *Journal of Applied Social Psychology*, *33*(6), 1313–1330. https://doi.org/10.1111/j.1559-1816.2003.tb01951.x

Vrabel, J. K., & Zeigler-Hill, V. (2020). Conscious Versus Unconscious Determinants of Behavior. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of Personality and Individual Differences* (pp. 855–858). Springer International Publishing. https://doi.org/10.1007/978-3-319-24612-3_1124

Watson, D. (2013). Bioclimatic Design. *Springer, New York, NY*. https://doi.org/10.1007/978-1-4614-5828-9_225

Wilson, B. (2013). Urban form and residential electricity consumption: Evidence from Illinois, USA. *Landscape and Urban Planning*, *115*, 62–71. https://doi.org/10.1016/j.landurbplan.2013.03.011

Zakeri, B., Paulavets, K., Barreto-Gomez, L., Echeverri, L. G., Pachauri, S., Boza-Kiss, B., Zimm, C., Rogelj, J., Creutzig, F., Ürge-Vorsatz, D., Victor, D. G., Bazilian, M. D., Fritz, S., Gielen, D., McCollum, D. L., Srivastava, L., Hunt, J. D., & Pouya, S. (2022). Pandemic, War, and Global Energy Transitions. *Energies*, *15*(17). Scopus. https://doi.org/10.3390/en15176114

Acknowledgements

I would like to express my deepest gratitude and appreciation to all those who have supported me throughout the process of completing my master's thesis. First and foremost, I would like to thank my university supervisor, Dr Tina Venema, for her guidance, expert insights, feedback, and encouragements during the past eight months. Her supervision played a crucial role in the completion of this thesis. It was a pleasure to work with her. Further, I would like to thank the second reader of this thesis, Dr Wen Liu, for her time in reviewing my work. I am also thankful for the support from my internship supervisor, Agnieszka Biedalak, the Head of Research and Innovation at Space&Matter (Amsterdam). Her expert knowledge of the built environment and practical feedback helped to shape this research. I extend my sincere appreciation to the team of Space&Matter in general, who has participated in group discussions and provided architectural knowledge to this research. Further, I would like to thank all participants that took time to share their valuable experiences in the survey questionnaire. Without their participation, this research would not have been possible. Finally, I am incredibly thankful for the support from friends and family, who have helped me incredibly during the survey distribution phase of this research and have provided encouragement and strength throughout this journey.

Although it is impossible to mention everyone individual, please know that your contributions have not gone unnoticed and are deeply appreciated. Thank you all for having been part of this journey and the role you have played in it.

Wednesday, 5th of July 2023

Anne-Jil Clohse

Appendices

Appendix A: Overview of all Variables

Legend:

- Variables that are numbered are used in the statistical analyses directly. The other variables have other uses more precisely described in the column "Use".
- Variables that are highlighted are variables for which the calculation is described more precisely in Appendix C.

	Variable	Type	Survey/ Datapoint	Description	Example	Use
Control (Basic Demographics)						
1	***Age***	Numeric Continuous	Text entry	Age of participant in years	24 years	Control
2	***Gender***	Categorical Nominal	MCQ	Gender of participant: Male, Female, Other, Prefer not to say	"Female"	Control
3	***TimeNL***	Numeric Continuous	Computed (Appendix C)	Time lived in the Netherlands by participant	1,4 years (1 year 5 months)	Control
	TimeNL_YR	Numeric Continuous	Form field (text entry)	Years lived in NL	1 year	Used to calculate TimeNL
	TimeNL_MO	Numeric Continuous	Form field (text entry)	Months lived in NL	5 months	Used to calculate TimeNL
4	***City***	Categorical Nominal	Text entry	City in which participant lives	Amsterdam	Control & Used to find local climatic data for the bioclimatic conditions.
5	***NbWorkHours***	Numeric Continuous	Text entry	Average number of hours worked per month	45 hours	Control
6	***Finances***	Categorical Ordinal	MCQ	Description of financial situation of the participant	"Spent some savings"	Control
Control (Energy Efficiency)						

7	***EnergyLabel***	Categorical Ordinal	EP-Online	The energy label of the building the participant lives in. It is determined using the following variables: City, HouseCorp, NameBuilding and/or PostCode.	Energy label B	Control
	HouseCorp	Categorical Nominal	MCQ	The housing corporation that owns the building the participant lives in.	SSH	Used to find the energy label of the building the participant lives in.
	NameBuilding	Categorical Nominal	Text entry	Name of the building the participant lives in.	Johanna	Used to find the energy label of the building the participant lives in.
	PostCode	Categorical Nominal	Text entry	The postcode and house number of the building the participant lives in separated by a “ , “.	3584SB, 29	Used to find the energy label of the building the participant lives in.
Outcome (Energy Behaviour)						
8	***EnergyBehaviour Score***	Numeric Continuous	Computed (Appendix C)	The score indicating how energy-consuming the behaviour of an occupant is. The higher the score, the more energy-consuming the behaviour.	4.7	Outcome
	EB_Oven	Numeric discrete	MCQ (Likert 5)	Frequency of use of oven per week	“On 1-2 days”	Computation of EnergyBehaviourScore
	EB_Microwave	Numeric discrete	MCQ (Likert 5)	Frequency of use of microwave per week	“On 1-2 days”	Computation of EnergyBehaviourScore
	EB_Dishwasher	Numeric discrete	MCQ (Likert 5)	Frequency of use of dishwasher per week	“On 1-2 days”	Computation of EnergyBehaviourScore

	EB_Laundry	Numeric discrete	MCQ (Likert 5)	Frequency of use of laundry machine per week	“On 1-2 days”	Computation of EnergyBehaviourScore
	EB_Dryer	Numeric discrete	MCQ (Likert 5)	Frequency of use of dryer per week	“On 1-2 days”	Computation of EnergyBehaviourScore
	EB_Hairdryer	Numeric discrete	MCQ (Likert 5)	Frequency of use of hairdryer per week	“On 1-2 days”	Computation of EnergyBehaviourScore
	EB_KettleCoffee	Numeric discrete	MCQ (Likert 5)	Frequency of use of electric kettle or coffee machine per day	“2 times/day”	Computation of EnergyBehaviourScore
	EB_TV	Numeric discrete	MCQ (Likert 5)	Frequency of use of TV per day	“2 times/day”	Computation of EnergyBehaviourScore
	EB_LightDay	Numeric discrete	MCQ (Likert 5)	Time period lights are turned on during daytime per day	“2-3 hours per day”	Computation of EnergyBehaviourScore
	EB_LightNight	Numeric discrete	MCQ (Likert 5)	Time period lights are turned on during evening per day	“2-3 hours per day”	Computation of EnergyBehaviourScore
	EB_StandBy	Numeric discrete	MCQ (Likert 5)	How many appliances are usually put on standby	“More than half of them”	Computation of EnergyBehaviourScore
	EB_Clothes	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Putting on clothes when cold	“Somewhat agree”	Computation of EnergyBehaviourScore.
	EB_Heater	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Turning up the heater when cold	“Somewhat agree”	Computation of EnergyBehaviourScore
	EB_Curtains	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Closing curtains to keep cold out	“Somewhat agree”	Computation of EnergyBehaviourScore
	EB_Doors	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Forgetting to close doors	“Somewhat agree”	Computation of EnergyBehaviourScore

	EB_Windows	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Forgetting to close windows	"Somewhat agree"	Computation of EnergyBehaviourScore
	EB_LightsForgotten	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Forgetting to turn off lights	"Somewhat agree"	Computation of EnergyBehaviourScore
	EB_BackgroundNoise	Numeric discrete	MCQ (Likert 5)	Disagree/Agree: Leaving TV/Radio/Music Box/Laptop on for background noise	"Somewhat agree"	Computation of EnergyBehaviourScore
	EB_HomeWeekTOT	Numeric Continuous	Matrix in survey Computed (Appendix C)	Score that indicates how much a participant is home during the week on a scale from 1 to 5.	3.5	Computation of EnergyBehaviourScore
Predictor (Bioclimatic conditions)						
9	***Orientation***	Categorical Nominal	MCQ	The orientation of the home of the participant in the building. They can check multiple. See BC_OrN to BC_OrNW.		
10	*BC_OrN*	Binary dummy	(Yes/No)	Northern orientation	Yes	Predictor
11	*BC_OrNE*	Binary dummy	(Yes/No)	North-Eastern orientation	Yes	Predictor
12	*BC_OrE*	Binary dummy	(Yes/No)	Eastern orientation	Yes	Predictor
13	*BC_OrSE*	Binary dummy	(Yes/No)	South-Eastern orientation	Yes	Predictor
14	*BC_OrS*	Binary dummy	(Yes/No)	Southern orientation	No	Predictor
15	*BC_OrSW*	Binary dummy	(Yes/No)	South-Western orientation	No	Predictor
16	*BC_OrW*	Binary dummy	(Yes/No)	Western orientation	No	Predictor
17	*BC_OrNW*	Binary dummy	(Yes/No)	North-Western orientation	No	Predictor

