A novel multidisciplinary paradigm for energy demand reduction in building sector: On the relationship between the energy efficiency, aesthetics and marketability of residential buildings

Yusuf Cihat AYDIN, BArch, MSc

Supervisors: Dr. Parham A. MIRZAEI, Prof. Jonathan HALE

Thesis submitted for fulfilment of the requirements for the degree of Doctor of Philosophy (Ph.D.) to the Department of Architecture and Built Environment

University of Nottingham

July 2019

Abstract

Despite the development of energy-efficient buildings (EEBs) and more stringent building energy regulations in recent decades, the building sector's energy demand has continued to drastically increase. This phenomenon is conceptualized in this study as the Inefficiency of Increased Building Energy Efficiency (IIBEE), which is different from Jevons paradox (the rebound effect). The phenomenon of IIBEE conceptualizes the inadequacy of existing measures to reduce the energy demand of the building sector and emphasises the necessity of developing new and more effective strategies. The phenomenon of IIBEE occurs mainly due to the lack of widespread EEB adoption as a result of market failure and applicability problems in the integrated design approach (IDA) in practice. A lack of interoperability between building stakeholders, high initial cost, unappealing aesthetic, and low market value of energy efficiency features are the fundamental reasons behind the market failure of EEBs. Aesthetic features are determined as the main driving force behind the marketability of buildings. Accordingly, increasing the number of EEBs with better marketability obtained by the enhancement of their aesthetic is introduced as a novel approach (widespread adoption approach) to reduce the energy demand of the building sector. However, applicability issues of IDA in practice and the difference of aesthetic judgement between architects and the public (buyers) are two main barriers to the aesthetic enhancement of EEBs and the applicability of the proposed widespread adoption approach. Accordingly, a novel paradigm named the Yin and Yang paradigm (YYP) was introduced to ensure the applicability of the proposed novel approach. YYP is a paradigm that offer to consider all factors involved in a decision-making process and establishing balance between them to offer multi-dimensional solution to a problem. YYP is a multidisciplinary approach that empowers individual specialists to see the perspectives of different disciplines, instead of bringing experts in different disciplines

together, as in IDA. In this way, each building stakeholder can see the impact of any design changes on buildings' different aspects simultaneously, and they can use this parametric information during their decision-making process. YYP can result in the initiation of new generation building simulation tools, effective in evaluating buildings' different aspects simultaneously (e.g. marketability, aesthetic, energy efficiency, occupant comfort, carbon footprint and price).

This thesis investigates the applicability of the proposed novel widespread adoption approach and the novel paradigm in practice. In order to investigate the applicability of the widespread adoption approach in practice, eight pre-studies and two comprehensive surveys with real-estate agencies (n = 289) were conducted across 26 UK cities and potential housing buyers with different demographic characteristics (n = 183). Window was determined as the dominant building parameter that has a high impact on housing aesthetic, marketability, and energy efficiency (simultaneously), as a result of conducted studies. Accordingly, the scope of this study was limited to the impact of seven window parameters (i.e. width, area, height, position, number, proportion, and symmetry) on detached and terraced UK housing aesthetic, marketability, and energy efficiency. The applicability of the proposed novel paradigm was investigated, via testing the performance of a novel multidimensional measurement model developed using artificial neural network (ANN) and decision tree-based predictive models. It was validated with building energy simulations (BES) and a comprehensive survey among 807 UoN students with different demographic characteristics. In addition, for developing predictive models, a novel mathematical model (symmetry index) was developed to parametrically measure the symmetry of building façades, validated with the results of a comprehensive survey of 145 UoN students with different demographic characteristics. The results provide strong empirical evidence supporting the existence of the phenomenon of IIBEE and the applicability of the proposed novel widespread adoption approach. In addition, promising indicators are revealed for the applicability of YYP in practice.

Author's biographical sketch

Yusuf Cihat AYDIN was born in Antalya, Turkey in 1987. He received a bachelor's degree in architecture (BArch) at Girne American University in 2009, and a master's degree (MSc) in the field of architectural engineering (Renewable Energy and Architecture) at the University of Nottingham in 2014. He submitted his Degree of Doctor of Philosophy (Ph.D.) (Architectural Science) in the Architecture and Built Environment Department at the University of Nottingham in 2019. His research interests are centred on energy efficient and sustainable buildings. He works in the interdisciplinary fields of architecture, architectural engineering, marketing, and cognitive psychology.

Email: yusuf.cihat.aydin@gmail.com

Acknowledgments

Firstly, I want to express my gratitude to my family (Mehmet & Emine AYDIN) for their support, without which it would not be possible to experience one of the most wonderful experiences of my life, studying for my Ph.D. I would like to particularly express my gratitude to my father (Mehmet AYDIN) for his financial support.

I specially express my gratitude to my mother, Emine AYDIN. She was diagnosed with cancer in the second year of my Ph.D. programme and had a major surgery. Even in those dark days, when she was walking on the thin line between death and life, she always kept supporting me. Therefore, I want to dedicate my Ph.D. thesis to this wonderful woman, my hero, role model, and lodestar.

I also want to express my gratitude to my main supervisor, Dr. Parham A. MIRZAEI. During my study, he was always very supportive, indulgent, and kind to me. He not only supported my academic work, but helped me to improve my personality, and generously shared his experiences gained over the years with me. Because I am so passionate about my work, I was sometimes stubborn when we had different opinions, and I was a headache for him sometimes, but he remained very patient with me and he has been much more than a supervisor; he has become a great role model for me. I hope I will be able to be such a great supervisor for young researchers who work with me in my future academic career. I also want to express my gratitude to my second supervisor Prof. Jonathan HALE. Unfortunately, I met him during the later stages of my Ph.D., he trusted me and accepted to work with me kindly, and was always be very supportive of my studies. I am really thankful for his contributions.

I also want to express my gratitude to my internal assessor, Dr. Benjamin JONES, who contributed to the development of my Ph.D. thesis with his detailed comments, suggestions, and criticism during my annual examinations. He was always kind and supportive, and his constructive criticism helped to enhance the quality of my thesis. I am also thankful to my external examiner Dr. Chengzhi PENG for his contributions.

I want to express my gratitude to Dr. Sanam AKHAVANNASAB, who kindly shared her knowledge and experiences, and who particularly contributed to the development of my first survey and my statistical analysis when I had a dilemma in the first year of my Ph.D. programme. I also want to express my gratitude to my friends, Thanun SRITHONGCHAI and Ssennoga TWAHA for our discussions. Finally, I want to express my gratitude to Thomas W. MARLEY, the proof-reader of this thesis, for his efforts.

Author's declaration

When I was a little child, I planted an olive seed in our garden, and after many years that small black olive seed which I held between my little fingers had grown into a fruitful olive tree bigger than me; this experience impressed me a lot. Today, as a young researcher and an architect at the beginning of my career, I am planting another seed, not in the dark soil, but in the infinite light of the science. Maybe this seed will evolve into another giant tree in the future and will benefit humanity for a long time with its wide branches and products. Of course, there is a possibility that this seed may also never sprout due to the lack of appropriate conditions. However, I will continue to water this beautiful seed with my hope, passion, persistence, and labour…

An idea begins with a dream, grows via the unconditional faith of the one, and becomes real when others share the same dream...

If aesthetic appreciation could be estimated through certain parameters with computational approaches, then it can also be developed via conscious alterations on the parameters that trigger aesthetic appreciation.

Enhancement of the energy efficient buildings' aesthetic is not only important to improve the visual quality of our habitat, but also important to help keeping our planet habitable for our children. *Y.C.A.*

Summary of the contributions within the timeframe of the Ph.D.

Novel Contributions

- A novel phenomenon was introduced: *The phenomenon of inefficiency of increased building energy efficiency (IIBEE*)

- A novel approach was proposed: *Widespread adoption approach: Increasing the number of energy efficient buildings via marketability enhancement obtained with aesthetic enhancement to decrease the energy demand of the building sector*

- A novel paradigm was introduced: *Yin and Yang paradigm (YYP): A paradigm that offer to consider all factors involved in a decision-making process and establishing balance between them to offer multi-dimensional solution to a problem. YYP can result in the initiation of new generation building simulation tools, effective in evaluating buildings' different aspects simultaneously*.

- A novel mathematical models were developed to parametrically measure the symmetry of visual stimuli (i.e. *symmetry index*)

- A novel multidimensional measurement model was developed: *Artificial neural network (ANN) and decision tree-based computational predictive models developed to predict the aesthetics, marketability, and energy efficiency of terraced and detached UK houses via different window parameters (i.e. width, area, height, position, number, proportion, and symmetry*)

Publications

Journal articles

- Aydin, Y. C., Mirzaei, P. A., & Akhavannasab, S. (2019). "On the relationship between building energy efficiency, aesthetic features and marketability: Toward a novel policy for energy demand reduction". *Energy Policy*, 128, 593-606.

Conference proceedings

- Aydin, Y. C., and Mirzaei, P. A., Akhavannasab, S., Wu, Y. (2017). "The Relation between Building Energy Efficiency, Appearance and Marketability" *in 16th International Conference on Sustainable Energy Technologies (SET 2017)* Bologna, Italy

- Aydin, Y. C., and Mirzaei, P. A. (2018). "How window features impact energy efficiency and marketability of residential buildings?" in *17th International Conference on Sustainable Energy Technologies (SET 2018),* Wuhan, China

- Aydin, Y. C., and Mirzaei, P. A. (2019). "Adoption of energy efficient buildings with improvement of their windows' aesthetic features" in *18th International Conference on Sustainable Energy Technologies (SET 2019),* Kuala Lumpur, Malaysia

Table of contents

List of tables

List of figures

List of equations

Eq. No	Equation (Eq.)	Description
1	$\mu = \frac{(\sum X_i)}{N}$	Mean
2	$SD = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2$	Standard deviation
3	$t = \frac{\underline{D} - \mu_D}{SD/\sqrt{N}}$	Paired-samples t-test
4	$r = \frac{cov_{xy}}{SD_x\, SD_y}$	Pearson Correlations
5	$\alpha = \frac{N.\bar{c}}{\bar{v} + (N-1).\bar{c}}$	Cronbach's alpha
6	$f_{act}(w.x + b)$	Eq. for the working principle of a single neuron
7	$f(x) = \frac{1}{1 + e^{-x}}$	Logistic sigmoid function
8	$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$	Hyperbolic tangent sigmoid function
9	$E = \frac{1}{2}\sum_{i=1}^{n}(t_i - ac_i)^2$	Delta (Widrow-Hoff) learning rule
10	$En(S) = -\sum_{i=1}^{n} p_i \, log_2\,(p_i)$	Entropy
11	$G(S,A) = E(S) - \sum_{v \in values\,(A)} \frac{\lvert S_v \rvert}{\lvert S \rvert}\, E(S)$	Information gain (or entropy reduction)

12	$Gini(S) = 1 - \sum_{i=1}^{n} {P_i}^2$	Gini index
13	$Gain(S, A) = Gini(S) - \sum_{v \in A} \left(\frac{\mid S_v \mid}{\mid S \mid} \; Gini(S_v) \right)$	
14	$Q_c + Q_{cv} + \; Q_s + \; Q_v + Q_i + \; Q_e = 0$	Heat equilibrium
15	$Q_c = k. A. (\Delta T/L)$	Conduction heat transfer
16	$Q_{cv} = h_c. A. \Delta T$	Convection heat transfer
17	$Q_s = A \,.\, I \,.\, \theta$	Solar heat gain
18	$A_{1,sh} = \frac{1}{2} \, (d_1 - p_1)^2 \tan \alpha$	The size of the shaded areas and the areas that solar beam reached
19	$A_{2,sh} = d_2{}' L + \frac{1}{2} \, (d_1 + d_2)^2 \tan \alpha - \frac{1}{2} \left(d_1 + p + d_2{}'' \right)^2 \tan \alpha$	
20	$Q_v = V. VSHa \,.\, \Delta T$	Heat gain or loss caused by ventilation
21	$V = (N. RV)/3600$	Ventilation rate
22	$Q_w = C_w A_{opening} F_{schedule2} WindS$	Wind-driven natural ventilation
23	$Q_s = C_D A_{opening} F_{schedule2} \sqrt{2g\Delta H_{NPL}(\lvert T_{zone} - T_{out} \rvert / T_{zone})}$	Buoyancy-driven natural ventilation
24	$infiltration = (F_{schedule}) \frac{A_L}{1000} \sqrt{C_8 \, \Delta T + C_w (WindS)^2}$	Infiltration
25	$SmI = \; 1 - \frac{\mathrm{DSm} - (\mathrm{DSm}_{\,\mathrm{min}})}{\mathrm{DSm}_{\,\mathrm{max}} - \mathrm{DSm}_{\,\mathrm{min}}}$	Symmetry index
26	$DSm = \frac{\left(\left(\lvert \sum_{i=1}^{n} PLCXi \; \rvert + \lvert \sum_{i=1}^{n} PLCYi \; \rvert \right) * 2 \right) + \left(\frac{\left\lvert \sum_{i=1}^{n} \left(\left(\frac{PLCXi}{\lvert PLCXi \rvert} \right) LLCi \right) \right\rvert + \left\lvert \sum_{i=1}^{n} \left(\left(\frac{PLCYi}{\lvert PLCYi \rvert} \right) LLCi \right) \right\rvert}{7} \right)}{2}$	The symmetry deviation according to linear components' lengths and position on the XY coordinates
27	$xn = \frac{x - min(x)}{max(x) - min(x)}$	Feature scaling (min-max normalization)
28	$MSE = \frac{1}{n} \sum_{i=1}^{n} (Yi - \check{Y}i)^2$	Total mean square error