18	***Shading***	Categorical Ordinal	MCQ (Likert 5)	The extent to which their home is shaded by vegetation or another element.	4	Predictor
19	***ArtificialLight***	Categorical Ordinal	MCQ (Likert 5)	The extent to which they need artificial light.	4	Predictor
20	***SolarRad***	Numeric continuous	>TU Delft Weather data portal	In combination with City, the local solar irradiation (amount of incoming sun). In kWh/(m^2day).	14.03	Predictor
21	***AmbTemp***	Numeric continuous	>TU Delft Weather data portal	In combination with City, the local ambient temperature. In °C.	8.64	Predictor
22	***WindSpeed***	Numeric continuous	>TU Delft Weather data portal	In combination with City, the local wind speed. In m/s.	4.715	Predictor
Predictor (Habits)						
23	***HabitScore***	Numeric continuous	Computed (Appendix C)	A score indicating how habitual the participant's behaviour is.	3.7	Predictor
	HabitHeater_Fr	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning the heater up when cold (Frequency)	Somewhat agree	Computation of HabitScore
	HabitHeater_Auto	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning the heater up when cold (Automaticity)	Somewhat agree	Computation of HabitScore
	HabitHeater_ID	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning the heater up when cold (Identity)	Somewhat agree	Computation of HabitScore
	HabitShower_Fr	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Taking a hot shower before or after a day (Frequency)	Somewhat agree	Computation of HabitScore
	HabitShower_Auto	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Taking a hot shower	Somewhat agree	Computation of HabitScore

				before or after a day (Automaticity)		
	HabitShower_ID	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Taking a hot shower before or after a day (Identity)	Somewhat agree	Computation of HabitScore
	HabitLight_Fr	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on a light when entering a room (Frequency)	Somewhat agree	Computation of HabitScore
	HabitLight_Auto	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on a light when entering a room (Automaticity)	Somewhat agree	Computation of HabitScore
	HabitLight_ID	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on a light when entering a room (Identity)	Somewhat agree	Computation of HabitScore
	HabitDevices_Fr	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on devices for background noise (Frequency)	Somewhat agree	Computation of HabitScore
	HabitDevices_Auto	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on devices for background noise (Automaticity)	Somewhat agree	Computation of HabitScore
	HabitDevices_ID	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Turning on devices for background noise (Identity)	Somewhat agree	Computation of HabitScore
Predictor (Moral Licensing)						
	EnergyInvest	Categorical Nominal	Yes/No	Investments into energy efficiency	Yes	Not used in data analysis, serves as reminders of pro-environmental behaviour to participants as a trigger for moral licensing.
	Meat	Categorical Nominal	Yes/No	Stopping/decreasing meat consumption	Yes	Idem EnergyInvest

	Bulk	Categorical Nominal	Yes/No	Buying in bulk/avoiding packaging	Yes	Idem EnergyInvest
	EnergyCons	Categorical Nominal	Yes/No	Conversations about energy conversation	Yes	Idem EnergyInvest
	DryerUse	Categorical Nominal	Yes/No	Using a clothes dryer	Yes	Idem EnergyInvest
	Recycling	Categorical Nominal	Yes/No	Recycling waste	Yes	Idem EnergyInvest
	AirTravel	Categorical Nominal	Yes/No	Avoiding flying as much as possible	Yes	Idem EnergyInvest
24	***MoralLicensingScore***	Numeric continuous	Computed (Appendix C)	The score indicating to what extent the participant is using moral licensing.	3.7	Predictor
	ML_Indulge	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Participant is entitled to indulge themselves from time to time even if it's not the best for the environment	Somewhat agree	Computation of MoralLicensingScore
	ML_Strictness	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: It's okay to be stricter in some areas than other for pro-environmental behaviour	Somewhat agree	Computation of MoralLicensingScore
	ML_Offset	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Bad environmental behaviour can be offset by pro-environmental behaviour in another area	Somewhat agree	Computation of MoralLicensingScore
	ML_Standby	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: It's okay to leave energy efficient appliances on standby	Somewhat agree	Computation of MoralLicensingScore
	ML_NoDishwasher	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Not using a dishwasher can make up for longer showers	Somewhat agree	Computation of MoralLicensingScore

	ML_Vegetarian	Numeric discrete	MCQ (Likert 5)	Agree/Disagree: Eating vegetarian can compensate for more driving	Somewhat agree	Computation of MoralLicensingScore

Appendix B: Survey Questionnaire

The following survey has been made using Qualtrics.

Start of Block: Introduction

Eligibility Hello there!

Before introducing the topic of my research, let's make sure you are eligible to participate in this survey. Answer the following three questions and you're good to go! (All data is anonymised and treated confidentially according to the GDPR).

Eligibility1 Are you a student?

- ○ Yes (1)
- ○ No (2)

Skip To: End of Survey If Are you a student? = No

Eligibility2 Do you live by yourself? (meaning without any housemates)

- ○ Yes (1)
- ○ No (2)

Skip To: End of Survey If Do you live by yourself? (meaning without any housemates) = No

Eligibility3 Do you live in the Netherlands in a building of a housing corporation (e.g., the SSH, DUWO, Xior etc.)?

- ○ Yes (1)
- ○ No (2)

Skip To: End of Survey If Do you live in the Netherlands in a building of a housing corporation (e.g., the SSH, DUWO, Xior... = No

Introduction If you are reading this, congrats: You passed the eligibility test!

Thank you for taking the time to read and fill out this survey. As part of my master’s thesis, I am researching how certain aspects (psychological and physical) influence **energy consumption behaviour**. This survey takes approximately 15-20min to complete and provides guidance on how to answer questions. Note that it is best to fill out this survey from home, as there are questions regarding physical features of your home.

Those who fill out the survey can participate in a **giveaway** draw separate from this survey (to ensure anonymity of results). In total, **3 people** will be drawn for the giveaway and will each receive a **50€ voucher for bol.com**. At the end, you will have the opportunity to obtain the results of this research. For any questions you can email me (Anne-Jil Clohse), the researcher, at **a.clohse@students.uu.nl.**

Participation in this survey is voluntary and you can quit the survey at any time without giving a reason and without penalty. Your answers to the questions will be shared with the research team. We will process your personal data confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act). All data will be reported as summaries across participants. Please respond to the questions honestly and feel free to say or write anything you like.

Thank you for your participation!

Informed consent

I confirm that:

- I am satisfied with the received information about the research.
- I have no further questions about the research at this moment.
- I had the opportunity to think carefully about participating in the study.
- I will give an honest answer to the questions asked.

I agree that:

- the data to be collected will be obtained and stored for scientific purposes.
- the collected, completely anonymous, research data can be shared and re-used by scientists to answer other research questions.

I understand that:

- I have the right to withdraw my consent to use the data as long as they can be identified.
- I have the right to see the research report afterwards.

Do you agree to participate?

○ Yes (1)

○ No (2)

Skip To: End of Survey If I confirm that: I am satisfied with the received information about the research; I have no further... = No

End of Block: Introduction

Start of Block: Basic demographics

Introduction **Basic demographics**

Reminder: All information is handled confidentially according to the GDPR.

Age What is your age (in years)?

____

Gender What is your gender?

- ○ Male (1)
- ○ Female (2)
- ○ Other (3)
- ○ Prefer not to say (4)

TimeNL How long have you been living in the Netherlands? (in years and months)

If you have lived in the Netherlands for 4 years and 5 months, write "4" in the first field, then "5" in the second. If it has been less than a year, write "0" in the first field and the number of months in the second field.

- ○ Years (1) ____
- ○ Months (10) ____

City In which city in the Netherlands do you currently live?

Write for example *"Amsterdam"*

____

NbWorkHours How many hours do you work on average per month (at a side job, to earn money next to your studies)?

Write for example "52" for 52 hours per month. If you do not have a side job/don't earn money on the side, write "0".

____

Finances How would you best describe your financial situation over this last year? During the past year, I ...

- ○ Saved money (2)
- ○ Just got by (3)
- ○ Spent some savings (4)
- ○ Spent savings and borrowed money (5)
- ○ Prefer not to say (6)

End of Block: Basic demographics

Start of Block: Building energy efficiency

Introduction **Building energy efficiency**

In order for me to find out which energy label the building you currently live in has, I need information on the housing corporation the building belongs to and the name of the building. All information given by you is handled confidentially according to the GDPR.

HouseCorp Which housing corporation owns the building you live in?

- ○ SSH (1)
- ○ Holland2Stay (2)
- ○ DUWO (3)
- ○ Xior (4)
- ○ Canvas (5)
- ○ The Fizz (6)
- ○ Other (7)

Skip To: NameBuilding If Which housing corporation owns the building you live in? != Other

HouseCorp2 You selected "Other" in the previous question. Please specify which housing corporation owns your building.

____

NameBuilding What is the name of the building you live in?

Write for example "Johanna" for the building on Bisschopssteeg in Utrecht from the SSH. Write **N/A** if you are giving the postcode and house number in the following question instead.

____

PostCode If you do not know the name of the building you live in, you can also alternatively give the postcode and house number of the building.

Write for example "3584SB, 29" for the postcode 3584 SB and the house number 29 (separated by a " , "). Write **N/A** if you have given the name of your building.

____

End of Block: Building energy efficiency

Start of Block: Energy behaviour

Introduction **Energy behaviour**

In the following section, multiple questions around behaviour in your home will be asked. This is important to better understand occupant behaviour and to assess it. While answering the following questions, take into account your behaviour in the building you currently live in as a student in the Netherlands.

<u>Keep the last 4-8 weeks as a reference for your behaviour (March and April 2023) when answering these questions.</u>

EB_Oven How often do you use the oven per week approx.?

If you do not own said appliance, you can check the box "Never".

- ○ Never (1)
- ○ On 1-2 days (2)
- ○ On 3-4 days (3)
- ○ On 5-6 days (4)
- ○ Every day (5)

EB_Microwave How often do you use the microwave per week approx.?

If you do not own said appliance, you can check the box "Never".

- ○ Never (1)
- ○ On 1-2 days (2)
- ○ On 3-4 days (3)
- ○ On 5-6 days (4)
- ○ Every day (5)

EB_Dishwasher How often do you use the dishwasher per week approx.?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- On 1-2 days (2)
- On 3-4 days (3)
- On 5-6 days (4)
- Every day (5)

EB_Laundry How often do you use the laundry machine per week approx.?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- On 1-2 days (2)
- On 3-4 days (3)
- On 5-6 days (4)
- Every day (5)

EB_Dryer How often do you use the dryer per week approx.?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- On 1-2 days (2)
- On 3-4 days (3)
- On 5-6 days (4)
- Every day (5)

EB_Hairdryer How often do you use a hairdryer per week?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- On 1-2 days (2)
- On 3-4 days (3)
- On 5-6 days (4)
- Every day (5)

EB_KettleCoffee How often do you use the electric kettle/coffee machine per day approx.?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- 1 time/day (2)
- 2 times/day (3)
- 3 times/day (4)
- 4+ times/day (5)

EB_TV How long do you watch TV per day approx.?

If you do not own said appliance, you can check the box "Never".

- Never (1)
- < 1 hour/day (2)
- 2 hours/day (3)
- 3 hours/day (4)
- 4+ hours/day (5)

EB_LightDay For how long are the rooms of your home lit during the daytime (when it is light outside)?

If you never turn on your lights during daytime, you can check the box "Never".

- Never (1)
- 0-1 hour/day (2)
- 2-3 hours/day (3)
- 4-5 hours/day (4)
- 6+ hours/day (5)

EB_LightNight For how long are the rooms of your home lit during the evening/night (when the sun sets)?

If you never turn on your lights during evening/night, you can check the box "Never".

- Never (1)
- 0-1 hour/day (2)
- 2-3 hours/day (3)
- 4-5 hours/day (4)
- 6+ hours/day (5)

EB_StandBy How many of your appliances do you put on stand-by (instead of turning them off)?

- None (1)
- Less than half of them (2)
- About half of them (3)
- More than half of them (4)
- All of them (5)

IntroStatements In the following part, different statements are given, and you are asked to agree/disagree with them on the basis of how well it applies to your own behaviour. The less likely you are to do it, the more you disagree (and vice versa).

Remember to take the last 4-8 weeks as a reference for your behaviour.

EB_Clothes "If I am feeling cold, I put on more clothes"

- Strongly disagree (5)
- Somewhat disagree (4)
- Neither agree nor disagree (3)
- Somewhat agree (2)
- Strongly agree (1)

EB_Heater "If I am feeling cold, I turn up my heater"

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

EB_Curtains "I close the curtains in the evening or when it is cold to avoid incoming cold/humidity"

If you do not have curtains, select "strongly disagree". If you close them, but for other reasons unrelated to energy savings, also select "strongly disagree".

- Strongly disagree (5)
- Somewhat disagree (4)
- Neither agree nor disagree (3)
- Somewhat agree (2)
- Strongly agree (1)

EB_Doors "I sometimes leave doors open behind me when I enter a room"

In case you live in a studio with only one room, select "strongly disagree".

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

EB_Windows "I leave windows open for longer than 15min to air out my home"

- Never (1)
- Sometimes (2)
- About half the time (3)
- Most of the time (4)
- Always (5)

EB_LightsForgotten "I sometimes leave lights on when I leave the house"

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

EB_BackgroundNoise "I leave the TV/radio/music box/laptop on for background noise while doing something else at home"

For example, while cleaning, studying, washing the dishes, etc.

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

EB_HomeWeekTOT In a typical week, how much time do you spend at home on average?

Indicate in the following matrix when you are usually home (you can check multiple per day).

The days don't play a very big role, it is more about how much time you spend at home in total. If you know you are not home 2 days/week usually, it doesn't matter which days you do not check.

	Monday (1)	Tuesday (2)	Wednesday (3)	Thursday (4)	Friday (5)	Saturday (6)	Sunday (7)
Morning (***HomeWeek_Morning***)	o	o	o	o	o	o	o
Afternoon (***HomeWeek_Afternoon***)	o	o	o	o	o	o	o
Evening (***HomeWeek_Evening***)	o	o	o	o	o	o	o
Night (***HomeWeek_Night***)	o	o	o	o	o	o	o

End of Block: Energy behaviour

Start of Block: Bioclimatic conditions

Introduction **Physical features and environmental context of your building**

The physical features of your home and its local environmental context can have an influence on how you use energy. Therefore, I need some insights from you on those. While answering the following questions, refer to the building you currently live in as a student in the Netherlands.

Orientation When you look outside the window(s) of you living space, which direction (N, E, S, W) are you looking at?

Choose multiple if your living spaces are on multiples sides of the building (e.g., on a corner).

iPhones should have an integrated compass app. You can find free compass apps on the AppStore (iPhone) or GooglePlay (Android). Alternatively, you can use an online compass (see websites below). Note that not every smartphone and very few laptops have magnetic sensors built in, so this compass will not work on every device.

Online Compass:

https://bytetool.web.app/en/compass/
https://lamplightdev.github.io/compass/

- ▢ North (1)
- ▢ North-East (2)
- ▢ East (3)
- ▢ South-East (4)
- ▢ South (5)
- ▢ South-West (6)
- ▢ West (7)
- ▢ North-West (8)

Shading To what extent do vegetation (e.g., a tree) or other elements (e.g., another building) shade either the façade or windows of your living spaces?

(from 1 = "not shaded at all" to 5 "completely shaded")

- ○ 1 (1)
- ○ 2 (2)
- ○ 3 (3)
- ○ 4 (4)
- ○ 5 (5)

ArtificialLight How much natural daylight do you have in your main living spaces? Provided you were to stay at home and work from there the whole day, indicate to what extent you (do not) need extra artificial light.

(from 1= “only need artificial light when it is dark out”, to 5 = “need artificial light at all times”).

- 1 (1)
- 2 (2)
- 3 (3)
- 4 (4)
- 5 (5)

End of Block: Bioclimatic conditions

Start of Block: Habits

Introduction **Psychological mechanisms I (Habits)**

To determine how habitual your behaviour is, you are asked to react to multiple statements relating to different behaviours within buildings. For each statement you are asked to agree/disagree on how frequently and automatically you do these things and how weird it would make you feel **not** to do them.

When answering these questions, keep the last 4-8 weeks as a reference in mind and answer truthfully.

HabitHeater "Turning up the heater when feeling cold is something..."

Indicate to what extent you agree/disagree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do frequently (***HabitHeater_Fr***)	○	○	○	○	○
I do automatically (***HabitHeater_Auto***)	○	○	○	○	○
That makes me feel weird if I do not do it. (***HabitHeater_ID***)	○	○	○	○	○

HabitShower "Taking a warm shower before starting the day or at the end of the day is something..."

Indicate to what extent you agree/disagree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do frequently (***HabitShower_Fr***)	○	○	○	○	○
I do automatically (***HabitShower_Auto***)	○	○	○	○	○
That makes me feel weird if I do not do it. (***HabitShower_ID***)	○	○	○	○	○

HabitLight "Turning the light on when entering a room is something..."

Indicate to what extent you agree/disagree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do frequently (***HabitLight_Fr***)	○	○	○	○	○
I do automatically (***HabitLight_Auto***)	○	○	○	○	○
That makes me feel weird if I do not do it. (***HabitLight_ID***)	○	○	○	○	○

HabitDevices "Turning on the TV, the radio or another device for background noise is something..."

Indicate to what extent you agree/disagree.

	Strongly disagree (1)	Somewhat disagree (2)	Neither agree nor disagree (3)	Somewhat agree (4)	Strongly agree (5)
I do frequently (***HabitDevices_Fr***)	○	○	○	○	○
I do automatically (***HabitDevices_Auto***)	○	○	○	○	○
That makes me feel weird if I do not do it. (***HabitDevices_ID***)	○	○	○	○	○

End of Block: Habits

Start of Block: Moral licensing

Introduction **Psychological mechanisms II**

Indicate (Yes/No) whether the following statements apply to your situation. It is not a question of frequency but rather statements that apply generally. Keep in mind what applies to your current living spaces/situation.

<u>When answering these questions, keep the last 4-8 weeks as a reference in mind (March and April 2023) and answer truthfully.</u>

EnergyInvest *"I have invested into energy efficient lighting in my (studio) apartment/room (e.g., switched to LEDs)."*

- ○ Yes (1)
- ○ No (2)

Meat *"I have stopped or decreased my meat consumption."*

- ○ Yes (1)
- ○ No (2)

Bulk *"I try to buy in bulk what I can (and avoid packaging where I can)."*

- ○ Yes (1)
- ○ No (2)

EnergyCons *"I have conversations about energy conservation with friends and/or family."*

- ○ Yes (1)
- ○ No (2)

DryerUse *"I use a clothes dryer."*

- ○ Yes (1)
- ○ No (2)

Recycling *"I recycle."*

- ○ Yes (1)
- ○ No (2)

AirTravel *"I avoid flying as much as possible."*

- ○ Yes (1)
- ○ No (2)

Introduction **Psychological mechanisms III**

ML_Indulge "I am entitled to indulge myself in something that is not entirely exemplary from an environmental perspective occasionally."

- ○ Strongly disagree (1)
- ○ Somewhat disagree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat agree (4)
- ○ Strongly agree (5)

ML_Strictness "When it comes to climate-relevant behaviour, it's OK if I'm less strict with myself in some areas than in others."

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

ML_Offset "Behaviour that is not so beneficial for the climate can be offset by environmentally friendly deeds elsewhere."

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

ML_Standby "If you have energy-efficient appliances, it's okay to leave them on standby."

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

ML_NoDishwasher "Not using a dishwasher can make up for longer showers."

- Strongly disagree (1)
- Somewhat disagree (2)
- Neither agree nor disagree (3)
- Somewhat agree (4)
- Strongly agree (5)

ML_Vegetarian "A vegetarian diet can compensate for more frequent driving."

- ○ Strongly disagree (1)
- ○ Somewhat disagree (2)
- ○ Neither agree nor disagree (3)
- ○ Somewhat agree (4)
- ○ Strongly agree (5)

End of Block: Moral licensing

Start of Block: FeedbackResults

Feedback Are there any aspects (personal preferences, aspects of your home, culture etc.) that influence your energy consumption that have not been addressed in this survey?

____

Results You can obtain the results of this research by sending an email to **a.clohse@students.uu.nl** with the subject **"Bioclimatic conditions and behaviour thesis"**. You will then receive an email back once the research is completed.

End of Block: FeedbackResults

Start of Block: Giveaway

Congrats, you did it! Now it's time to enter the giveaway draw if you'd like!

Introduction **Giveaway**

As announced at the start of this survey, you get the chance to win a prize by participating in a giveaway draw. **3 people** will be drawn randomly out of the participants of the giveaway, who will each win a prize worth **50€**. The giveaway is organized in a separate survey so as to guarantee that the responses of the main survey remain **anonymized**. All data is handled according to the GDPR.

Consent Would you like to participate in the giveaway of this research?

By clicking "Yes" you will be brought to a separate website for the giveaway. If you click "No" you will simply be brought to the end of this survey.