Nomenclature and abbreviations

Nomenclature

μ	The population mean (-)
X_i	All scores presented in the population (-)
N	The total number of cases in the population (-)
σ	Standard deviation (-)
Mo	Mode – the most often given answer (-)
$\underline{D}$	The mean difference between samples (-)
μ_D	The differences between population means (-)
r	Pearson correlations (-)
cov	The covariance (-)
α	Cronbach's alpha (-)
$\bar{c}$	The average inter-item covariance among the items (-)
$\bar{v}$	The average variance of each component (-)
f_{act}	Activation function (-)
w	The weight assigned for input (-)
x	Input variable (-)
b	Bias or error value (-)
e	Euler's constant value (-)
E	The total error over the training pattern (-)
t	The target value in the output layer (-)
ac	The actual output (-)
En	Entropy (-)
p_i	the probability of getting the i^{th} value when randomly selecting one from the set (-)
G	Information gain (-)
$Gini$	Gini index (-)
P_i	The relative frequency of class i in S (-)
v	any possible values of attribute (-)
Q_c	Heat transfer via conduction (W)
U	Thermal transmittance (U-Value) (W/m^2K)
A	The surface area (m^2)
ΔT	The temperature difference between the outdoor and indoor of building (K)
Q_{cv}	Heat transfer via convection (W)
h_c	Convective heat transfer coefficient $(W/m^2\ K)$
Q_s	Heath gain from solar radiation on opaque surfaces (W)
I	Radiation heat flow density (W/m^2)
θ	Solar gain factor of the window glass (-)
A_{sh}	Shaded areas (m^2)
d_1	depth of outside reveal (m)
d_2	depth of inside reveal (m)
L	window height and width
p_1	distance from outside or inside surface of frame to glazing midplane (m)
Q_v	Heat exchange caused by ventilation (W)
V	Ventilation rate (m^3/s)
$VSHa$	volumetric specific heat of air $(Jm^3°C)$
AC	Air changes per hour (m^3/h)
RV	Room volume (m^3)
Q_w	Volumetric air flow rate derived by wind (m^3/s)
C_w	Opening effectiveness (-)
$A_{opening}$	Opening area (m^2)
$F_{schedule2}$	The open area fraction (-)
$WindS$	Local wind speed (m/s)
Q_s	Volumetric flow rate due to stack effect (m^3/s)
C_D	Discharge coefficient for opening (-)
ΔH_{NPL}	Height from midpoint of lower opening to the natural pressure level (m)
T_{zone}	Zone air dry-bulb temperature (K)
T_{out}	Local outdoor air dry-bulb temperature (K)
A_L	Effective air leakage area that corresponds to a 4 Pa pressure differential (cm^2)
C_8	The coefficient for stack-included infiltration $((L/s)^2/(cm^4.K))$
C_w	The coefficient for wind-included infiltration $((L/s)^2/(cm^4.(m/s)^2))$
Q_i	Internal heat gain (W)
Q_e	Evaporative cooling (W)
SI	Symmetry index (-)
DSm	The symmetry deviation according to linear components' lengths and position on the XY coordinates (-)
$PLCX$	The position of the linear components' centre on the X axis centred on the visual stimuli (m)
$PLCY$	The position of the linear components' centre on the Y axis centred on the visual stimuli (m)
LLC	The length of the linear components (m)
Y	The observed value (-)
d_2''	Depth of shadow cast by frame (m)
$\check{Y}$	The predicted value (-)

Abbreviations

±∞:	Negative and positive infinity
ANN:	Artificial neural network
ASHRAE:	The American Society of Heating, Refrigerating and Air-Conditioning Engineers
BES:	Building energy simulation
CART:	Classification and regression trees
CEPHEUS:	A project about the multi-storey passive houses built for low-income buyers
CFD:	Computational Fluid Dynamics
CHAID:	Chi-squared automatic interaction detection
EEB:	Energy efficient building
EEG:	Electroencephalography
EPC:	Energy performance certificate
ES:	Energy simulation
ET:	Eye tracking
EU:	European union
Eq.	Equation
fMRI:	Functional magnetic resonance imaging
Fig.	Figure
HVAC:	Heating, ventilation, and air conditioning systems
IDA:	Integrated design approach
IEA:	International energy agency
IIBEE:	The phenomenon of Inefficiency of Increased Building Energy Efficiency (*proposed novel phenomenon*)
IT:	Information technology
MMM:	Multidimensional measurement model
MSE:	Total mean square error
Mtoe	Million Tonnes of Oil Equivalent
OED:	Oxford English dictionary
PM:	Predictive model
PS:	Pre-study
S:	Survey
SAP:	The Government's Standard Assessment Procedure for Energy Rating of Dwellings calculations
SDS:	Semantic differential scales
SI:	Symmetry index (*proposed novel symmetry measurement model*)
SRM:	Self-report methods
tanH:	Hyperbolic tangent sigmoid function
UK:	United Kingdom
UoN:	University of Nottingham
YYP:	Yin and Yang paradigm (*proposed novel paradigm*)

CHAPTER I

INTRODUCTION

CHAPTER I.

INTRODUCTION

This chapter briefly outlines the thesis structure and gives a fundamental background and a brief overview of this Ph.D. thesis. Novel theories and concepts that introduced in this thesis, and supportive arguments will be provided in the next chapters.

In order to contribute to restrict global warming, this thesis focuses on reducing the energy consumption of the building sector, which has a significant impact on global energy consumption and carbon emissions (Conti et al., 2016). In this thesis, the inadequacy of existing measures[1] to reduce the energy demand of the building sector is conceptualized through a novel phenomenon named Inefficiency of Increased Building Energy Efficiency (IIBEE) (Section 2.1). Increasing the number of energy efficient buildings (EEBs)[2] with better marketability obtained via aesthetic[3] enhancement is proposed as a novel approach (i.e. widespread adoption approach) for energy demand reduction in the building sector and to propose a solution for the phenomenon of IIBEE (Section 2.2). A novel multidisciplinary paradigm named Yin and Yang paradigm (YYP) has been developed to implement the proposed widespread adoption approach (Section 2.3). An artificial neural network (ANN) and decision tree-based predictive models were developed to predict the aesthetics, marketability, and energy efficiency of detached and terraced UK houses via window parameters to generate a multidimensional measurement model and test the applicability of YYP in practice (Section 5.4). Consequently, this Ph.D. thesis aims to investigate the applicability of the proposed novel approach and paradigm in practice, and to propose supportive arguments about the existence of the phenomenon of IIBEE.

---

[1] Such as the energy efficiency enhancement of buildings and stringent building energy regulations.

[2] EEB refers to buildings with energy performance above the minimum standards set by building energy regulations.

[3] An ‘aesthetic’ experience is operationally defined as a pleasing experience, which creates a positive impression (e.g. attractiveness and beauty), which more particularly refers to visually attractive architecture in this study.

1.1 Background: Statement of the problem

This section gives a fundamental overview of the research problem and explains the rationale behind the focus and scope of this study.

The increase in global surface temperature[4] (NASA-GCC, 2019) and the increased number and intensity of climate-related natural disasters around the world[5] (UNISDR, 2012) are the conspicuous consequences of global warming. With current rates of global warming, the mean global temperature is expected to increase by 4-5°C by 2100 compared to its pre-industrial level (IPPC-CC, 2014). Therefore, some measures such as the Paris Agreement, which aims to limit the global temperature increase to below 2°C (UN-FCCC, 2015), have become operational to minimize the irreversible damage of global temperature increases on the equilibrium of nature.

Increasing growth in global energy demand[6] is among the primary factors that cause global warming due to increasing CO_2 emissions[7] . In 2016, more than two-thirds of this energy was produced by fossil sources (Conti et al., 2016). Therefore, efforts to reduce global energy demand have gained increasing popularity and political traction in many countries. However, as highlighted in the International Energy Agency's (IEA) *2016 Energy Efficiency Market Report*, improvements in the energy demand reduction achieved with the existing measures are too slow to achieve the specified Paris Agreement targets (Sadamori, 2016). Global energy consumption is projected to increase 48% by 2040 compared to 2012, mainly due to the rising global population[8] (UN-WPP, 2015) and rising living standards[9] (Conti et al., 2016). However, the rise of the global primary energy demand can be limited to an increase of only 27% by 2050

---

[4] The global surface temperature has increased by 0.8 °C from the 1880s to 2019 (NASA-GCC, 2019)
[5] The number of climate-related natural disasters tripled between 1980 and 2011 (UNISDR, 2012)
[6] Global energy demand almost doubled between 1990 and 2016 (Conti et al., 2016)
[7] CO_2 emissions increased approximately 65% between 1990 and 2016 (Conti et al., 2016)
[8] Global population increased 167% between 1950 and 2015 (UN-WPP, 2015)
[9] The growing rate of global primary energy consumption is higher than the growing rate of global population (Pérez-Lombard, Ortiz, & Pout, 2008)

through better energy demand reduction strategies (WEC-WES/2050, 2013). Therefore, new and more effective strategies are urgently needed to significantly accelerate the reduction of the global primary energy demand.

The building sector has a crucial role in global energy demand reduction strategies as it is responsible for 60% of the global electricity demand (Johansson, Patwardhan, Nakicenovic, & Gomez-Echeverri, 2012), accounting for 20% of the total delivered energy consumed worldwide in 2016 (Conti et al., 2016). In particular, residential buildings are of remarkable importance to minimize energy demand in this sector due to two main reasons: (1) their number is considerably greater than the commercial ones (e.g. 74% of EU building stock in 2012), and mainly constitutes low-rise houses (66% of EU residential buildings in 2012) (Gynther, Lapillonne, & Pollier, 2015); (2) people spend 90% of their time in indoor spaces (Vardoulakis et al., 2015), while the time being spent in residential buildings is almost four times higher than that spent in commercial ones (Lai et al., 2004). The energy consumed by residential buildings is predicted to grow by an average of 1.4% per year between 2012-2040 (Conti et al., 2016). However, there is a great potential for reducing the energy consumption of residential buildings; their energy demand can potentially be reduced by 75% in new buildings (IPCC, 2007), and by 50% with retrofitting of pre-existing structures (Johansson et al., 2012).

Thus, energy reduction potential in the building sector with the energy performance enhancement of buildings has become a primary policy goal in many countries (UNEP, 2011). However, despite tremendous progress in the development of EEBs (e.g. passive building, and zero-energy buildings) and the stringent building energy regulations[10] emerging under current energy-oriented government policies (EU_FS, 2017); (Schnieders & Hermelink, 2006), the energy demand of the building sector (in global) is exhibiting a contemporaneous rapid

[10] For example, German building space heating demand standards call for a third of the energy requirement of the 1982 standards (Schnieders & Hermelink, 2006) and according to Directive 2010/31/EU of the European Parliament, the minimum energy performance requirements of new buildings must be nearly zero-energy by 2020 (EU_FS, 2017)

increase, and is projected to be 42% greater in 2040 compared to 2012 (Conti et al., 2016). Similarly, the overall final energy demand of the UK households is projected to increase approximately %7 (3 Mtoe) by 2033 compared to 2008 (46 Mtoe) (GOV.UK, 2019). This is therefore a worrisome problem for energy reduction of building sector in world-wide. In this thesis, the inadequacy of existing measures to reduce energy demand of the building sector was conceptualized as a novel phenomenon named the Inefficiency of Increased Building Energy Efficiency (IIBEE). The details of the phenomenon of IIBEE are discussed in Section 2.1.

The lack of widespread EEB adoption (EU, 2017) as a result of their market failure is the main reason behind the phenomenon of IIBEE (see Section 2.1). Accordingly, in order to overcome the phenomenon of IIBEE, the elevation in the number of operated EEBs obtained with better marketability should also be targeted, rather than merely focusing on energy efficiency features' enhancements.

Aesthetic features are recognized as the main driving forces behind the marketability of buildings in addition to the estate value (added value) (e.g. (Parkinson, De Jong, Cooke, & Guthrie, 2013); (Fuerst, McAllister, & Murray, 2011) (see Section 2.2.1). Despite the remarkable importance of aesthetic features on buildings' marketability, aesthetic features are not given enough consideration in EEBs design. The unappealing aesthetic of EEBs was broadly reported in previous studies (e.g. (Buckley & Logan, 2016); (Ryghaug & Sørensen, 2009)) (see Section 2.2.1). Therefore, better marketability of EEBs can be achieved by aesthetic enhancements, and widespread EEB adoption can be achieved with better marketability. Accordingly, in this thesis, increasing the number of EEBs by improving their marketability by aesthetic enhancement, is proposed as a novel approach (widespread adoption approach) for energy demand reduction in the building sector. The details of the proposed novel approach are discussed in Section 2.2.

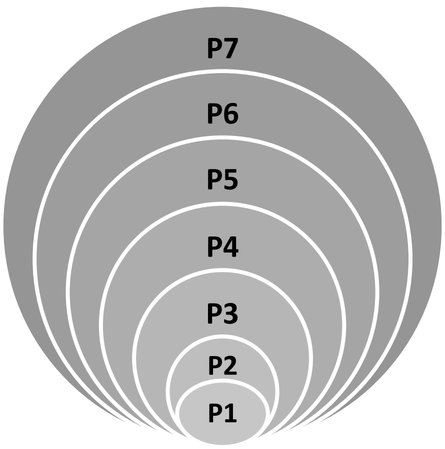
The applicability issues of integrated design approach (IDA) in practice (e.g. (Serpell, Kort, & Vera, 2013)) and the difference of aesthetic judgement between architects and the public (buyers) (e.g. (Garip & Garip, 2012)) are determined as two main barriers to the aesthetic enhancement of EEBs and the applicability of the proposed widespread adoption approach (See Section 2.2.1). Therefore, in order to ensure the applicability of the proposed widespread adoption approach in practice, this thesis posits the novel Yin and Yang paradigm (YYP). YYP is discussed in detail in Section 2.3.

1.2 Thesis overview

This section gives an overview about the fundamentals of the thesis and its structure.

1.2.1 Research problem

The focus stages of the research problem (P) is shown gradually in Figure 1. Details about the research problem can be found in Section 2.1 and 2.2.



P7: Global warming

P6: High global energy consumption

P5: High energy consumption of the building sector

P4: The phenomenon of IIBEE

P3: Lack of widespread EEB adoption

P2: Insufficiency of the existing approaches to increase the number of EEBs

P1: The ambiguity about the applicability of the proposed widespread adoption approach and YYP in practice

Figure 1: Gradual illustration of the focused research problem

1.2.2 Motivations

There are five fundamental motivations behind this research:

- Since current measures are too slow to meet the target of limiting global warming below to 2°C (i.e. according to the Paris agreement) (Sadamori, 2016), there is an urgent need to develop more effective strategies to accelerate the reduction of global energy consumption.