- ○ Yes (1)
- ○ No (2)

End of Block: Giveaway

Appendix C: Calculation of Variables

C1 Computation of TimeNL

TimeNL is the continuous variable that describes how long participants have lived in the Netherlands (in years). Participants were asked to answer how many years (*TimeNL_YR*) and months (*TimeNL_MO*) they had been living in the Netherlands. *TimeNL_YR* and *TimeNL_MO* are used to calculate *TimeNL* in the following way:

$$TimeNL = TimeNL\_YR + \left(\frac{TimeNL\_MO}{12}\right)$$

C2 Computation of EnergyBehaviourScore

EnergyBehaviourScore is an average of scores from 19 variables concerning occupant behaviour related to energy consumption. After the different variables have been re-coded from categorical ordinal to numeric discrete ones, the variable *EnergyBehaviourScore* is calculated as follows:

$$\begin{aligned} &EnergyBehaviourScore \\ &\quad = \frac{1}{19}(EB\_Oven + EB\_Microwave + EB\_Dishwasher + EB\_Laundry \\ &\quad + EB\_Dryer + EB\_Hairdryer + EB\_KettleCoffee + EB\_TV + EB\_LightDay \\ &\quad + EB\_LightNight + EB\_StandBy + EB\_Clothes + EB\_Heater + EB\_Curtains \\ &\quad + EB\_Doors + EB\_Windows + EB\_LightsForgotten + EB\_BackgroundNoise \\ &\quad + EB\_HomeWeekTOT) \end{aligned}$$

The variable is continuous and measured on a scale from 1 to 5 with 1 indicating the least energy consuming behaviour possible and 5 the most.

C3 Computation of EB_HomeWeekTOT

EB_HomeWeekTOT is calculated by taking the average of 28 variables and multiplying it by 5 such that it is measured on a continuous scale from 0 to 5. The 28 variables are created by Qualtrics when using a matrix question with multiple checkboxes. The question that participants are asked to answer is the following:

EB_HomeWeek In a typical week, how much time do you spend at home on average?

Indicate in the following matrix when you are usually home (you can check multiple per day).

The days don't play a very big role, it is more about how much time you spend at home in total. If you know you are not home 2 days/week usually, it doesn't matter which days you do not check.

	Monday (1)	Tuesday (2)	Wednesday (3)	Thursday (4)	Friday (5)	Saturday (6)	Sunday (7)
Morning (***EB_HomeWeek_Morning***)	o	o	o	o	o	o	o
Afternoon (***EB_HomeWeek_Afternoon***)	o	o	o	o	o	o	o
Evening (***EB_HomeWeek_Evening***)	o	o	o	o	o	o	o
Night (***EB_HomeWeek_Night***)	o	o	o	o	o	o	o

Hence, for each day of the week, 4 variables are created to indicate whether or not a participant is usually home at that time, i.e., 1 if Yes and 0 if No. The formula of ***EB_HomeWeekTOT*** is then:

$$
\begin{aligned}
EB\_HomeWeekTOT \\
= \frac{5}{28}(&\mathrm{EB}_{HomeWeek_{MONMorning}} + \mathrm{EB}_{HomeWeek_{MONAfternoon}} + \mathrm{EB}_{HomeWeek_{MONEvening}} \\
&+ \mathrm{EB}_{HomeWeek_{MONNight}} + \mathrm{EB}_{HomeWeek_{TUEMorning}} + \mathrm{EB}_{HomeWeek_{TUEAfternoon}} \\
&+ \mathrm{EB}_{HomeWeek_{TUEEvening}} + \mathrm{EB}_{HomeWeek_{TUENight}} + \mathrm{EB}_{HomeWeek_{WEDMorning}} \\
&+ \mathrm{EB}_{HomeWeek_{WEDAfternoon}} + \mathrm{EB}_{HomeWeek_{WEDEvening}} + \mathrm{EB}_{HomeWeek_{WEDNight}} \\
&+ \mathrm{EB}_{HomeWeek_{THUMorning}} + \mathrm{EB}_{HomeWeek_{THUAfternoon}} + \mathrm{EB}_{HomeWeek_{THUEvening}} \\
&+ \mathrm{EB}_{HomeWeek_{THUNight}} + \mathrm{EB}_{HomeWeek_{FRIMorning}} + \mathrm{EB}_{HomeWeek_{FRIAfternoon}} \\
&+ \mathrm{EB}_{HomeWeek_{FRIEvening}} + \mathrm{EB}_{HomeWeek_{FRINight}} + \mathrm{EB}_{HomeWeek_{SATMorning}} \\
&+ \mathrm{EB}_{HomeWeek_{SATAfternoon}} + \mathrm{EB}_{HomeWeek_{SATEvening}} + \mathrm{EB}_{HomeWeek_{SATNight}} \\
&+ \mathrm{EB}_{HomeWeek_{SUNMorning}} + \mathrm{EB}_{HomeWeek_{SUNAfternoon}} + \mathrm{EB}_{HomeWeek_{SUNEvening}} \\
&+ \mathrm{EB}_{HomeWeek_{SUNNight}})
\end{aligned}
$$

C4 Computation of HabitScore

After all the variables concerning how habitual behaviour is have been re-coded from categorical ordinal to numeric discrete variables, the variable ***HabitScore*** is calculated as an average of these variables:

$$\begin{aligned}HabitScore = \frac{1}{12}(&HabitHeater\_Fr + HabitHeater\_Auto + HabitHeater\_ID \\ &+ HabitShower\_Fr + HabitShower\_Auto + HabitShower\_ID + HabitLight\_Fr \\ &+ HabitLight\_Auto + HabitLight\_ID + HabitDevices\_Fr \\ &+ HabitDevices\_Auto + HabitDevices\_ID)\end{aligned}$$

C5 Computation of MoralLicensingScore

After the different variables used to calculate ***MoralLicensingScore*** have been re-coded from categorical ordinal to numeric discrete variables, ***MoralLicensingScore*** is calculated as an average of these:

$$\begin{aligned}&MoralLicensingScore \\ &\quad = \frac{1}{6}(ML_{Indulge} + ML_{Strictness} + ML_{Offset} + ML_{Standby} + ML_{NoDishwasher} \\ &\quad + ML_{Vegetarian})\end{aligned}$$

Appendix D: Descriptive statistics overview

Table D1 *Descriptive Statistics of EnergyBehaviourScore (Dependent Variable)*

N	*Valid*	530
	Missing	0
Mean		2.28
Std. Error of Mean		.01
Median		2.24
Mode		2.08[a]
Std. Deviation		0.31
Variance		0.10
Skewness		0.31
Std. Error of Skewness		.11
Kurtosis		0.36
Std. Error of Kurtosis		.21
Range		1.98
Minimum		1.38
Maximum		3.36
Sum		1,207.46

[a]Multiple modes exist. The smallest value is shown

Table D2 *Descriptive Statistics of HabitScore & MoralLicensingScore (Independent Variables)*

		HabitScore	***MoralLicensingScore***
N	*Valid*	530	530
	Missing	0	0
Mean		2.90	2.80
Std. Error of Mean		.030	.03
Median		3.00	2.83
Mode		3.00	3.33
Std. Deviation		0.70	0.70
Variance		0.50	0.43
Skewness		-0.20	-0.16
Std. Error of Skewness		.11	.11
Kurtosis		-0.31	-0.40
Std. Error of Kurtosis		.21	.21
Range		3.67	3.50
Minimum		1.00	1.00
Maximum		4.67	4.50
Sum		1,539.58	1,481.17

Table D3 *Descriptive Statistics of Age, TimeNL and NbWorkHours (Control Variables)*

		Age	*TimeNL*	*NbWorkHours*
N	*Valid*	530	528	530
	Missing	0	2	0
Mean		23.21	13.19	18.41
Std. Error of Mean		.13	.48	1.08
Median		23.00	18.08	6.00
Mode		23	0.67	0
Std. Deviation		3.07	11.08	24.87
Variance		9.43	122.76	618.50
Skewness		0.72	-0.01	1.49
Std. Error of Skewness		.11	.11	.11
Kurtosis		0.98	-1.86	1.74
Std. Error of Kurtosis		.21	.21	.21
Range		20	30.83	120
Minimum		17	0.17	0
Maximum		37	31.00	120
Sum		12,303	6,961.42	9,756

Table D4 *Descriptive Statistics of Shading, ArtificialLight, SolarRad, AmbTemp and WindSpeed*

		Shading	*ArtificialLight*	*SolarRad*	*AmbTemp*	*WindSpeed*
N	*Valid*	530	530	530	530	530
	Missing	0	0	0	0	0
Mean		1.65	2.09	136.08	7.92	4.32
Std. Error of Mean		.05	.05	.28	.01	.02
Median		1.00	2.00	134.53	8.07	4.46
Mode		1	1	135.38	8.10	4.53
Std. Deviation		1.06	1.11	6.43	0.32	0.53
Variance		1.12	1.23	41.38	0.10	0.28
Skewness		1.56	0.86	1.12	-1.14	1.40
Std. Error of Skewness		.11	.11	.11	.106	.11
Kurtosis		1.46	-0.02	-0.18	0.49	6.76
Std. Error of Kurtosis		.21	.212	.21	.21	.21
Range		4	4	19.30	1.12	3.68
Minimum		1	1	129.05	7.16	3.40
Maximum		5	5	148.34	8.28	7.08
Sum		876	1,108	72,121.53	4,194.95	2,288.51

Appendix E: Frequencies and Percentages

Table E1 *Frequencies and Percentages of Gender*

Gender		f	%	Valid %	Cumulative %
Valid	*1 (Male)*	218	41.1	41.7	41.7
	2 (Female)	293	55.3	56.0	97.7
	3 (Other)	12	2.3	2.3	100.0
	Total	523	98.7	100.0	
Missing	*4 (Prefer not to say)*	7	1.3		
Total		530	100.0		

Table E2 *Frequencies and Percentages of Finances*

Finances		f	%	Valid %	Cumulative %
Valid	*1 (Saved money)*	122	23.0	24.0	24.0
	2 (Just got by)	141	26.6	27.8	51.8
	3 (Spent some savings)	134	25.3	26.4	78.1
	4 (Spent savings and borrowed money)	111	20.9	21.9	100.0
	Total	508	95.8	100.0	
Missing	*5 (Prefer not to say)*	22	4.2		
Total		530	100.0		

Table E3 *Frequencies and Percentages EnergyLabel*

EnergyLabel		f	%	Valid %	Cumulative %
Valid	*1 (A)*	281	53.0	71.1	71.1
	2 (B)	27	5.1	6.8	78.0
	3 (C)	59	11.1	14.9	92.9
	4 (D)	13	2.5	3.3	96.2
	5 (E)	4	.8	1.0	97.2
	6 (F)	1	.2	.3	97.5
	7 (G)	10	1.9	2.5	100.0
	Total	395	74.5	100.0	
Missing		135	25.5		
Total		530	100.0		

Table E4 *Frequencies and Percentages of City*

City		f	%	Valid %	Cumulative %
Valid	*1 (Amsterdam)*	25	4.7	4.7	4.7
	2 (Breda)	8	1.5	1.5	6.2
	3 (Delft)	105	19.8	19.8	26.0
	4 (Den Haag)	52	9.8	9.8	35.8
	5 (Eindhoven)	23	4.3	4.3	40.2
	6 (Groningen)	49	9.2	9.2	49.4
	7 (Haarlem)	6	1.1	1.1	50.6
	8 (Leiden)	48	9.1	9.1	59.6
	9 (Maastricht)	57	10.8	10.8	70.4
	10 (Tilburg)	14	2.6	2.6	73.0
	11 (Utrecht)	75	14.2	14.2	87.2
	12 (Wageningen)	46	8.7	8.7	95.8
	13 (Zwolle)	22	4.2	4.2	100.0
	Total	530	100.0	100.0	

Table E5 *Frequencies and Percentages of BC_OrN to BC_OrNW*

	BC_OrN	*BC_OrNE*	*BC_OrE*	*BC_OrSE*	*BC_OrS*	*BC_OrSW*	*BC_OrW*	*BC_OrNW*
N	528	528	528	528	528	528	528	528
f	88	81	81	66	76	62	91	53
Valid %	16.7	15.3	15.5	12.5	14.3	11.7	17.2	10.0

The sum of frequencies from BC_OrN to BC_OrNW is equal to 598. Given that 528 participants answered the question relating to the orientation of their building, a maximum of 70 participants had chosen (at least) 2 orientations for their home.