- Increasing the number of EEBs with better marketability obtained with the enhancement of their aesthetic features has considerable potential for energy demand reduction in the building sector.

- Investigating the relationship between aesthetics, energy efficiency, and marketability fills a clear gap in literature.

- Introduced the phenomenon of IIBEE, widespread adoption approach and YYP are novel concepts and have the potential to significantly contribute in further reducing buildings' energy consumption and meeting related energy policy goals.

- YYP has the potential to initiate new generation simulation tools effective in the evaluation of buildings' different aspects simultaneously (e.g. marketability, aesthetic, energy efficiency, occupant comfort, and initial cost). This also has the potential to start a transformation in design review protocols, building regulations, building engineering, architecture, and future cities.

1.2.3 Research question and hypothesis

1.2.3.1 Research question

Is the proposed novel widespread adoption approach applicable in practice in the UK?

Sub-question:

- Is YYP applicable in practice?

1.2.3.2 Hypothesis

- There is a negative correlation between the energy efficiency and marketability of residential buildings.
- It is possible to achieve widespread EEB adoption with better marketability achieved by aesthetic enhancement.
- It is possible to predict the exterior visual aesthetic of residential buildings with computational models.

1.2.4 Aim and objectives

1.2.4.1 Aim

To investigate the applicability of the proposed widespread adoption approach and the novel paradigm (YPP) in practice and to propose supportive arguments about the existence of the phenomenon of IIBEE.

1.2.4.2 Objectives

- Development of a measurement model to parametrically measure the symmetry level of building façades to develop predictive models.

- Determination of the predominant physical parameters associated with residential building exteriors that simultaneously influence their aesthetics, marketability, and energy efficiency.
- Discovering the impact of the configurations applied on determined predominant physical parameters on aesthetics, marketability, and energy efficiency of residential buildings.
- Development of a multi-dimensional measurement model (i.e. ANN and decision tree-based predictive models) to test the applicability of YYP.

1.2.5 Novelty

- A novel phenomenon was introduced (*The phenomenon of inefficiency of increased building energy efficiency (IIBEE)*).
- A novel approach was proposed (*Widespread adoption approach*)
- A novel paradigm was introduced (*Yin and Yang paradigm (YYP)*).
- A mathematical model (*symmetry index*) was developed for the first time to parametrically measure symmetry of visual stimuli.
- The comprehensive investigation of the relationships between the aesthetics, energy efficiency, and marketability of residential buildings has not been done before.
- The impact of different window configurations on aesthetics, energy efficiency, and marketability of residential buildings was discovered for the first time.
- A multi-dimensional measurement model (predictive model) that can be utilised by non-experts has been developed for the first time, to estimate the aesthetics and marketability of low-rise residential buildings (based on window parameters in the UK).

1.2.6 *Scope and the limitations*

The scope of this research is limited to the overlap area of three disciplines (i.e. architecture, marketing, and engineering) as shown in Figure 2. This study is limited to the impact of 7 window parameters[11] (see Section 4.1.2 for the rationale) on the aesthetic, energy efficiency and marketability of low-rise terraced and detached brick residential buildings in the UK (see Section 4.2.2 for the rationale).

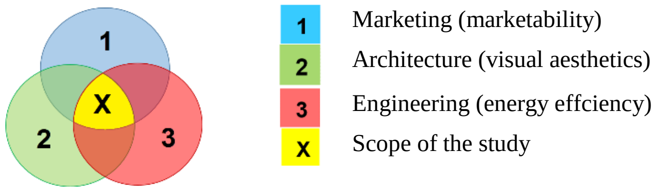


Figure 2: The focus and scope of the research

1.2.7 *Research methodology*

This section provides a brief summary of the methodologies utilised in this study, as shown in Table 1. Utilised methodologies are categorised under three headings, namely prediction, data collection, and data analysis. Utilised methodologies are summarised in the flowchart shown in Figure 3, and a more detailed overview of the workflow is shown in Figure 5. Further details about the methodology can be found in Chapter III.

Table 1: Brief summary of the methodologies utilised in this study

Data collection	Data analysis	Prediction
Literature review	Statistical models	Artificial neural network (ANN)
Multiple surveys		Decision tree
Building energy simulations		
Bespoke mathematical model		

[11] Window area, height, number, position, proportion, symmetry and width

Framework	Details
The phenomenon of IIBEE was introduced	The inadequacy of existing measures to reduce energy demand of the building sector was determined by a comprehensive literature review, conceptualized with a novel phenomenon (IIBEE) (see Section 2.1)
As a solution	
Widespread adoption approach was proposed	Increasing the number of EEBs with better marketability obtained via their aesthetic enhancement is proposed as a novel approach to reduce building sector's energy demand (see Section 2.2) and as a solution to the phenomenon of IIBEE. The applicability of the proposed widespread adoption approach in practice was tested with eight pre-studies (PS1 to PS8 in Figure 5), and two comprehensive surveys. One of the surveys was conducted with real-estate agencies (n = 289) across 26 UK cities (S1 in Figure 5), and the other was conducted with potential hosing buyers (UoN staff with diverse demographic characteristics (n = 183) (S2 in Figure 5)).
To ensure its applicability	Applicability problems of the integrated design approach (IDA) in practice and the aesthetic judgement differences between architects and non-architects (clients) were determined as the main obstacles to aesthetic enhancement of EEBs. Therefore, in order to ensure the applicability of the proposed novel approach a novel Yin and Yang paradigm (YYP) was proposed.
Yin and Yang paradigm (YYP) was proposed	YYP (see Section 2.3) is a paradigm that offer to consider all factors involved in a decision-making process and establishing balance between them to offer multi-dimensional solution to a problem. YYP is a multidisciplinary approach that empowers individual specialists to see the perspectives of different disciplines, instead of bringing experts in different disciplines together, as in IDA. In this way, each building stakeholder can see the impact of any design changes on buildings' different aspects simultaneously, and they can use this parametric information during their decision-making process. YYP can result in the initiation of new generation building simulation tools, effective in evaluating buildings' different aspects simultaneously (e.g. marketability, aesthetic, energy efficiency, occupant comfort, carbon footprint and price). In order to facilitate this, a multidimensional measurement model was needed to measure UK low-rise detached and terraced housing aesthetic, energy efficiency, and marketability.
To test its applicability	
Multidimensional measurement model	For this purpose, ANN and decision tree-based predictive models were developed based on the results of three main studies: • Mathematical model (symmetry index) was developed to measure the symmetry of building façades parametrically, validated by a survey conducted with 145 UoN students with different demographic characteristics (see Section 5.1) • A survey was conducted with 867 UoN students to investigate the impact of different window parameters on aesthetic and marketability of UK housing (see Section 5.2) • Building energy simulations (BES) were conducted to investigate the impact of different window parameters on the annual energy consumption of detached and terraced UK housing (see Section 5.3)

Figure 3: Framework of the Ph.D. thesis

1.3 Thesis layout

This section gives a fundamental overview of the thesis structure and layout. This thesis contains seven chapters, as shown in Figure 4. In the first chapter, the concepts introduced in this Ph.D. thesis are briefly introduced (i.e. the phenomenon of IIBEE, a novel approach, and YYP) and the overview of the thesis is provided to reader. In the second chapter, proposed concepts are discussed in detail and the reasoning behind them supported based on the literature review undertaken. Utilised methodologies are discussed in chapter three. The details of conducted studies to investigate the applicability of the proposed widespread adoption approach and YYP are discussed in the fourth and fifth chapters, respectively. The sixth chapter presents the results of the conducted studies, and the final chapter contains the overall summary of the thesis and the conclusion.

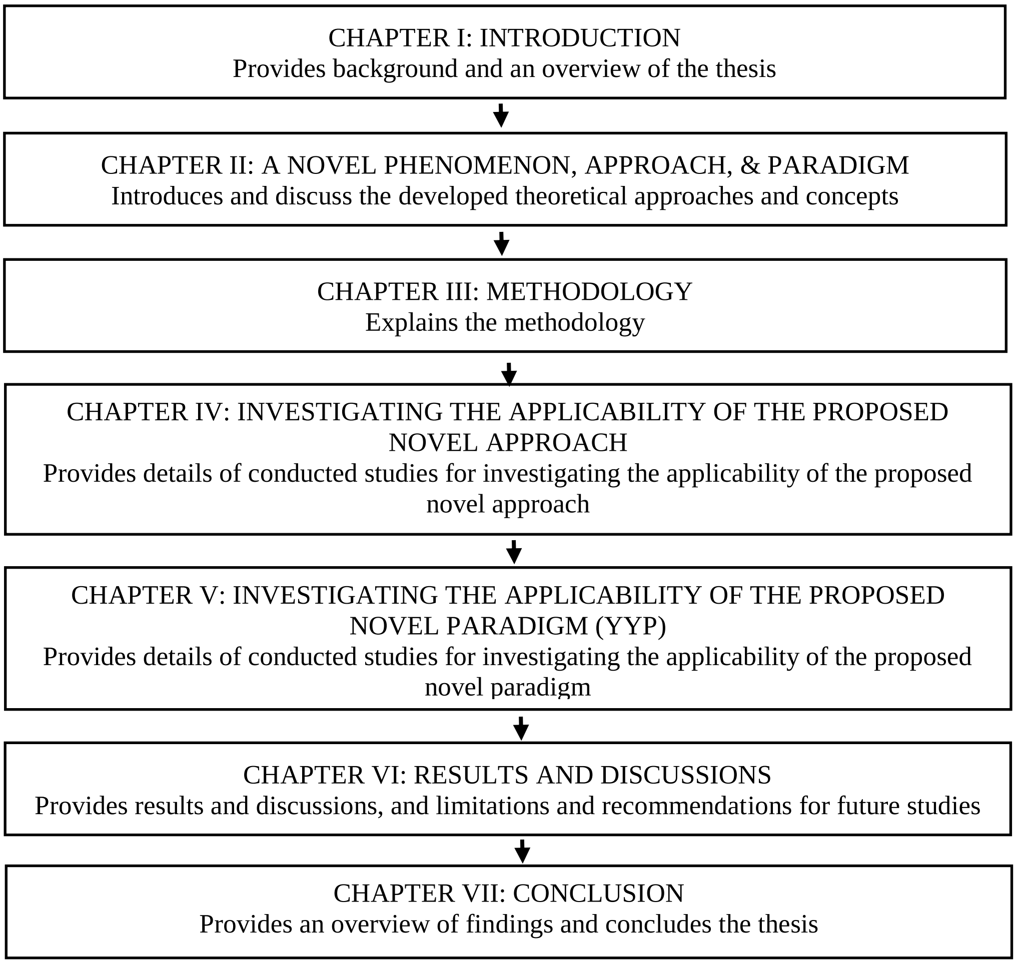


Figure 4: An overview of the thesis structure

CHAPTER II

A NOVEL PHENOMENON, APPROACH, &

PARADIGM

CHAPTER II.

A NOVEL PHENOMENON, APPROACH, & PARADIGM

This chapter presents the core of the thesis, it explains the details of the phenomenon of IIBEE, the widespread adoption approach, and the YYP. It discusses six key points: (1) the underlying reasons behind the phenomenon of IIBEE, (2) the difference between the phenomenon of IIBEE and Jevons paradox (rebound effect), (3) the applicability issues of integrated design approach (IDA) in practice, (4) the differences between the aesthetic judgement of architects and non-architects (clients), (5) the philosophy and the driving forces behind the YYP, and (6) the differences between the YYP and IDA.

2.1 The phenomenon of inefficiency of increased building energy efficiency (IIBEE)

Recent developments in EEBs enable energy savings of approximately 85% compared to conventional buildings (Schnieders & Hermelink, 2006). In the case of zero-energy building, this is further improved to 100%. Nevertheless, despite the fact that the first attempts to construct an energy-efficient building (in the modern sense) can be dated to the 1950s (Laustsen, 2008), the building sector has continued to demand a considerable amount of the total delivered worldwide energy over recent decades (e.g. 20% in 2016) (Conti et al., 2016). There is no doubt that recent developments in buildings' energy efficiency have helped to slow down the rapid rise in the energy demand of the building sector. However, the energy demand is projected to increase 42% by 2040 compared to its level in 2012 (Conti et al., 2016). Despite the very low alteration rate in the existing building stock[12] and the presence of increasingly stringent energy efficiency regulations[13], even in Europe an elevation of approximately 17% in energy demand of residential buildings is projected by 2040 compared to 2012 levels (Conti et al., 2016).

The phenomenon of IIBEE conceptualizes the inadequacy of existing measures[14] to reduce the energy demand of the building sector and emphasises the necessity of developing new and more effective strategies. The phenomenon of IIBEE reveals that there is an imbalance between the potential and actual achieved energy reduction in the building sector. The phenomenon of IIBEE has many causes, such as the lack of widespread EEB adoption, rapid net expansion of building stock, increased energy demand related to changes in lifestyle and comfort standards of occupants, Jevons paradox (rebound effect) (e.g. (Laustsen, 2008); (Johansson et al., 2012)), and so on.

As one of the main causes for the phenomenon of IIBEE, the lack of widespread EEB adoption can be proven by the low number of buildings according to the four most common energy certifications in the world (Table 2). Furthermore, the Energy Performance Certificate (EPC)[15] distribution in European (EU) building stock (Table 3) is another valuable evidence, stating that only 38% of current EU building stock is at the EEB level, between EPC A and EPC C. Moreover, as the energy efficiency ratio of buildings increases, the ratio of EEBs in the EU decreases significantly; for example, only 4% of the current EU building stock belongs to A-level EPC (Table 3).

---

[12] The annual new construction rate varies between 0.8 and 2% (in 2006) (Huovila, Ala-Juusela, Melchert, & Pouffary, 2007) The destruction rate of the existing housing stock varies between 0.025 and 0.23% (in 2003) (Meijer, Itard, & Sunikka-Blank, 2009)

[13] For example, German building space heating demand standards are 1/3 of 1982 standards (Schnieders & Hermelink, 2006)and according to Directive 2010/31/EU of the European Parliament, the minimum energy performance requirements of new buildings must be nearly zero-energy by 2020 (EU_FS, 2017)

[14] Energy efficiency enhancement and stringent energy efficiency regulations.

[15] The explanation of EPC and details of the criteria about the EPC levels (e.g. EPC A, EPC B) is given in the Appendix J.

Table 2: Worldwide number of energy-certified buildings with four most common energy certifications

Certification	Origin	The year of the first launched	Number of certified buildings worldwide since its inception	Source
ENERGY STAR	U.S.	1992	1,629,700	(ENERGYSTAR, 2017)
BREEAM	U.K.	1990	561,914	(BREEAM, 2017)
LEED	U.S.	2000	80,000	(LEED, 2017)
GREEN STAR	Australia	2003	1,462	(GREENSTAR, 2017)

Table 3: Percentage of EPC distribution (for all buildings) for available EU countries' building stock in 2014 and 2015[16] (EU, 2017)

Country	Year of the available data	EPC: A (%)	EPC: B (%)	EPC: C (%)	Total: A to C (%)	EPC: D (%)	EPC:<D (%)	Total: D to G (%)
Bulgaria	2015	0.44	1.54	2.85	4.83	15.13	80.04	95.17
Denmark	2015	10.28	11.97	38.32	60.54	27.81	11.62	39.43
Finland	2014	1.10	11.60	26.90	39.60	14.40	46.00	60.40
France	2015	7.95	11.91	14.77	34.63	29.77	35.60	65.37
Hungary	2015	10.65	12.97	5.17	28.79	11.29	59.92	71.21
Ireland	2015	0.98	11.56	36.88	49.42	25.35	25.23	50.58
Italy	2014	1.60	5.10	8.80	15.5	11.20	73.30	84.50
Lithuania	2014	0.31	16.71	30.51	47.53	10.73	41.74	52.47
Portugal	2015	7.61	26.06	33.20	66.87	19.93	13.20	33.13
Slovakia	2015	4.86	64.17	25.61	94.64	3.04	2.32	5.36
Slovenia	2015	0.51	2.61	14.10	17.22	26.90	55.88	82.78
Spain	2014	0.24	0.70	3.55	4.49	12.05	83.46	95.51
UK	2015	0.15	8.32	26.79	35.36	41.07	23.67	64.74
Average		3.59	14.25	20.56	38.4	19.13	42.47	61.6

[16] The most updated data for different countries were varied in the report, this is why there some data belongs to 2014 and others 2015.

The low number of EEBs in the existing EU building stock can be related to the low EU reconstruction rate,[17] but as it will be discussed in the Section 6.1.2.3 and 6.1.4.4, lower market demand for EBBs is more likely to explain the lack of widespread EEB adoption. Therefore, it is clear that in order to overcome the phenomenon of IIBEE, the elevation in the number of operated EEBs obtained with better marketability should be also targeted in future policies, rather than merely focusing on building energy efficiency enhancement and stringent building energy regulations. However, several substantial barriers, known as market barriers in the literature, obstruct the marketability of EEBs. Therefore, in order to understand and tackle the phenomenon of IIBEE these barriers first must be well-addressed, while more effective strategies and valid motivations should be introduced.

2.1.1 Overview of the barriers against the widespread adoption of energy-efficient buildings

The most prevalent governmental and private-sector barriers against the widespread EEB adoption are summarized in Table 4. Governmental barriers are based on regulation and policy. Private-sector barriers are based on voluntary approaches (i.e. building market-oriented mechanisms). There is no doubt that the governmental encouragement approaches have a key role in the promotion of EEBs, but they drastically depend on a series of economic and political limitations. Private-sector approaches can be more effective as they offer more cost-effective, practical, and flexible solutions to encourage private sector investment in EEBs (Lee & Yik, 2004). The low market value, unappealing aesthetic and, high initial cost of EEBs, and lack of interoperability between building stakeholders (see Section 2.2.1) are determined as the main private-sector barriers (Table 4), based on previous studies (see Section 2.1.1).

[17] The annual new construction rate varied between 0.8 and 2% in 2006 (Huovila et al., 2007) and the destruction rate of the existing housing stock varied between 0.025 and 0.23% in 2003 (Meijer et al., 2009)

Table 4: Some of the barriers against the construction of energy-efficient buildings

Governmental barriers

Administrative and regulatory barriers	Lack of attempts to inform public and stakeholders	Lack of incentives	Lack of buildings post-occupancy performance data
(Johansson et al., 2012) (Ryghaug & Sørensen, 2009); (Laustsen, 2008)	(Johansson et al., 2012); (Laustsen, 2008)	(Serpell et al., 2013); (Johansson et al., 2012); (Laustsen, 2008)	(Johansson et al., 2012)

Private sector barriers

Delays due to permission and control protocols of EEBs	(Laustsen, 2008); (Hoffman & Henn, 2008); (Aabrekk & Haavik, 2007)
High initial cost	(Serpell et al., 2013); (Robichaud & Anantatmula, 2011); (Laustsen, 2008); (Hoffman & Henn, 2008); (Audenaert, De Cleyn, & Vankerckhove, 2008); (Aabrekk & Haavik, 2007); (Schnieders & Hermelink, 2006)
Lack of environmental concerns among public	(Serpell et al., 2013); (Laustsen, 2008)
Lack of infrastructure, availability, and procurement	(Laustsen, 2008); (Hoffman & Henn, 2008)
Lack of interoperability between stakeholders	(Halicioglu, Arditi, & Gunhan, 2013); (Serpell et al., 2013); (Johansson et al., 2012); (Robichaud & Anantatmula, 2011); (Ryghaug & Sørensen, 2009); (Laustsen, 2008); (Hoffman & Henn, 2008)
Lack of knowledge - awareness of buyers	(Serpell et al., 2013); (Johansson et al., 2012); (Laustsen, 2008); (Hoffman & Henn, 2008);
Lack of knowledge of designers	(Halicioglu et al., 2013); (Serpell et al., 2013); (Johansson et al., 2012); (Ryghaug & Sørensen, 2009); (Laustsen, 2008); (Hoffman & Henn, 2008)
Lack of marketability of EEBs	(Serpell et al., 2013); (Parkinson et al., 2013); (Johansson et al., 2012); (Ryghaug & Sørensen, 2009); (Schnieders & Hermelink, 2006)
Lack of university programs that focus on EEBs	(Serpell et al., 2013); (Johansson et al., 2012)
Low market value of energy efficiency	(Serpell et al., 2013); (Parkinson et al., 2013); (Johansson et al., 2012); (Hauge, Thomsen, & Berker, 2011); (Robichaud & Anantatmula, 2011); (Laustsen, 2008); (Schnieders & Hermelink, 2006); (Isaksson & Karlsson, 2006)
Low market value of operational costs	(Johansson et al., 2012); (Robichaud & Anantatmula, 2011); (Laustsen, 2008); (Schnieders & Hermelink, 2006);
Prejudices and misconceptions	(Serpell et al., 2013); (Robichaud & Anantatmula, 2011); (Laustsen, 2008); (Hoffman & Henn, 2008)

2.1.1.1 *Low market value of energy efficiency features*

Market barriers are mainly exacerbated by a vicious circle between the low number of constructed EEBs and limited attempts to build new units. Motivations such as market demand and quick financial payback must be at the centre of strategies to convince construction stakeholders to invest in and construct more EEBs, but the existing steps in this regard are manifestly insufficient (Shafii, Arman Ali, & Othman, 2006). Low market value of energy efficiency features is one of the main reason for the limited attempts to build new EEBs.

Empirical evidence shows that in practice energy efficiency has a low market value in the eyes of clients (e.g. (Johansson et al., 2012); (Schnieders & Hermelink, 2006)) and other stakeholders (e.g. (Johansson et al., 2012); (Ryghaug & Sørensen, 2009)), while architectural features (e.g. attractive site, existence of balcony and typology of buildings (Schnieders & Hermelink, 2006)) and economic profits are the main driving force in the buying decision-making process. For example, according to conducted questionnaires and interviews in China, stakeholders' reluctance to utilise energy-saving technologies was recognized as the main reason for the lack of widespread adoption of those technologies in China (Du, Zheng, Xie, & Mahalingam, 2014). Even in socially conscious Scandinavian countries, the main reason for buyers' preference to purchase 20 low-energy terraced houses in Gothenburg (Sweden) (Isaksson & Karlsson, 2006) and 56 energy-efficient flats in Norway (Hauge et al., 2011) was buildings' architectural characteristics rather than their energy efficiency. According to a survey conducted by McGraw-Hill Construction Company (2006) of over 400,000 participants, only 24% of them stated that being environmentally friendly is an important factor in their buying decision-making process (Robichaud & Anantatmula, 2011). More surprisingly, the marketing experience from multi-storey passive houses built for low-income buyers in the CEPHEUS project in Hannover (Germany) revealed that the construction company's first advertising campaign, which mainly focused on the energy efficiency, received a very weak response; the subsequent revised campaign, which emphasised architectural features (e.g. attractive site, existence of balcony and typology of buildings (Schnieders & Hermelink, 2006)), was conversely very successful in selling all houses in a short period of time (Schnieders & Hermelink, 2006). This marketing experience clearly shows that even if EEBs become cheaper, their market demand elevation cannot be guaranteed (see Section 6.1.4.3, and Section 6.1.4.4 for further evidence). Therefore, the development of more effective marketing strategies is necessary to ensure widespread EEB adoption.

The relatively low market value of energy-efficient buildings is attributable to negative perceptions among consumers (including contractors and end buyers) linked to numerous reasons, including: (1) discomfort associated with energy efficiency (e.g. (Hauge et al., 2011); (Hoffman & Henn, 2008); (Aabrekk & Haavik, 2007)) (e.g. low comfort due to a smaller glazing area, operation difficulties of new technologies and systems (Hauge et al., 2011), smaller space, and unappealing aesthetics (Hoffman & Henn, 2008)); (2) resistance to new concepts and fear of the unknown (e.g. (Hoffman & Henn, 2008); (Aabrekk & Haavik, 2007)); (3) complex, time-consuming, and unfamiliar bureaucratic requirements for construction procedures and approvals that could cause delays in construction time, and also an attenuation in profit (e.g. (Aabrekk & Haavik, 2007)); (4) distrust of unfamiliar indoor climate technologies, which could cause confusion for occupants (e.g. (Hauge et al., 2011); (Isaksson & Karlsson, 2006)); and (5) restrictions due to energy efficiency requirements (e.g. although they are requested intensively by European buyers, passive building requirements forbid the inclusion of traditional fireplaces and ovens, due to their super insulated structures (Hauge et al., 2011); (Isaksson & Karlsson, 2006)). In general, it is reasonable to claim that if any attempt to increase energy efficiency overlaps with buyer's expectations or comfort, strong opposition to those features can occur. Therefore, the expectations and features that have a high market value in the eye of house buyers should be considered during the EEBs development and design process.

2.1.1.2 *High initial cost*

One of the biggest obstacles against the marketability and widespread EEB adoption is the fact that they are more expensive solutions compared to ordinary buildings. The extra initial cost can reach up to 20%, mainly due to the cost of materials' and technological implementations (Johansson et al., 2012). The high initial cost of EEBs was declared as one of the main marketability obstacles according to surveys by Global Green Building Trends in 2008 (n = 700) and McGraw-Hill Construction Company in 2006 (n = 400,000) (Robichaud & Anantatmula, 2011). Accordingly, any attempt to increase the initial price of such buildings can face significant opposition among contractors and clients. Furthermore, as another crucial barrier, building buyers tend to considerably overestimate EEBs' initial costs (by up to 28%) compared to the reality (Hoffman & Henn, 2008). In other words, there is significant and widespread prejudice against EEBs.

The long payback period and the low amount of monthly monetary return from EEBs' energy savings (especially in residential buildings) are other crucial barriers. For example, according to a study of eleven different low-energy and passive houses, the payback period varies between 8-20 years (Audenaert et al., 2008), which is not enough to meet the financial expectations of many house buyers. In general, housings' operational energy saving has a low priority for many buyers, as the energy bills are distributed over several years. While the substantial capital outlay for the high initial cost of EEBs is perceived to be a big burden, monthly energy bills are not perceived as a considerable difficulty, at least at the selling point of house (Johansson et al., 2012). For example, in the UK, a typical four-bedroomed house price is about £200,000 (UK_Gov, 2018), with average monthly bills of £49 for electricity and £48 for gas, totalling £97 (UK_Power, 2018). Energy savings of approximately 85% are possible with passive buildings (Schnieders & Hermelink, 2006), while the extra initial cost of EEBs can reach up to 20% of the housing price

(Johansson et al., 2012). Accordingly, in this representative scenario, a buyer is expected to make an investment of approximately £40,000 for a monthly saving of only £83. Therefore, as highlighted in the International Energy Agency's 2008 report, the initial cost of buildings is overwhelmingly crucial for buyers and decision makers, yet little attention is attributed to the operational costs (Laustsen, 2008).

These negative cost-benefit perceptions that inhibit the widespread EEB adoption in most countries are exacerbated where energy prices are relatively cheap due to the abundance of energy resources, or government subsidies. For example, energy prices in Saudi Arabia are at least 95% lower than the international market price (Naceur, 2015). Thus, because of the unassailable cheapness of the conventional energy (i.e. fossil-fuel based), a long-term operational energy and economic saving, which is one of the key rationales behind construction of EEBs (according to consumer perceptions), totally loses its profit motive in such countries (Naceur, 2015); (Laustsen, 2008).

2.1.1.3 Lack of interoperability between building stakeholders

EEBs' development requires more advanced expertise and coordination (i.e. effective IDA) than that of ordinary buildings. Interoperability between building stakeholders (e.g. architects, engineers, contractors, and clients), particularly in the early stages of the design, is crucial for minimizing the extra initial cost of EEBs (Laustsen, 2008), and the risk of market failure (Halicioglu et al., 2013). Effective collaboration between stakeholders minimizes complications and encourages decision-makers to support EEBs (Halicioglu et al., 2013).