Appendix F: Histograms and Bar Charts

Figure F1 *Histogram of EnergyBehaviourScore*

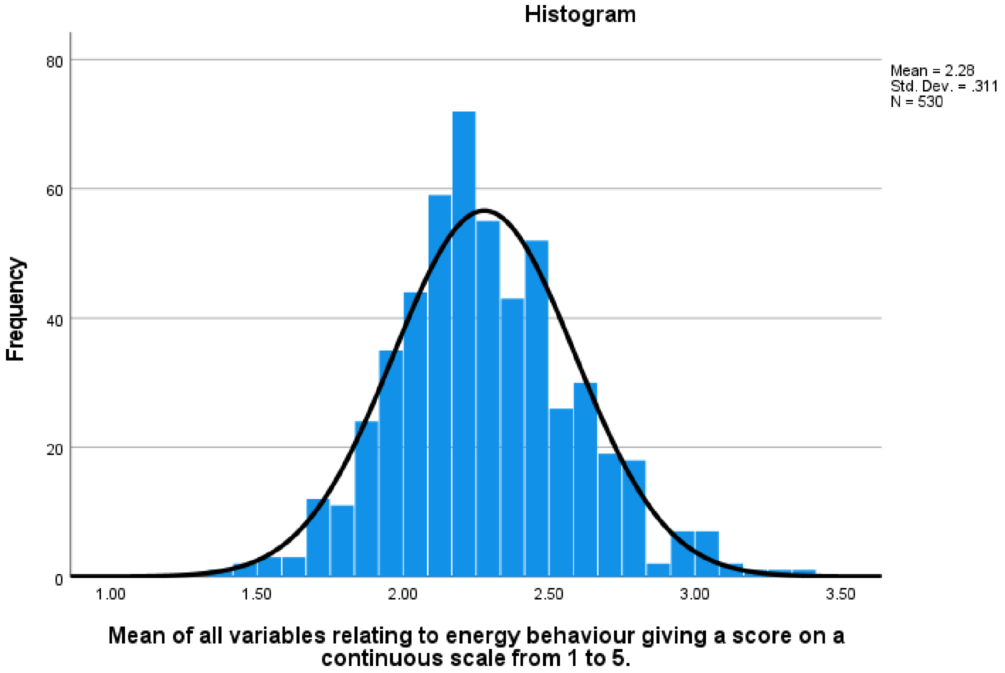


Figure F2 *Histogram of HabitScore*

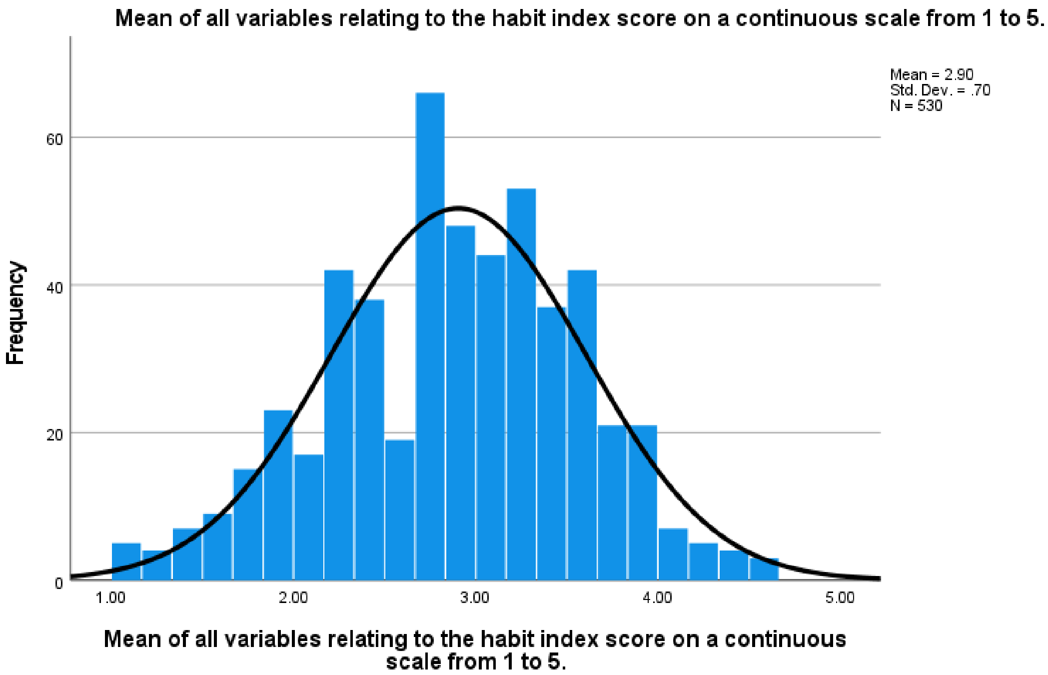


Figure F3 *Histogram of MoralLicensingScore*

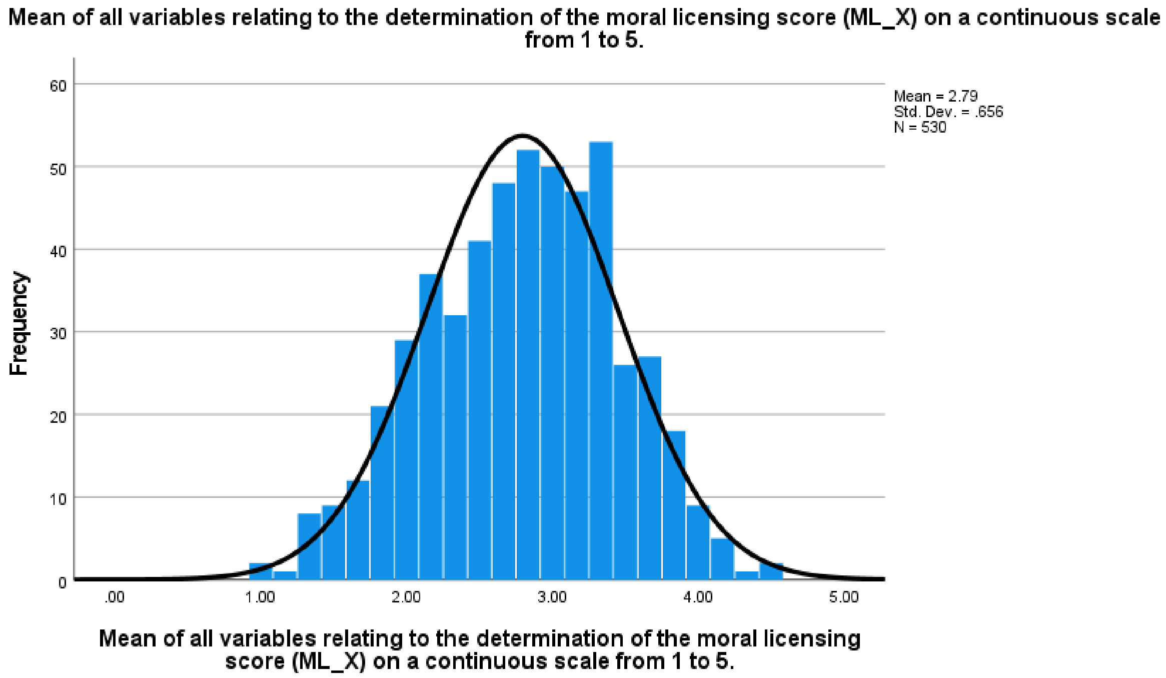


Figure F4 *Histogram of Age*

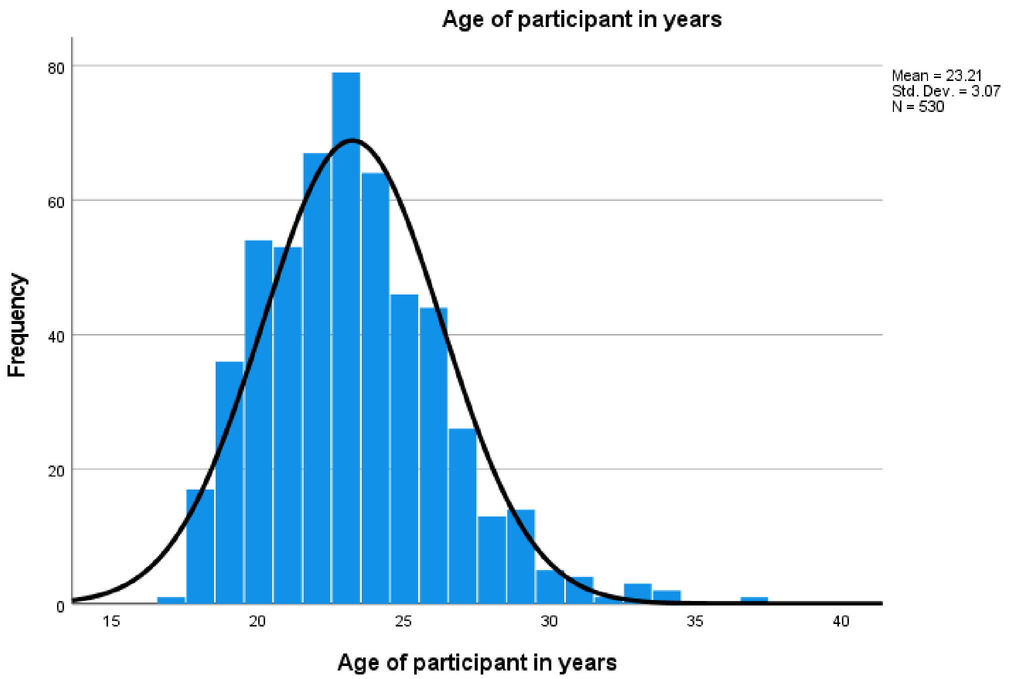


Figure F5 *Histogram of TimeNL*

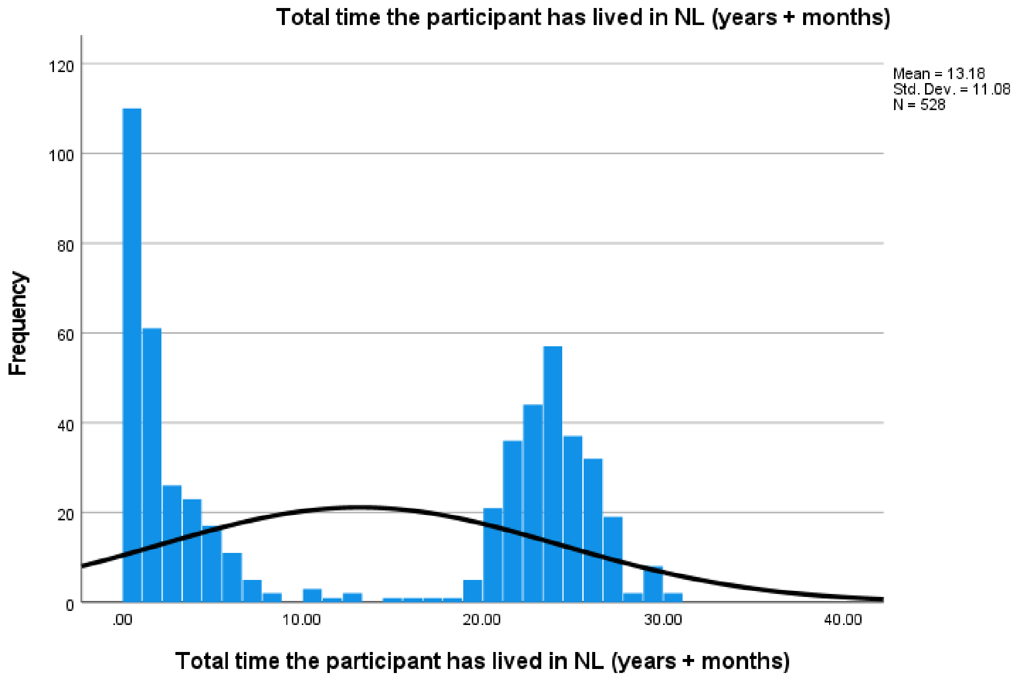


Figure F6 *Histogram of NbWorkHours (N = 530)*

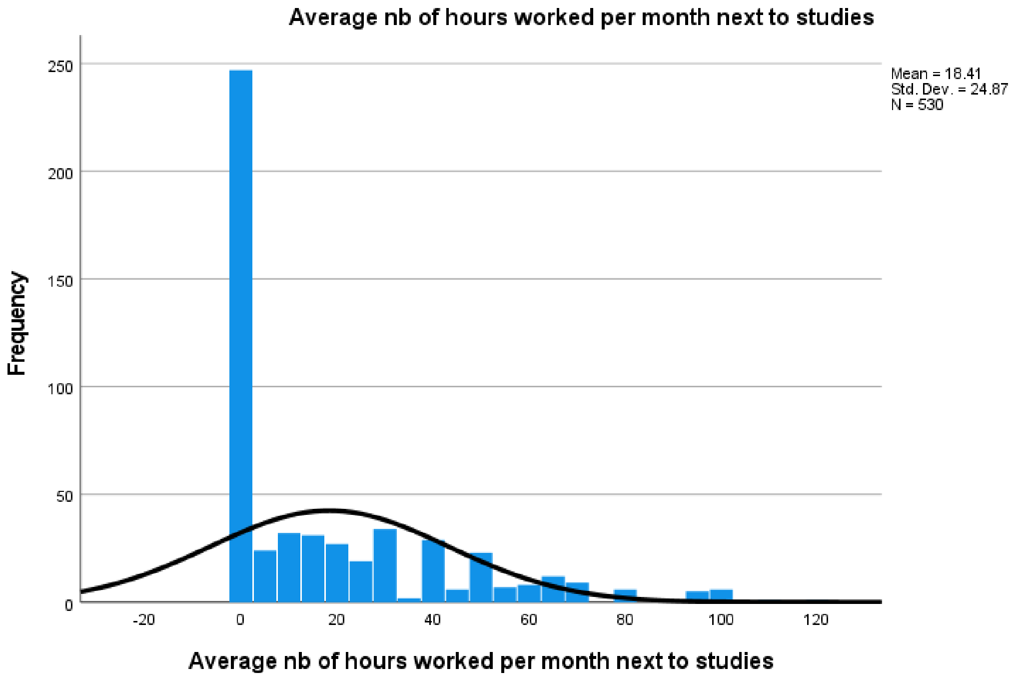


Figure F7 *Histogram of NbWorkHours Excluding Non-Working Participants (N = 287)*