Despite its importance in EEB construction, the lack of interoperability between building stakeholders was broadly reported in previous studies (e.g. (Serpell et al., 2013); (Ryghaug &

Sørensen, 2009)). For example, this was reported as the second main barrier to EEB construction in Chile (Serpell et al., 2013). The reason was mainly associated with the applicability problems of the IDA. The inadequacy of the interoperability between building stakeholders has already initiated attempts to develop different approaches, such as IDA, which is a valuable approach to handle problems in a multidisciplinary manner and set a balance between different building design aspects (e.g. energy efficiency, aesthetics, and marketability, etc.), because in this approach experts from different disciplines are encouraged to work together in the early stages of building design.

However, the application of IDA in practice is not always straightforward, due to the challenge of setting a balance between different priorities, such as energy efficiency, cost, and aesthetic features (Halicioglu et al., 2013); (Robichaud & Anantatmula, 2011). The conflicts between experts from different disciplines is rooted in the difference in their priorities and mentalities (e.g. (Ryghaug & Sørensen, 2009)) and their aesthetic judgements (particularly between architects and others) (e.g. (Garip & Garip, 2012); (Gifford, Hine, Muller-Clemm, & Shaw, 2002)). In general, different building stakeholders have different perspectives, concerns, motivations, and expectations that influence their decision-making process. For example, conflicts and communication problems between architects and engineers were reported as the main reasons behind the low market success of energy-efficient buildings in Norway. Most technological measures to enhance buildings' energy efficiency are considered aesthetically ugly by Norwegian architects (Ryghaug & Sørensen, 2009). Aesthetics was reported as the dominant concern for most Norwegian architects who participated in the study, yet they paid scant attention to buildings' energy efficiency. It was also reported that low energy efficiency and occupant comfort do not matter for Norwegian architects if the building does not look good (Ryghaug & Sørensen, 2009). Most of the architects have little or no knowledge about building energy efficiency (Ryghaug & Sørensen, 2009), and they have a tendency to oppose energy-efficient strategies if they clash with aesthetic aspirations or architectural design (Hoffman & Henn, 2008).

The conflict between building stakeholders has shown a negative impact on construction time and quality as well as several macroeconomic impacts on the national and global levels (Johansson et al., 2012). For example, based on a comprehensive survey by the US Department of Commerce Technology Administration, inadequate interoperability in the US building sector causes annual losses of $15.8 billion for the US economy (Gallaher, O'Connor, Dettbarn, & Gilday, 2004). Therefore, new strategies to improve the applicability of IDA or alternative strategies should be developed.

2.1.2 The difference between the phenomenon of IIBEE and Jevons paradoxes

The phenomenon of IIBEE has a fundamental difference from the Jevons paradox (known as the rebound effect). The ecological economist William Stanley Jevons (1865) first revealed the existence of the eponymous paradox in his famous book "*The Coal Question*" (Alcott, 2005). The Jevons paradox can be simplified by the example of a factory production chain. If the efficiency of an energy source in a factory increases, the price of energy used per unit of the produced merchandise decreases; cheaper merchandise increases the demand in the market, thus the volume of produced merchandise increases, which consequently increases the energy demand. Consequently, the amount of energy used in the factory exceeds the level before the efficiency elevation of the factory.

According to the Jevons paradox, as efficiency increases, the rate of consumption of a resource (e.g. energy) rises rather than being reduced, due to the increase in the demand achieved by cheaper energy costs built into products. Previous studies present some valuable evidences about the validity of this paradox in the context of EEBs; for example, according to the report by the IEA (2008), companies and individuals consume more energy than required to satisfy a basic comfort level in EEBs (Laustsen, 2008), which can exceed up to 30% for the space heating and 70% for the space cooling (Johansson et al., 2012). In contrast, as discussed in more detail in the Section 6.1.2, in the phenomenon of IIBEE, there is a negative correlation between efficiency and demand (e.g. marketability), rather than a positive correlation as postulated in the Jevons paradox.

It should be emphasised that the phenomenon of IIBEE is not an alternative or an opposition to the Jevons paradox. In both, increasing energy efficiency is not enough to reduce energy consumption as an expected level. However, the Jevons paradox is a problem pertinent after the sale of an EEB, but the phenomenon of IIBEE is an essential problem that arises during the sale process. In other words, it is mainly associated with the lack of widespread EEB adoption due to market failure of EEBs. In terms of EEBs, the Jevons paradox is essentially associated with occupants' behaviour in the post-occupancy period, while in the phenomenon of IIBEE it is mainly associated with buyers' buying decision-making process. Accordingly, while strategies are being developed to reduce the energy demand of the building sector, preventive measures for the occurrence of the Jevons paradox should be also taken into account, as well as the phenomenon of IIBEE.

2.1.3 *Summary*

- The inadequacy of existing measures to reduce the energy demand of the building sector is conceptualized through a novel phenomenon named Inefficiency of Increased Building Energy Efficiency (IIBEE).

- The lack of widespread EEB adoption as a result of marketability issues is the main (though not the only) reason behind the phenomenon of IIBEE.

- The low market value of energy efficiency features, the high initial cost of EEBs, the lack of interoperability between building stakeholders, and the unappealing aesthetics of EEBs are determined as the most dominant barriers that obstruct EEB marketability.

- The phenomenon of IIBEE has a fundamental difference from the Jevons paradox. According to the Jevons paradox, as efficiency increases, the rate of consumption of a resource (e.g. energy) rises rather than being reduced, due to the subsequent increase in demand achieved by lower product costs. In contrast, in the phenomenon of IIBEE, there is a negative correlation between efficiency and demand (e.g. marketability).

- The phenomenon of IIBEE is not an alternative or an opposition to the Jevons paradox; both should be considered during EEB design, and preventative measures should be developed.

2.2 A novel approach for energy demand reduction in the building sector

In this section, the details of proposed widespread adoption approach is discussed; empirical evidences about its applicability can be found in Section 6.1.

All the aforementioned shortcomings of the current building sector energy demand reduction measures emphasise the necessity for the development of new strategies, particularly to achieve widespread EEB adoption (see Section 2.1). Therefore, new motivations to enhance market demand for EEBs are necessary to overcome the phenomenon of IIBEE, but these motivations should ultimately depend on consumer preferences, not the technical (energy efficiency) priorities of professionals, which currently dominate EEB design and construction. Both utilitarian and hedonic motivations drive a client to buy a dwelling, but compared to utilitarian motivations, the hedonic stimuli have priority in marketing strategies as they trigger several crucial positive reactions in consumers (e.g. tendencies and willingness to pay higher prices, attribute more emotional value to the product, and greater desire for expedited possession) (Reimann, Zaichkowsky, Neuhaus, Bender, & Weber, 2010). As a hedonic motivation, aesthetic features have an important role in marketability (e.g. (Parkinson et al., 2013); (Hauge et al., 2011)), individuals' satisfaction, and happiness (e.g. (Parkinson et al., 2013); (Reis & Lay, 2010)). The crucial role of aesthetic features on the marketability of EEBs was also highlighted in an EEB marketing guide outlining factors in EEB success and failure in seven different countries[18] (Aabrekk & Haavik, 2007). Accordingly, exterior aesthetic enhancement of EEBs can be an effective motivation to respond to the marketability challenge and increasing the number of deployed EEBs. This novel approach is referred to as the 'widespread adoption approach' in this thesis.

[18] Austria, Canada, Germany, Netherlands, Sweden, Switzerland, and USA

2.2.1 *The role of visual aesthetic on buildings' marketability*

The negative impacts of market barriers, such as the high initial cost of EEBs and low market value of energy efficiency features, can be minimized via the improvement of the exterior aesthetics. This implies raising the worth of EEBs according to consumer perceptions rather than decreasing initial costs. Aesthetic features have a considerable impact on the estate value (added value). For example, in the UK, the rental values of energy-efficient workplaces are significantly associated with buildings' aesthetic while no association with energy-efficiency features has been reported (Parkinson et al., 2013). In the US, office buildings with better aesthetic features have attract 7% higher rent, and 17% higher selling prices (Fuerst et al., 2011). According to an empirical analysis on the sale data of 5,000 homes in New Zealand, attractive neighbouring buildings provide 37% additional value to a house (Bourassa, Hoesli, & Sun, 2004). In other words, aesthetic quality of a building also influences the added value of the neighbouring buildings.

Exterior aesthetics have a more significant impact compared to interior aesthetics, as the satisfaction level of a building's external aesthetic is directly correlated with the satisfaction level of the entire dwelling (Reis & Lay, 2010). The internal and external aesthetic aspects of 12 dwellings in Brazil was investigated via several interviews and questionnaires; 70% of participants described the external aesthetics of their buildings as unappealing, while only 10% were dissatisfied with internal aesthetics (Reis & Lay, 2010). Participants particularly identified ugly windows and ordinary/common façade design as causes of their dissatisfaction. According to another study in Sweden surveying 3,059 homeowners, most of them tended to modify their building envelopes due to aesthetic considerations (Nair, Gustavsson, & Mahapatra, 2010).

Despite its remarkable importance on buildings' marketability, aesthetic features are not given enough consideration in EEB design. The unappealing aesthetic of EEBs was broadly reported in previous studies (e.g. (Buckley & Logan, 2016); (Ryghaug & Sørensen, 2009); (Hoffman & Henn, 2008)). According to a survey on more than 1,000 participants in 13 different countries[19], 86% of the participants believed that EEBs are not aesthetically pleasing (Buckley & Logan, 2016). Similarly, according to other studies conducted in Norway (Ryghaug & Sørensen, 2009) and the US (Hoffman & Henn, 2008), buyers associated EEBs with terms such as "unappealing aesthetic" (Ryghaug & Sørensen, 2009); (Hoffman & Henn, 2008), "small space", and "low comfort" (Hoffman & Henn, 2008). Accordingly, it is clear that, the priority given to energy efficiency should be also directed to the aesthetic of the EEBs to enhance their marketability.

In order to improve the aesthetic of the EEBs, an integrated design approach (IDA) is required. IDA encourages to bring together different building stakeholders in the early stages of EEB design to promote increased integration and synchronization among them. While IDA is clearly beneficial in theory, there are issues of applicability in practice (e.g. (Serpell et al., 2013)) (see Section 2.1.1.3), which causes difficulties for the aesthetic enhancement of EEBs in practice. Another important point causing difficulties to improve the aesthetic of the EEBs is differences between aesthetic judgements of architects and non-architects (housing buyers) (Garip & Garip, 2012); (Gifford et al., 2002). Even if IDA can be successfully applied, better marketability obtained with aesthetic enhancement of EEBs cannot be guaranteed, because aesthetic enhancement is mainly implemented in the architectural field, and architects often have different aesthetic judgement and tastes from housing buyers. Therefore, a supplementary approach by establishing a balance and harmony between different disciplines and giving priority to public (particularly client)

[19] Mexico, the Australia, Brazil, China, Colombia, Germany, India, Poland, Saudi Arabia, Singapore, South Africa, UK, and US.

aesthetic judgement is required to improve the aesthetic of the EEBs and obtain widespread EEB adoption (i.e. ensure the applicability of proposed widespread adoption).

2.2.2 Summary

- Increasing the number of deployed EEBs with better marketability strategies can be a practical and efficient supplementary approach for energy reduction in the building sector.

- Aesthetic enhancement of EEBs can be an effective motivation to enhance their marketability and to minimize the negative impacts of the high initial cost of EEBs and low market value of energy efficiency features.

- The unappealing aesthetic of EEBs was broadly reported in previous studies. Accordingly, the given priority to the energy efficiency should be also directed to the aesthetic of the EEBs to enhance their marketability.

- The IDA is required to enhance aesthetic of EEBs, yet there is an applicability problem for the IDA in practice and differences between aesthetic judgements of architects and non-architects (housing buyers). Accordingly, new strategies to improve the applicability of the IDA or alternative strategies to it are necessary to be developed.

2.3 Yin and Yang paradigm

This section introduces a novel multidisciplinary paradigm to ensure the applicability of the proposed novel widespread adoption approach. Furthermore, this section includes supportive arguments about the applicability of the proposed paradigm, discusses the core philosophy behind it, and explains its fundamental difference from the IDA and the conventional paradigm, which made the building sector one of the dominant sectors in global energy demand and caused the phenomenon of IIBEE. Further evidences about the applicability of the proposed novel paradigm can be found in Sections 2.3.2 and 6.2.

The OED[20] defines the notion of a paradigm as: "*a pattern or model of something*" and "*a world view underlying the theories and methodology of a particular scientific subject*" (OED, 2018). In the philosophy of science, the notion of paradigm is associated with the book called "*The Structure of Scientific Revolutions*" (1962) by Thomas Kuhn, a historian and philosopher of science. Kuhn describes paradigms thus: "*Normal science proceeds within such a framework or paradigm. A paradigm does not impose a rigid or mechanical approach but can be taken more or less creatively and flexibly*". According to Kuhn, a paradigm typically emerges in response to the accumulation of anomalies inherited from past approaches when they cannot be solved within its framework (Blackburn, 2016). Like Kuhn's claim, the YYP is proposed in this Ph.D. thesis based on an observation that the inherited problems created by the conventional paradigm cannot be solved within its framework. The driving force behind the YYP is based on a philosophical concept that is well known in an apocryphal remark attributed to Einstein ("*We cannot solve our problems with the same thinking we used when we created them*").

[20] Oxford English Dictionary.

In order to understand the YYP explicitly, it is first necessary to understand the ontology underlying its name. The name of this paradigm is rooted to a doctrine in the Chinese philosophy and Taoism which is classically represented by the Taijitu (Yin-Yang symbol[21]). The Yin-Yang symbol posits Yin (dark, representing chaos and destruction) and Yang (light, representing order and construction) as a part of the same creative dynamo that iterates the universe (thus the principle is displayed in a circle). In the Yin-Yang symbol, within the centre of Yin there is Yang, and in the centre of Yang there is Yin. Yin and Yang are intrinsic to each other and part of a whole, in harmony and balance. In Taoism, the Taoist seeks to transcend contention (as far as possible) and attain to the Tao (way) by balancing and ultimately negating these extremes (Yin-Yang) (Zai, 2015). Accordingly, the name of the YYP is based on the doctrine that seemingly contradictory or opposing phenomena may actually be complementary, interconnected, and interdependent, and that they can reinforce each other when they interrelate to each other. According to this doctrine, negotiation of the extremes, balance and harmony, and transcending the contention between different opposing phenomena are the key factors to attain goals.

In order to provide further clarification, YYP and its relationship with the content of this thesis can be understood via a simplified analogy using the circular Yin-Yang symbol (taijitu) to represent the building design and construction process. The Yin (black) part may represents the perspective of engineering and the Yang (white) part may represents the architectural perspective. Despite these two disciplines (engineering (black) and architecture (white)) being essentially different and contradictory in their mentality [22], they are in fact complementary and interdependent, and they interrelate and reinforce each other (ideally in perfect balance and harmony) within the

[21] 

[22] For example, architecture is more subjective and has blurred boundaries and rules, mainly based on creative design. Conversely, engineering is more concrete, with sharp and clear boundaries and rules, based on mainly functional and efficiency considerations.

whole circle of building design. Of course, the design and construction process of a building is too complex to be limited to just two disciplines (i.e. architecture and engineering), thus other disciplines (e.g. marketing, sociology, psychology, urban planning and so on) also have interrelated impacts, both mutually with architecture and engineering, and also among themselves. Therefore, it would theoretically be possible to involve more colours in a more comprehensive symbol to represent the entirety of construction project stakeholders, but the logic and the underlying philosophy would be same with Yin-Yang symbol and its doctrine. In other words, as an overview, YYP can be summarised as a paradigm that offers to take into account all pertinent factors involved in a decision-making process and establishing a balance between them. YYP is not only limited to building design and construction, rather it is a paradigm that can be applied on any field of life. YYP can be confused with optimization method[23], but the former is a paradigm with a philosophy behind it, while optimisation is only a technique and/or model that can be utilized to reach the targets of YYP.

In order to provide a clearer understanding about the need for this novel paradigm, it is first necessary to understand the conventional paradigm and the problems inherited from it. In its simplest definition, conventional paradigm is an approach that seeks a solution for a problem via the hegemony of a single discipline and task-based reasoning (e.g. focusing only on reducing the energy consumption of buildings to reduce the energy demand of the building sector). The conventional paradigm is one of the fundamental reasons behind the phenomenon of IIBEE. The current impasse of the conventional paradigm can be understood better from the historical development of buildings. Prior to the 1970s OPEC (The Organization of the Petroleum Exporting Countries) oil crisis, energy efficiency was not a priority in building design, rather other architectural and monetary concerns were predominant. Due to the temporal concern-oriented

[23] According to OED; optimisation is the action of making the best or most effective use of a situation or resource.

approach of the conventional paradigm, an imbalance between architectural concerns and energy efficiency in building design resulted in the building sector becoming one of the main causes of global energy consumption and therefore global warming.

The energy consumption of the building sector is now a massive and unsustainable burden on the environment (NASA-GCC, 2019) and the economy (UNISDR, 2012), thus the energy efficiency of buildings has become a priority in most countries. Since the distinguishing feature of EEBs is the energy efficiency, the engineering discipline was dominant during the design and development of EEBs. Focusing on only energy efficiency enhancement of buildings has been ultimately insufficient in reducing building sector energy demand (see Section 2.1). Building design is a very complex process, and there ought to be equilibrium between various factors. The conventional paradigm, which is limited by the unidimensional approach, is insufficient to establish this balance. As a result, the drive for increased energy efficiency in buildings overlooked side effects on other factors such as initial cost, construction time, marketability, and aesthetics. Consequently, this imbalance created the phenomenon of IIBEE (Section 2.1).

In brief, the conventional paradigm is creating a vicious circle, generating overlooked side effects on other factors. In other words, with the conventional paradigm we are trying to solve our problems with the thinking we used when we created them, so we are in fact creating new and unpredicted problems in long term. Conversely, the YYP paradigm seeks a multi-dimensional solution to the problem by establishing a balance between different disciplines. In the YYP different interdependent disciplines complement and strengthen each other instead of competing, establishing a balanced and cohesive project. In contrast to the conventional paradigm, the YYP avoids task-based reasoning to handle the problem with a wider perspective. Accordingly, solutions proposed by the YYP are less likely to encounter problems that are unpredictable in practice (e.g. the phenomenon of IIBEE) compared to the solutions proposed by the conventional paradigm, because while the conventional paradigm is limited to the perspective of only one dominant discipline, the YYP combines the perspectives of different disciplines to approach the problem in a multidimensional manner. Thus, it can identify problems that cannot be seen from a single point of view, and it gives an opportunity to develop appropriate strategies accordingly.

Further clarity about the YYP can be provided with an illustrative scenario. If the YYP had been utilised to reduce the energy demand of the building sector rather than conventional paradigm, the emergence of the phenomenon of IIBEE could have avoided. When seeking a solution to reduce the energy demand of the building sector with the YYP, the impact of energy efficiency enhancement of buildings on other aspects such as aesthetics, initial cost, and marketability of buildings could have been observed. As a result of this, directly proportional relationship between energy efficiency and initial cost of buildings (see Section 2.1.1 and 6.1.2), and the inverse relationship between initial cost and marketability of buildings (see Section 6.1.2) could have recognized in the early stages of the strategy development process, to reduce the building sector's energy demand. Consequently, it could have foreseen that focusing only on increasing the energy efficiency of the buildings would lead to market failure, and as a result of this, the energy demand of the building sector would not be reduced as expected due to the lack of widespread EEB adoption. Therefore, widespread EEB adoption and much remarkable energy demand reduction in the building sector could have achieved via putting more effort into the setting a balance between the marketability and energy efficiency of buildings.

2.3.1 The difference between the YYP and integrated design approach (IDA)

The YYP offers the ability to see the perspectives of different disciplines by a single specialist instead of encouraging the experts in different disciplines to come together in contrived collaboration, as in IDA. In this way, each building stakeholder can see the impact of any design changes on building aesthetic, energy efficiency, marketability, and other aspects simultaneously, and they can use this parametric information during their decision-making process. In brief, the YYP is a paradigm that can result in the development of new generation of building simulation tools, which can be simultaneously utilised in the evaluation of different aspects of a building (e.g. marketability, aesthetic, energy efficiency, occupant comfort, and initial cost). Monitoring the different aspects of buildings can contribute to: (1) applicability of the IDA, (2) minimized issues related to differences in aesthetic judgement between architects and housing buyers, (3) set harmonise and balance between different disciplines, and (4) development and transformation in design review protocols, building regulations, building engineering, architecture, and future cities.

It should be clarified that YYP is not a new generation simulation tool, rather it is a paradigm that can be applied any field of life. For example, an individual can implement YYP in dietary decisions, considering the different aspects of food such as healthy, budgetary, environmental, satisfaction, and time-demand aspects. In other words, YYP essentially takes into account all pertinent factors involved in a decision-making process, establishing balance between them. In the context of EEBs, a multidimensional measurement model or a new generation simulation tool is needed to provide empirical data about different aspects of buildings, such as energy efficiency, aesthetics, and marketability, to establishing balance between them, and ensure the applicability of YYP.

Although there are simulation tools that are capable to simulate many aspects of buildings (e.g. occupant comfort, energy efficiency, and initial costs), there is no common tool to evaluate various aspect of buildings such as aesthetic and marketability. In particular, it is difficult and controversial to measure building aesthetic with scientific methodologies, due to the subjective nature of aesthetic appreciation. Two fundamental questions arise in this regard: (1) is there a common aesthetic taste? (2) Is it possible to predict common aesthetic judgement via scientific methodologies? Despite an ongoing debate about the answers to these philosophical questions since ancient times, with the development of the fields of experimental and computational aesthetic approaches, previous studies have provided promising results about the existence of common instincts regarding aesthetic tastes (e.g. (Langlois, Ritter, Roggman, & Vaughn, 1991); (Langlois, Roggman, & Rieser-Danner, 1990)), and the possibility to simulate aesthetic judgement (e.g. (Bhattacharya, Sukthankar, & Shah, 2010); (Eisenthal, Dror, & Ruppin, 2006)).

2.3.2 The applicability of aesthetic enhancement of EEBs in practice

In order to enhance the aesthetic of EEBs, it is necessary to understand the dynamics of individuals' aesthetic judgment and to determine the parameters associated with aesthetic appreciation. A desire to understand the dynamics of the aesthetic appreciation can be traced back to ancient times (Eysenck, 1941). Since antiquity, there have been ongoing debates about the subjectivity and universality (objectivity) of aesthetic appreciation. Subjectivist doctrine postulates that beauty is subjective and differs from person to person, instead of a common aesthetic taste. In contrast, the objectivist doctrine suggests that there is a fundamental universal aesthetic that is common for most human beings.

After the initiation of evolutionary aesthetics theory, which is based on evolutionary psychology roots in Darwinian evolution (Voland & Grammer, 2003), the debate about subjectivist and objectivist doctrines has been more intensified than ever before (Voland & Grammer, 2003). This theory postulates that evolution and natural selection have shaped humans' mind and behaviour, and the majority of human behaviour is based on subconscious codes coming from survival and adaptation instincts. After the initiation of experimental psychology by Fechner (1876), the ongoing debate about the dynamics of individuals' aesthetic judgment has continued within the framework of experimental methods. Researchers such as Rashevsky (Rashevsky, 1938), Birkhoff (Birkhoff, 1933), and Emch (Emch, 1900) pushed the boundaries further to formulate aesthetic appreciation and to initiate computational aesthetics. Although computational approaches can be traced back to Pythagoras (c. 570 – c. 495 BC), who is probably the first person to establish a connection between mathematics and music (Eysenck, 1941), Birkhoff's aesthetic measure equation[24] first initiated a big debate about the plausibility in the prediction of the common aesthetic judgement with mathematical models. When neuroaesthetics was transformed into scientific discourse by the pioneers such as Semir Zeki, understanding of the aesthetic judgment dynamics in neurological contexts became more promising (Chatterjee, 2011).

Some previous studies offer valuable empirical findings for the existence of a common instinctual aesthetic appreciation, independent of the learning process through cultural transmission and education. For example, according to the numerous magnetic resonance imaging (MRI) experimental studies, the experience of beauty (in general terms) is correlated with activities in a region of the brain (medial orbitofrontal cortex (mOFC)) that has been generally associated with pleasure and reward (Tomohiro Ishizu & Zeki, 2017), which is in favour of Kant's view of aesthetics: "aesthetic judgement is based on feeling pleasure or displeasure". A positive linear relationship between the strengths of activation in mOFC and the declared intensity of the experience of beauty was reported in previous studies (T. Ishizu & Zeki, 2011). Different empirical studies reported that young infants can distinguish between attractive and unattractive faces (as categorized by adults), expressing a more positive reaction and less withdrawal rate to attractive faces compared to unattractive ones, accounting for race, gender, and age (e.g. (Langlois et al., 1991); (Langlois et al., 1990)). Similar results were also reported for the reactions of infants to various objects (Langlois et al., 1990). Furthermore, the existence of a common aesthetic appreciation for adults with different demographic characteristics was reported in a meta-analysis

[24] (i.e. $M = O / C$, the amount of pleasure derived (M) = amount of order (O) / the amount of complexity (C)).

covering more than 19,000 respondents and 3,281 visual stimuli in 107 relevant studies (Stamps III, 1999).

In addition to observational scientific studies, recent advancements in computational aesthetic approaches have shown promising results to simulate individuals' aesthetic judgments and perceptions. For example, Marquardt (1997) developed a well-known method on the basis of symmetry and proportional theories called "Phi mask" or "Golden Decagon" to analyse human faces' attractiveness for surgical, cosmetic, and identification purposes (Marquardt, 1997); it was reported that it is possible to explain the variance of judgements in facial attractiveness up to 75% via Phi mask (Bashour, 2006). In addition, in this thesis, as influential parameters that affect aesthetic judgement, individuals' symmetry perceptions on photographic images were simulated with developed mathematical models with a success (see Section 6.2.1).

Applications of advanced methods such as ANNs and machine learning have become new milestone for computational aesthetic judgement approaches. Previous works have shown promising results to simulate individuals' aesthetic judgments about the attractiveness of different visual stimuli, such as photographic images (e.g. (Bhattacharya et al., 2010)), and human faces (e.g. (Eisenthal et al., 2006)). It was reported that predictive models can reach up to 86% accuracy in predicting the attractiveness of visual stimuli (Bhattacharya et al., 2010). Furthermore, currently there is a publicly accessible photograph aesthetic quality rating tool (Aesthetic Quality Inference Engine (ACQUINE)) available. This online system, which developed in Penn State University, U.S, allows users to upload their photographs and rate their aesthetic automatically (real-time) (Datta & Wang, 2010).

All the above-mentioned studies on the aesthetic judgements provide promising results for the existence of universality (objectivity) in aesthetic appreciation. However, claiming the validity of a pure version of either subjectivist or objectivist doctrines seems implausible. It is possible to find studies to support the existence of both approaches in the literature. The pure version of the subjectivist approach is not enough to explain the reasons for the existence of a common instinctual aesthetic appreciation, beyond gradual learning through cultural transmission. Similarly, the objectivist approach is not enough to explain the reasons for the differences in the aesthetic taste of different individuals. Accordingly, the likelihood of the validity of both approaches is higher than the validity of a pure version of either approach. Up to a certain threshold, there may be a common sense of aesthetics, yet it may differ after that threshold, due to the influence of other parameters learned through cultural transmission or personal experiences. In other words, up to the border lines of a threshold for a common aesthetic, predicting the aesthetic judgment of majority (a common aesthetic sensation) can be possible. If aesthetic appreciation can be estimated through certain parameters with computational approaches, then the parameters that trigger aesthetic appreciation can be developed with conscious modifications in the future.