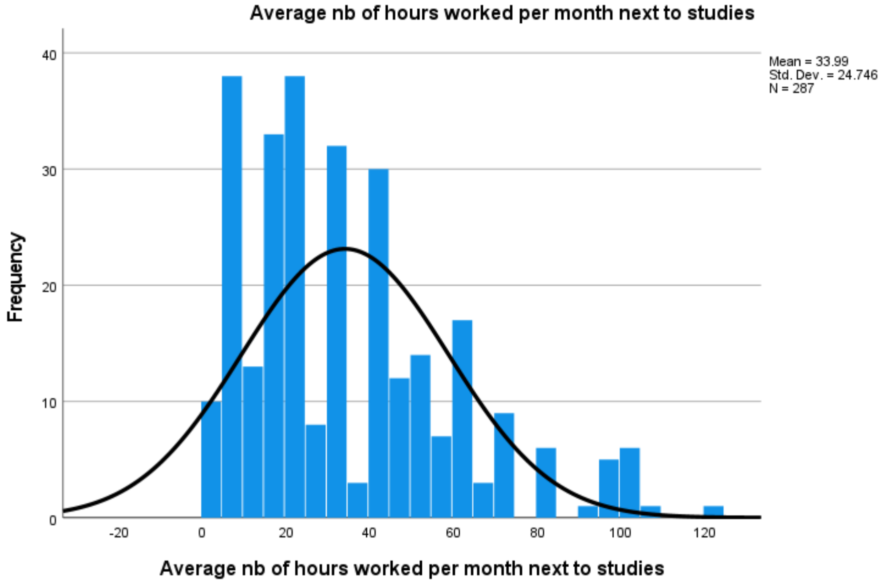


Figure F8 *Bar Chart of City*

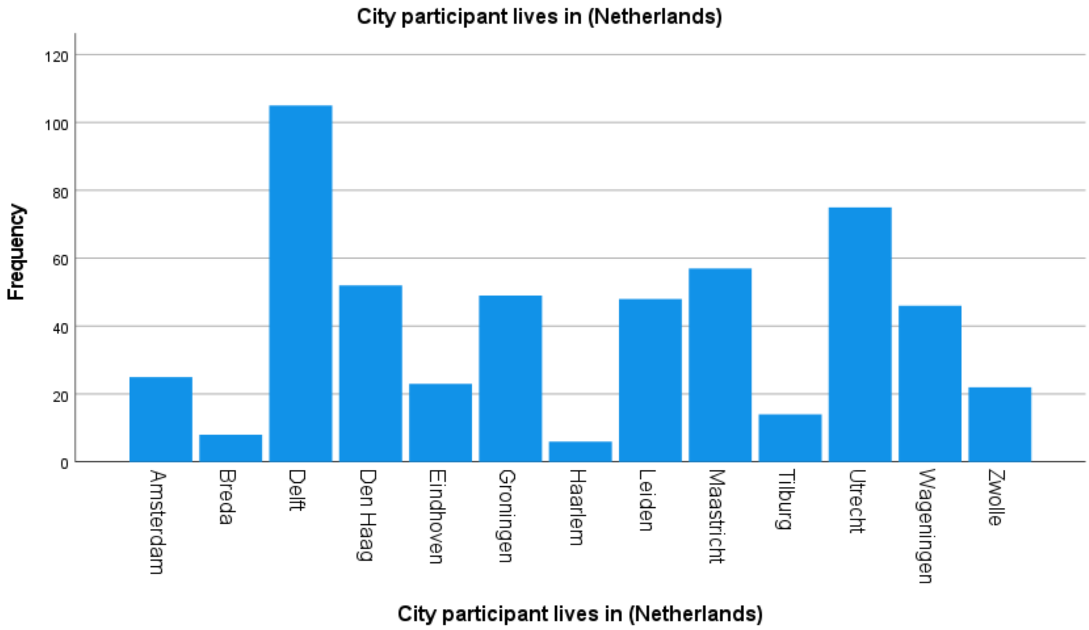


Figure F9 *Bar Chart of EnergyLabel*

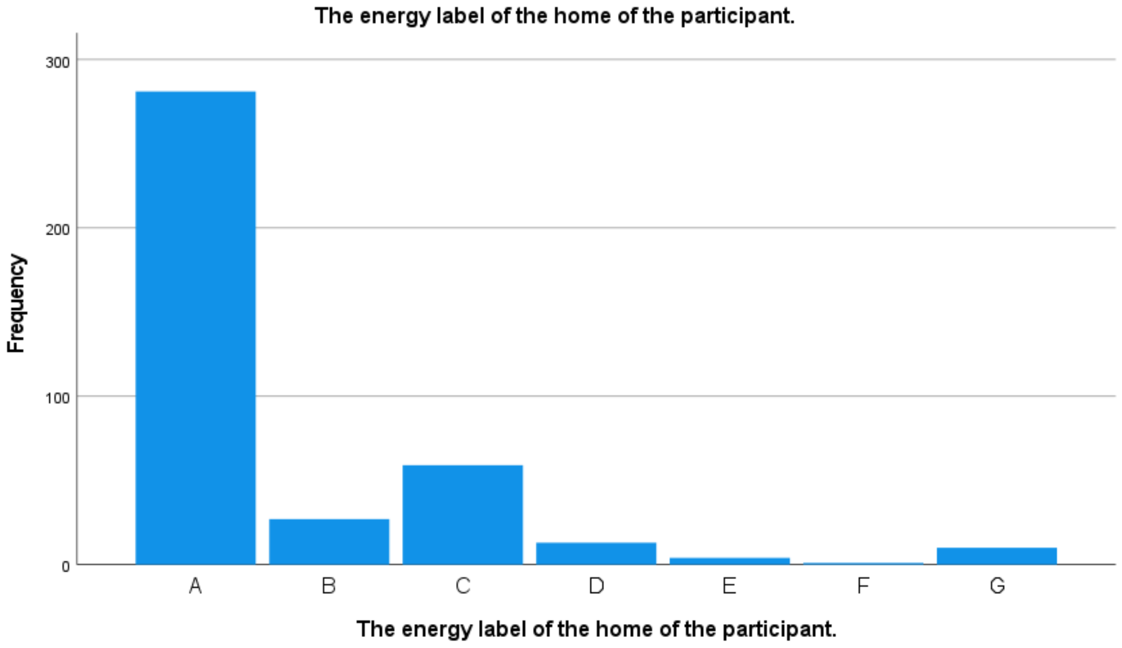


Figure F10 *Histogram of Shading*

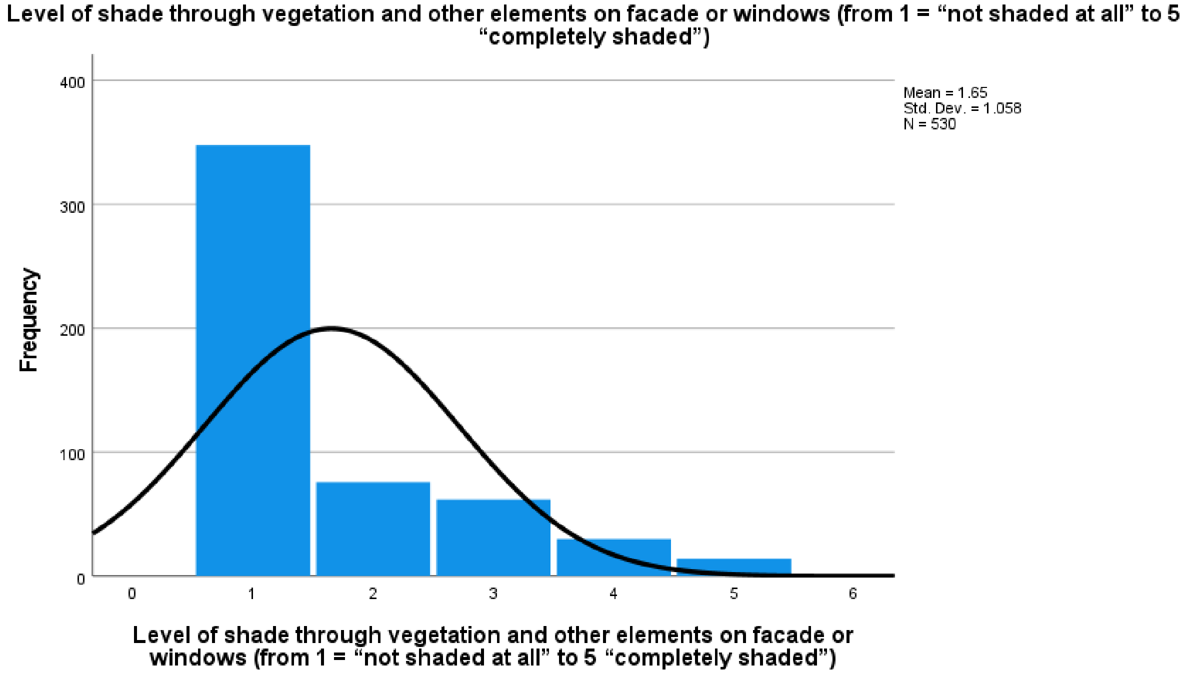


Figure F11 *Histogram of ArtificialLight*

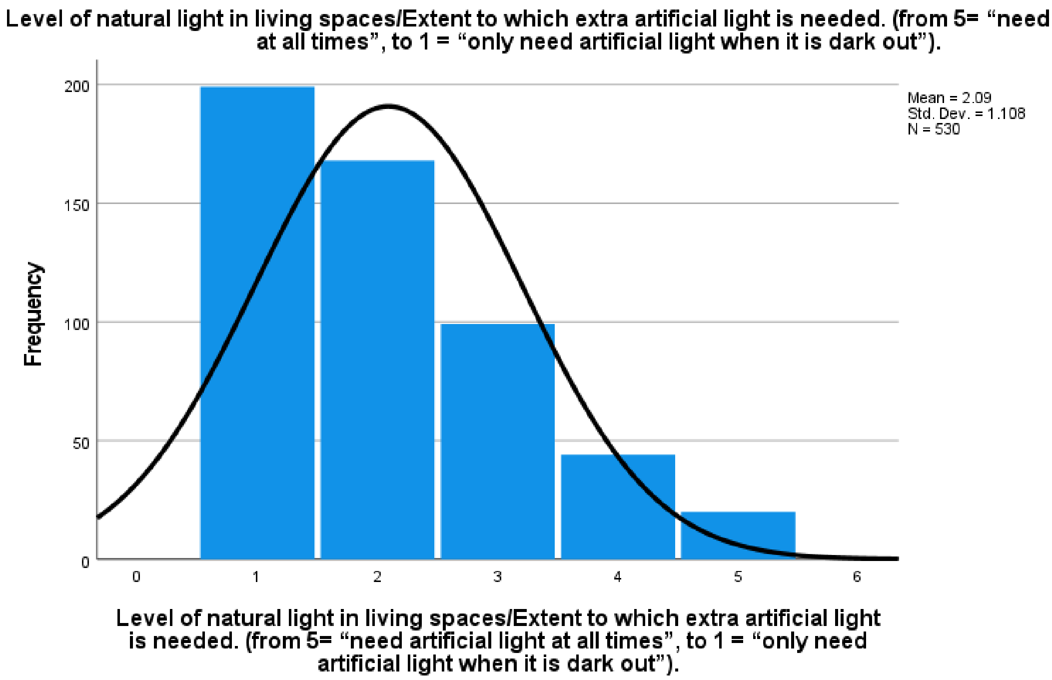


Figure F12 *Histogram of SolarRad*

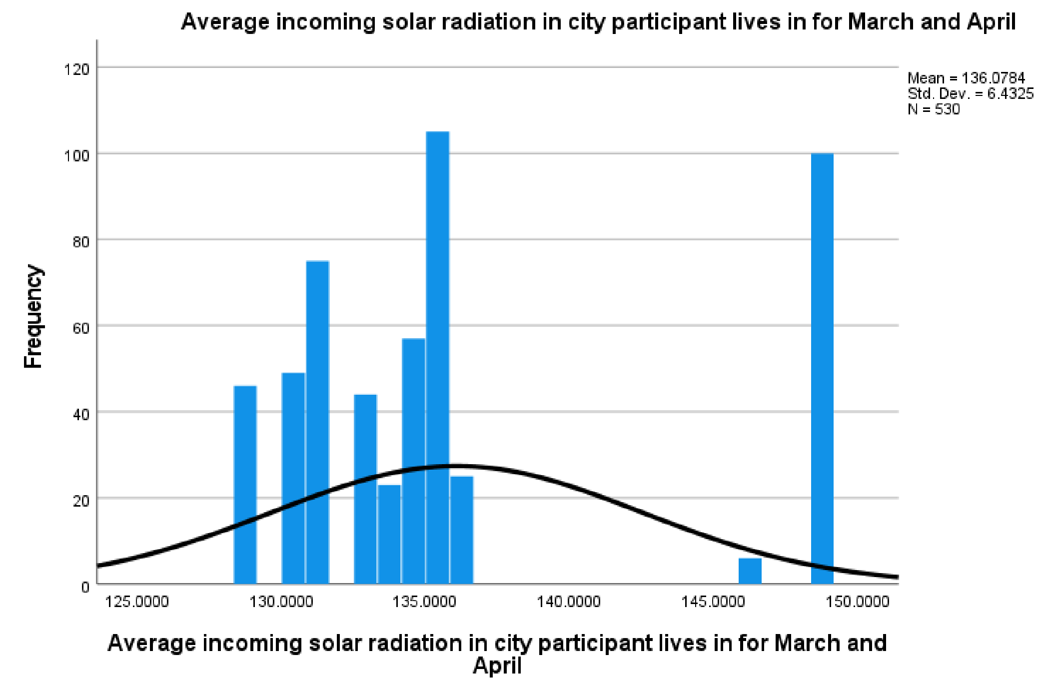


Figure F13 *Histogram of AmbTemp*

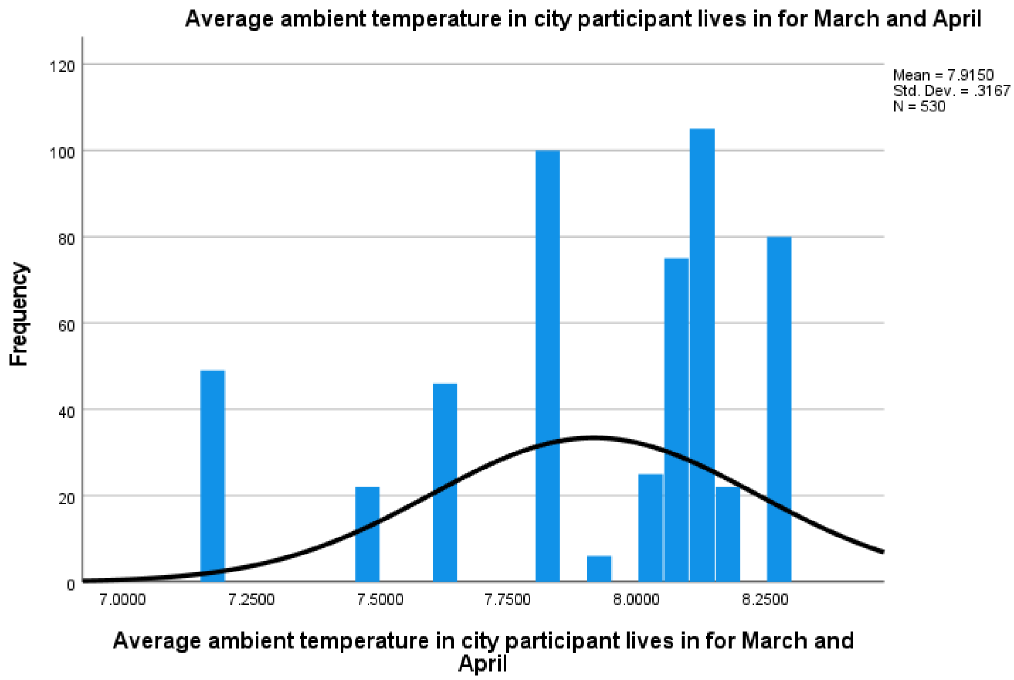
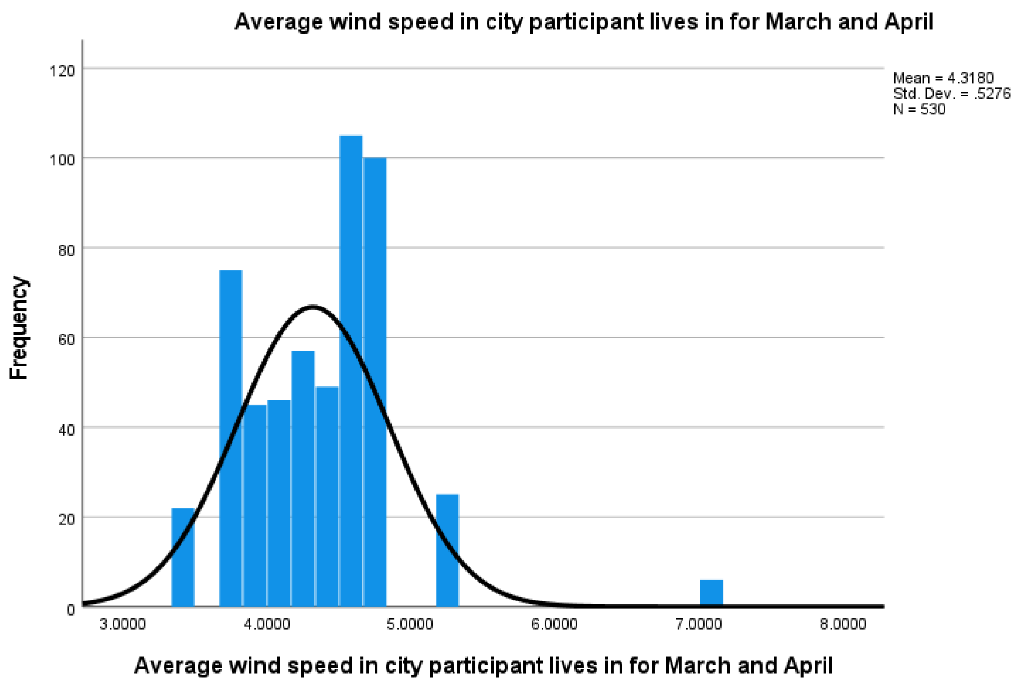


Figure F14 *Histogram of WindSpeed*



Appendix G: Internal Consistency of *EnergyBehaviourScore*

Cronbach's Alpha was calculated for *EnergyBehaviourScore* with all 19 variables considered, i.e., $\alpha = 0.37$. If *EB_Curtains* is left out, $\alpha = 0.41$. Usually, Cronbach's Alpha needs to be higher than 0.7 to be considered acceptable. If reflects how reliably different items of a scale measure a certain concept. An explanatory factor analysis is conducted to see whether the 19 variables used to calculate *EnergyBehaviourScore* can be grouped into factors. However, the explanatory factor analysis identifies 8 different factors. When interpreting which variables are grouped together, not much sense can be made of the pairing, e.g., Factor 5 pairs *EB_Microwave*, *EB_HomeWeekTOT*, *EB_Windows* and *EB_Hairdryer* together. Another approach was to check Pearson's correlation coefficients between the different variables to try to identify the factors to conduct a confirmatory factor analysis. However, there are no strong correlations between the variables, with 2 exceptions, i.e., *EB_Laundry* and *EB_Dryer* have a correlation coefficient of 0.62 (at the 0.01 significance level) and *EB_Clothes* and *EB_Heater* have a correlation coefficient of 0.44 (at the 0.01 significance level). The more people do laundry per week, the more they need to use a dryer. The more people put clothes on when feeling cold, the more inclined they are to turn up the heater when feeling cold too.