Compared to other fields such as the aesthetics of photographic images and facial attractiveness, determination of the parameters affecting the individuals' aesthetic judgement on buildings is a relatively easier task, because in buildings the distinction between parameters and components are much sharper and clearer, while the transition between different components are smooth and vague in other fields (e.g. appraising human facial beauty). Accordingly, considering the achieved success in predicting aesthetic taste derived from complex visual stimuli such as human faces and photographs with advanced computational methods such as ANN, it is reasonable to expect to make successful estimations about the aesthetic appreciation driven from building features. Nonetheless, the parameters affecting the individuals' aesthetic judgement on buildings is barely studied via experimental approaches. Accordingly, determination of such parameters and discovering the probability to predict majorities' aesthetic judgement can be a good start for testing the applicability of YYP.

2.3.3 Summary

- The YYP emerged based on the observation that the inherited problems resultant from the conventional paradigm cannot be solved within its framework.

- The YYP is a multi-disciplinary approach that introduces solutions for existing problems by establishing a balance between different disciplines. YYP can be summarised as a paradigm that offers to takes into account all pertinent factors involved in a decision-making process and establishing a balance between them. The YYP combines the perspectives of different disciplines to approach a problem in a multidimensional manner. It can consequently identify problems that cannot be seen from a single point of view, and gives an opportunity to develop appropriate strategies accordingly.

- The YYP is different from the IDA; the YYP offers an insight into the perspectives of different disciplines by a single specialist instead of encouraging the experts in different disciplines to come together in an active collaborative process, as in IDA.

- The YYP can result in the development of new generation building simulation tools simultaneously effective in the evaluation of buildings' different aspects (e.g. marketability, aesthetic, energy efficiency, occupant comfort, and initial cost).

- The YYP is not a simulation tool, it is a paradigm that seeks a multi-dimensional solution to a problem by establishing a balance between different disciplines. Multidimensional measurement tools or new generation simulation programs are required to ensure the applicability of YYP.

- Some previous studies offer valuable empirical findings for the existence of a common instinctual aesthetic appreciation and the possibilities to predict common aesthetic appreciation with advanced computational approaches such as ANN and machine learning.

- YYP is not only limited to building design and construction, rather it is a paradigm that can be applied any field of life.

- YYP can be confused with optimization method, but the former is a paradigm with a philosophy behind it, while optimisation is only a technique and/or tool that can be utilized to reach the targets of YYP.

CHAPTER III

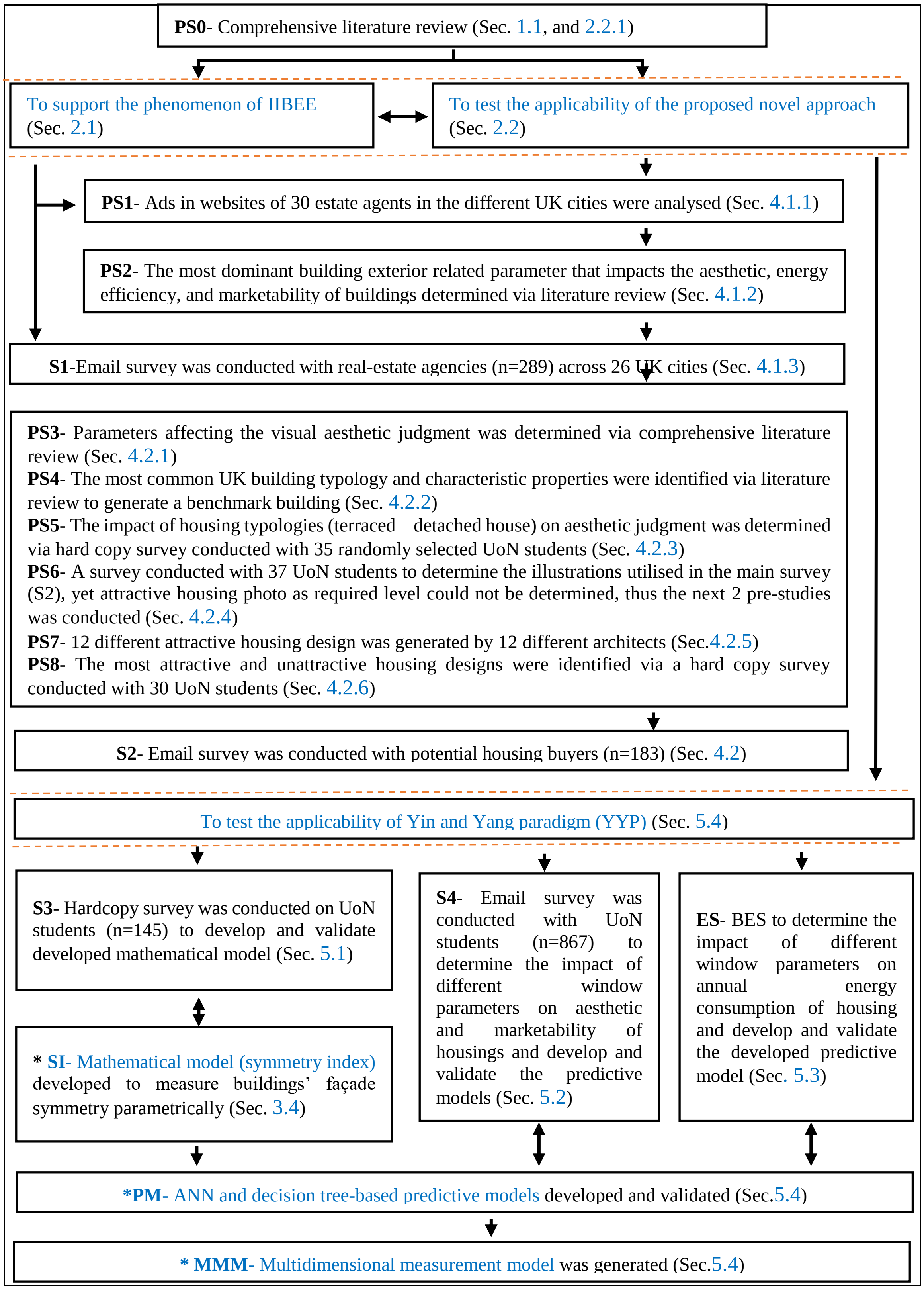
METHODOLOGY

CHAPTER III.

METHODOLOGY

This chapter provides a fundamental overview of the utilised methodologies in this thesis and the relationships between different studies. In addition, this chapter contains fundamental background about surveying techniques, building energy simulations (BES), computational predictive models (i.e. decision tree and ANN), and a mathematical model (symmetry index) developed to parametrically calculate symmetry of buildings' façades.

The methods included (1) eight surveys (four main surveys (S1 – S4), three surveys for pre-studies (PS5, PS6, and PS8), and one survey for the test-retest protocol for the first main survey (S1)), (2) four advanced nonlinear computational predictive models (ANN and decision tree) (i.e. one ANN and decision tree for predicting aesthetic and marketability of housings (see Section 6.2.4.1), and one ANN and decision tree for predicting the annual energy consumption of housings (see Section 6.2.4.2)), (3) BES with 28 different scenarios (Section 3.3), and (4) a novel symmetry index (Section 3.4) (see Figure 5). Utilised measurement tools, their relationships, and sequences are shown in a flowchart in Figure 5 to map this Ph.D. thesis. Each study was represented with abbreviations (e.g. S: Survey, PS: pre-study etc.) (Figure 5), and these abbreviations are used to refer to the studies in the following sections. As shown in Figure 5, conducted studies can be summarised under 12 stages, and two main sections. The first section is covers studies conducted to test the applicability of the proposed novel approach and the existence of the phenomenon of IIBEE. The second section is developed to test the effectiveness of YYP in ensuring the applicability of the proposed widespread adoption approach (Figure 5).



(PS: Pre-study, S: Survey, SI: symmetry index, ES: BES, PM: Predictive model, MM: multidimensional measurement tool, and blue coloured text: novel contributions.

Figure 5: Overview of the utilised methodologies and their relationships

3.1 Survey

The impact of different cognitive and physical parameters on the aesthetic judgement in various disciplines was investigated with different methodologies, such as self-reported methods (SRM), eye tracking (ET) (e.g. (Hasse & Weber, 2012)), functional magnetic resonance imaging (fMRI) (e.g. (Boccia et al., 2016); (Jacobsen, Schubotz, Höfel, & Cramon, 2006); (Yue, Vessel, & Biederman, 2006); (Jacobsen et al., 2006)), and electroencephalography (EEG) (e.g. (Jacobsen & Höfel, 2003)). SMR is one of the most popular methods to assess subjective phenomena such as attitudes, beliefs, opinions, and aesthetic judgements, which is largely due to its expediency, requiring minimal financial and facility resources compared to other methods (e.g. (Garip & Garip, 2012); (Dinc & Yuksel, 2010); (Erdogan, Akalin, Yildirim, & Erdogan, 2010a)). Both interview (e.g. (Ferdous, 2013); (Hassab, 2011); (Erdogan, Akalin, Yildirim, & Erdogan, 2010b)) and survey SMRs (e.g. (Ozbudak Akca, Erdogan, & Akalin, 2015); (Liu, Lughofer, & Zeng, 2015); (Akca, 2011)) have been broadly utilised in previous aesthetic judgement studies.

Although interview method provides the opportunity to diagnose misunderstandings about questions during interactions between participants and interviewers (Schaeffer & Presser, 2003), and asking more complex questions (BRACE, 2013), it is more time consuming in its survey and data analysis processes (Saris & Gallhofer, 2007). Moreover, the interviewer and participant interaction involves standardization issues (Schaeffer & Presser, 2003), self-presentation bias (BRACE, 2013), psychological pressure-related biases (Alwin & Krosnick, 1991), a rise of the stereotype threat, and social desirability bias (Saris & Gallhofer, 2007). However, questionnaires are less time-consuming to administer and to analyse the resultant data, particularly email and online questionnaires (Saris & Gallhofer, 2007); (BRACE, 2013), which also have less social desirability bias and stereotype threat compared to interview method (Saris & Gallhofer, 2007). However, in email questioners, respondents can read all questions before they answer (BRACE, 2013), skip a question that should be answered (Saris & Gallhofer, 2007), and more importantly participants are limited to internet users in the target population, thus those with no internet access due to lack of infrastructure, capability, or preference cannot be represented with email questionnaires method (Ilieva, Baron, & Healey, 2001), although this is increasingly irrelevant in most contexts with the ubiquitous global rollout of broadband internet.

There are three types of question design: structured (closed), unstructured (open), and semi-structured (mixed) questions (Thayer-Hart, 2010). Open-ended questions (unstructured) are less common than structured questions in attitude and opinion surveys, despite the advantages of providing unexpected responses and providing flexibility to respondents to more accurately express their views. Because of response resistance from participants and time constraints in the data analysis process, there are usually lower response rates using open-ended method and more issues to interpret, categorize, and analyse (Thayer-Hart, 2010); (Schaeffer & Presser, 2003). Structured questions are popular in attitude and opinion surveys due to their related advantages, such as the easiness to answer (response alternatives are normally provided), and less time necessary for answering, interpreting, and analysing the responses (Thayer-Hart, 2010).

There are two common structured question type broadly utilised to investigate aesthetic appreciation in previous studies, including rating scales (e.g. (Vessel, Stahl, Maurer, Denker, & Starr, 2014); (Ferdous, 2013); (Dinc & Yuksel, 2010)), which are rating the objects according to their evaluative dimension with a common scale, and ranking scales (e.g. (Hassab, 2011); (Erdogan et al., 2010a); (Groat, 1982)), which order the objects according to the dominance of their evaluative dimension. Rating scales are more popular than ranking scales due to their associated drawbacks, such as limitations in the number of objects, more time and mental effort demand, and limitations of interpretation (Schaeffer & Presser, 2003). Likert scales, semantic differential scales

(SDS), and slider scales are the most commonly used rating scales to assess the subjective phenomena such as attitudes, beliefs, opinions, or behavioural frequency and intensity (Weijters, Cabooter, & Schillewaert, 2010); (Schaeffer & Presser, 2003); (Preston & Colman, 2000). In particular, the literature recommends the following scale types for their relatively higher reliability: fully and verbally labelled (Alwin & Krosnick, 1991); seven-point SDS scales (Preston & Colman, 2000); (Alwin & Krosnick, 1991); and five-point Likert scales (Krosnick & Fabrigar, 1997). Survey method (SMR) was utilised in this thesis in the studies abbreviated as S1-S4, PS5, PS6, and PS8 (Figure 5).

3.1.1 Statistical models

The selected statistical models are determined according to the table adapted from (Field, 2013) and (UCLA, 2017) (see Appendix A). The conditions to prefer each statistical model are categorized according to criteria such as survey target, number of variables, type of predictors and outcomes (e.g. continuous and categorical), number of predictors, and assumptions of linearity (see Appendix A). The preference of inferential statistical models (e.g. T-Test, ANOVA, Pearson correlation) is made according to the criteria in Appendix A. In addition, several descriptive statistical models are also utilised for generating tables and graphs. In overall, this study utilises eight different statistical models for various purposes, as described below.

3.1.1.1 Mean

Mean (Eq.1) is the average score of the population on a given variable, which is used as shown below:

$$\mu = \frac{(\sum X_i)}{N} \tag{1}$$

where, μ represents the population mean, $(\sum X_i)$ is the sum of all scores presented in the population, and N represents the total number of individuals or cases in the population.

3.1.1.2 Standard deviation

Standard deviation (σ) (Eq.2) is a measure of spread (variability) of scores on a given variable. σ is the square root of the variance. The σ of the results is utilised to give more details in descriptive statistics:

$$\sigma = \frac{1}{N}\sum_{i=1}^{N}(X_i - \mu)^2 \tag{2}$$

where σ presents the population standard deviation

3.1.1.3 Paired-samples T-test

Paired-samples t-test (Eq.3) gives the statistical significance of differences between a pair of means. Paired-samples T-test is utilised in this study to determine the statistical significance of differences between different variables:

$$t = \frac{\underline{D} - \mu_D}{\sigma/\sqrt{N}} \tag{3}$$

where t is the t-statistic, $\underline{D}$ is the mean difference between samples, μ_D is the differences between population means, and $\sigma/\sqrt{N}$ is the standard error of the differences.

3.1.1.4 ANOVA

One-way analysis of variance (ANOVA) gives the statistical significance of a difference between more than two means. ANOVA is utilised in this study to determine the statistical significance of the differences between different variables. The working principle of ANOVA is same as Paired-samples T-test, the only difference being that T-test is utilised for two variables and ANOVA is used for more than two variables.