Both Cronbach's Alpha and inter-item Pearson's correlations indicate a rather low internal consistency. However, *EnergyBehaviourScore* is a variable that tries to measure a construct with many different facets. All questions of *EnergyBehaviourScore* were based on previous research surveys conducted on energy consumption behaviour within homes (Chen et al., 2013; Gram-Hanssen, 2003). Hence, it is built upon scientific research to integrate many facets of real-life energy consumption inside homes.

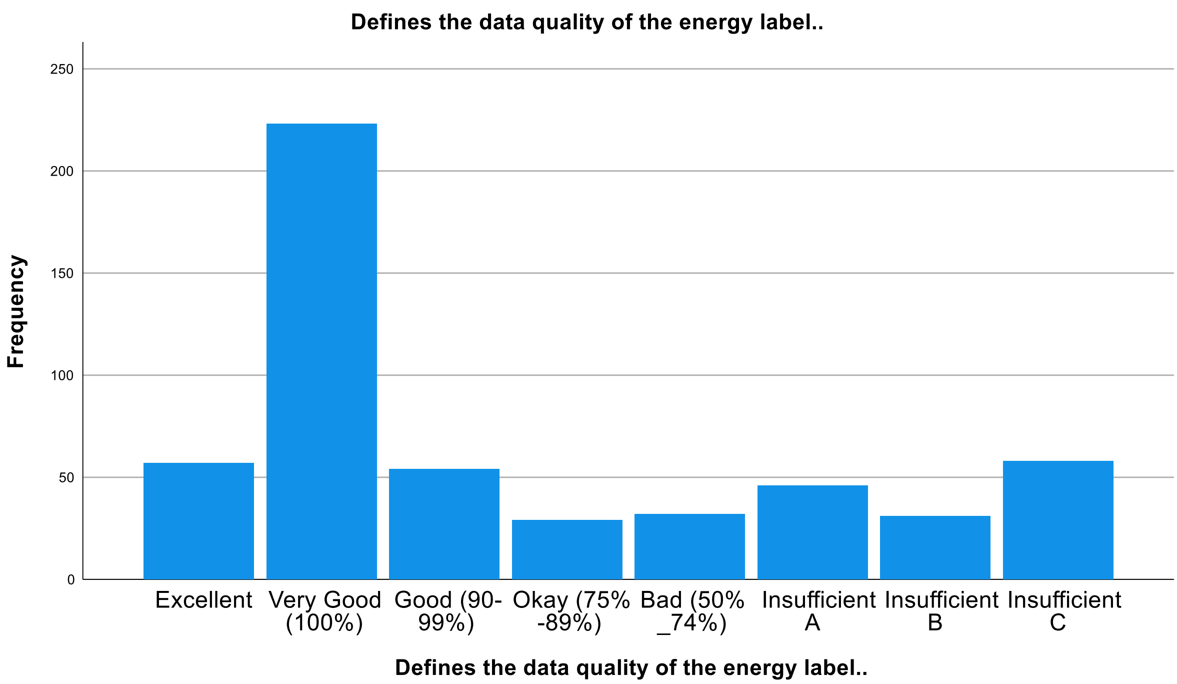
Appendix H: Data Quality of *EnergyLabel*

EL_Qual defines the quality of data in EnergyLabel. Frequencies and percentages are shown in Table G, whereas the distribution is shown in Figure G.

Table H *Frequencies and Percentages of EL_Qual*

EL_Qual		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	*1 (Excellent)*	57	10.8	10.8	10.8
	2 (Very Good)	223	42.1	42.1	52.8
	3 (Good)	54	10.2	10.2	63.0
	4 (Okay)	29	5.5	5.5	68.5
	5 (Bad)	32	6.0	6.0	74.5
	6 (Insufficient A)	46	8.7	8.7	83.2
	7 (Insufficient B)	31	5.8	5.8	89.1
	8 (Insufficient C)	58	10.9	10.9	100.0
	Total	530	100.0	100.0	

Figure H *Bar Chart of EL_Qual*



Only 10.8% of participants gave their full address. For these, individual energy label registrations could be found on EP-online. Next, 42.1% of participants gave a partial address

but all energy labels were the same (100% certitude). Hence, 52.8% of the energy labels could be found and are not approximations. They correspond to the real energy labels of the participants' homes. On the other hand, 10.2% of energy labels had a "Good" quality, 5.5% were "Okay" and 6% were "Bad". For these three categories (21.7% of energy labels), approximations had to be made. These estimations differed in certitude as indicated by the different categories but were still included in the analyses to improve the variety of energy labels in the sample. Lastly, a total of 25.4% of energy labels had an insufficient quality and were hence defined as missing values (8.7% as "Insufficient A", 5.8% as "Insufficient B" and 10.9% as "Insufficient C").