3.1.1.5 Hochberg GT2

Hochberg GT2 is a post hoc test that can be performed to analyse the details of variances between subgroups in ANOVA. Hochberg GT2 post hoc test is preferred in this study over other common post hoc tests (e.g. Tukey) due to the unequal subgroup sizes of the demographic cohorts.

3.1.1.6 Pearson correlations

Pearson correlations (Eq.4) measure the linear correlation between two variables to determine the correlation between them:

$$r = \frac{cov_{xy}}{\sigma_x . \sigma_y} \tag{4}$$

where cov is the covariance, σ_x is the σ of the first variable, and σ_y is the σ of the second variable.

3.1.1.7 Cronbach's alpha

Cronbach's alpha (Eq.5) is a measure of internal consistency, utilised to test the reliability of conducted surveys. It can be mathematically expressed as:

$$\alpha = \frac{N.\bar{c}}{\bar{v} + (N-1).\bar{c}} \tag{5}$$

where, N is the number of components (items), $\bar{c}$ is the average inter-item covariance among the items, and $\bar{v}$ is the average variance of each component.

3.1.1.8 Mean square error

Mean square error (Eq.6) is a measure of the performance of an estimator, utilised to measure the performance of developed advanced computational predicative models (PM in Figure 5). It can mathematically be expressed as:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Yi - \check{Y}i)^2 \tag{6}$$

where Y is the observed value, and Ῡ is the predicted value

3.2 Advanced nonlinear computational approaches to develop predictive models

Advanced non-linear computational approaches such as ANN, decision tree, and machine learning have gained popularity in many different disciplines due to their high performance. In particular, these methods allow processing nonlinear data and handling imprecise and fuzzy information, and they are very successful at providing accurate predictions and generalizing a large amount of complex data (Basheer & Hajmeer, 2000). Particularly, better performances of ANNs compared to other models such as regression models and decision tree was reported in previous studies (Tso & Yau, 2007).

Although ANN and decision tree methods have become popular in building-related studies, such as perception of urban environment prediction (e.g. safe, depressing, and beautiful) (e.g. (Dubey, Naik, Parikh, Raskar, & Hidalgo, 2016)), housing energy consumption (e.g. (Tso & Yau, 2007)), indoor air temperature of buildings (e.g. (Mirzaei et al., 2012)), and house price projection (e.g. (Limsombunc, 2004)), the visual aesthetic of building features has barely been studied with these advanced computational methods. ANN and decision tree methods was utilised in this thesis in the studies abbreviated as PM and MMM (Figure 5).

3.2.1 ANN

ANNs is a computational model that inspired by the working principles of the mammalian brain (biological neural networks). In the simplest definition, ANN is a self-learning algorithm. The fundamental working principle of a single cell artificial neuron is shown in Figure 6. The basic equation for a single neuron can be defined as shown in Eq.7.

$$f_{act}(w.x + b) \tag{7}$$

where f_{act} is activation function, w is the weight assigned for input (x), x is input variable and b is bias or error value.

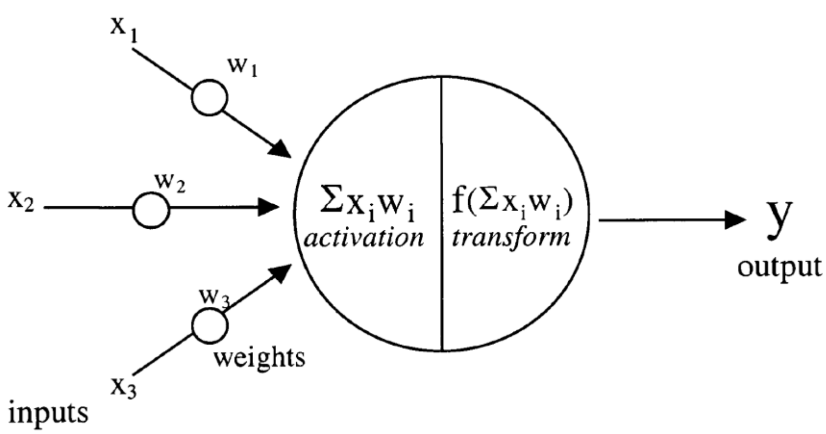


Figure 6: Model of an artificial neuron (Agatonovic-Kustrin & Beresford, 2000)

The flow of actions of a single cell artificial neuron can be simply summarised as follows. First, random weights (w) are assigned to each input variable (X), then the weighted sum is calculated in the input function, and a bias is added. The result of the input function triggers the activation function. Accordingly, if the requirements of the activation functions have been met, the cell is activated, or no action is taken (see Figure 6).

In general, there are different activation functions available for different purposes and conditions. Step (binary), linear (identity), logistic sigmoid (uni-polar sigmoid) and hyperbolic tangent sigmoid (tanH) functions are the most common activation functions. The step function is a threshold based binary function. If the weighted sum value is above a certain threshold value, then that cell is activated (output=1) otherwise no action has been taken (output=0). The linear function is linear and proportional to the weighted sum value, and its output ranges between negative and positive infinity (±∞). Sigmoid functions are the most popular activation functions in ANNs due to their performance on nonlinear problems (Almási, Woźniak, Cristea, Leblebici, & Engbersen, 2016). Logistic sigmoid function (Eq. 8) is a nonlinear function that ranges the net input from negative to positive infinity to the outputs between 0 and 1. Hyperbolic tangent sigmoid function (tanH) (Eq.9) is a developed version of the log-sigmoid function. TanH functions range net input from negative to positive infinity to outputs between -1 and 1. A better performance of tanH function comparing to log-sigmoid function is reported in previous comparative studies (e.g. (Karlik & Olgac, 2011)).

$$f(x) = \frac{1}{1 + e^{-x}} \tag{8}$$

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}} \tag{9}$$

where e is Euler's constant value and x is net input value

ANN learning algorithms differ under three main categories, namely supervised, unsupervised, and reinforcement learning algorithms. Supervised learning algorithms develop a predictive model based on both input and output data. In supervised learning, both input (variables) and output (target values) values are known and are given to ANN for the learning process, whereby ANN adjusts appropriate weight error correction values to obtain the best match with the given target values. In unsupervised learning algorithms, only input data are known and given to ANN. ANN groups (clusters) and interprets data based only on input data. In reinforcement learning, the developed artificial neural model learns according to the process of trial-and-errors (i.e. reward-penalty) in order to reach the expected value or criterion.

There are different learning rulers available for unsupervised (e.g. Hebbian learning rule), supervised (e.g. perceptron, delta (Widrow-Hoff) and correlation learning rules) and reinforcement learning algorithms (e.g. associative reward-penalty reinforcement learning rule). One of the most commonly learning rules in supervised learning algorithms is delta (Widrow-Hoff) learning rule, which is a good example to explain the fundamental working principles of ANNs. The mathematical expression of delta (Widrow-Hoff) learning rule is as shown in Eq.10 (Hassoun, 2018).

$$E = \frac{1}{2}\sum_{i=1}^{n}(t_i - ac_i)^2 \tag{10}$$

where E is the total error over the training pattern, t is the target value in the output layer, and ac is the actual output.

The delta learning rule is an iterative process that helps ANNs to improve their performance in each iteration until reaching an adequately reliable level. In each iteration, the delta learning rule calibrates the weights according to the computed difference between the target outputs and the actual output calculated by ANN.

3.2.2 Decision tree

ANNs' black-box nature is their main drawback. Accordingly, ANNs are not suitable to provide illustrations or outcomes suitable for interpretation. In contrast, the decision tree method has a white-box nature and is a very powerful model to provide simple but effective predictive outcomes suitable for interpretation even by non-expert individuals. In addition, this method gives clear information about the importance and hierarchical impact order of factors for estimation and classification purposes. Nonetheless, decision tree models do not perform as well as ANNs on nonlinear problems (Tso & Yau, 2007). Accordingly, despite it was not necessary, in this study both ANN and decision tree method were utilized to benefit from the advantages associated with each model. As a more flexible approach ANN could be enough to develop predictive models. Yet, in order to provide a visual model that can be utilized even by non-experts (see Figure 38, and Figure 40), decision tree was utilized as additional study in this thesis.

The decision tree is a popular method in data mining and machine learning. It is a supervised learning algorithm and a predictive model, working with a logic that resembles human reasoning for estimation or classification. The decision tree can be depicted with visual and analytical decision support tools. It has a flow chart-like tree structure, and models certain decisions and their possible consequences after being trained with a set of data. Decision trees consist of nodes, branches, and leaves. Nodes specify the flow direction in the flow diagram by testing whether certain attributes or conditions are met. Branches represent the possible outcomes when certain attributes or conditions at the nodes are met. Leaves represent the decision taken after computing all attributes (see Figure 7). Once the decision tree constructed with the training stage, it can be utilised for new data sets via following the appropriate paths, from the root to the leaf.

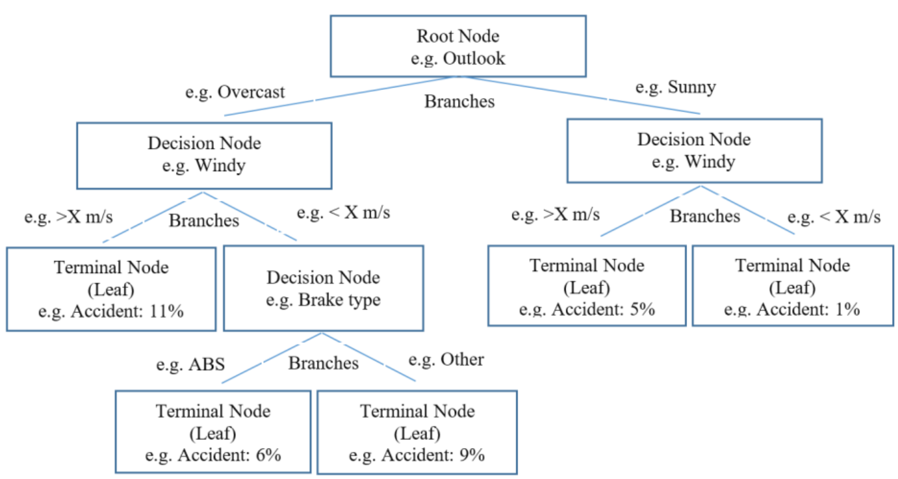


Figure 7: Structural diagram of the decision tree with an example of the percentage prediction for the daily accident increase in a city

There are different decision tree algorithms, such as Iterative Dichotomiser 3 (ID3), C4.5, classification and regression trees (CART), and chi-squared automatic interaction detection (CHAID). ID3 and C4.5 are the algorithms utilized for classification purposes, ID3 is the first decision trees implementations and C4.5 is an extension of ID3. While ID3 handles only categorical data and do not handles missing data, C4.5 handles both categorical and numeric data and handle missing data. CART is the algorithms utilized for classification and prediction purposes, it handles both categorical and numeric data and handle missing data. CART models are utilized mainly for predictive analysis whereas CHAID models are utilized mainly for descriptive analysis. CHAID and CART models are mainly differ in two points: (1) learning algorithms categories; CART is a supervised model (i.e. it develop a predictive model based on both input and output data) and CHAID is an unsupervised model (only input data are given to and model interprets data based only on input data), (2) the tree growth stopping process; in the CART model, firstly the decision tree is grown, and then branches that do not contribute significantly to the accuracy of the tree are pruned to achieve simplicity and compactness in the developed tree. In the CHAID model, statistical model called the Chi-Square test utilize to stop tree growth. In this model, data compare with hypothetical values, and when values are far off from hypothetical values the tree stops at that branch.

There are two popular approaches to create a decision tree, including information gain (e.g. ID3 and C4.5), and Gini index (e.g. CART) approaches. Both approaches aim to maximize the compactness of the decision tree. Values for all existing attributes are calculated according to these criteria, then the orders of the attributes in the decision tree are arranged according to their calculated values, whereby attributes with the highest values are placed at the root of the tree, and branches are arranged accordingly in descending order of value. In the information gain approach, first the homogeneity of the sample is calculated with an entropy (a measure of disorder) equation (Mitchell, 1997); the mathematical expression of entropy can be shown as in Eq.11:

$$En(S) = -\sum_{i=1}^{n} p_i \,.\, log_2\,(p_i) \tag{11}$$

where *En* is entropy, *En(S)* is entropy for a set and p_i is the probability of getting the i^th value when randomly selecting one from the set.

Then, the information gain (or entropy reduction) can be calculated by Eq. 12:

$$G(S, A) = E(S) - \sum_{v \in values\,(A)} \frac{|S_v|}{|S|} E(S) \tag{12}$$

where G is information gain, values (A) is the set of all possible values for attribute A, and S_v is the subset of S, for which attribute A has the value v.

Gini index (Eq.13 and Eq. 14) approach works with a similar logic, but it is utilised with a different algorithm:

$$Gini(S) = 1 - \sum_{i=1}^{n} {P_i}^2 \tag{13}$$

$$Gain(S, A) = Gini(S) - \sum_{v \in A} \left(\frac{|\,S_v\,|}{|\,S\,|} . Gini(S_v) \right) \tag{14}$$

where P_i is the relative frequency of class i in S, v represents any possible values of attribute A, S_v is the subset of S for when attribute A has the value of v, $|S_v|$ is the number of elements in S_v, and $|S|$ is the number of elements in S. Further details can be found in (Mitchell, 1997).

3.3 Building energy simulations (BES)

BES is the process of estimating the impacts of different environment, construction, and/or system-based configurations on the energy consumption of buildings with computational approaches. In the BES, a replica of a building, system and environmental conditions is modelled and the impact of different scenarios on the heating, cooling, and lighting loads of buildings is examined under certain conditions. The working principle of BES can be summarized under five fundamental steps: (1) divide the building into different zones, (2) calculate heat gains and loss for each zone, (3) calculate the energy consumption to keep building in certain pre-defined indoor temperature based on the selected heating, ventilation, and air conditioning (HVAC) system, and selected weather data (4) calculate the energy consumption for auxiliary equipment, water heating, electronic devices in the building, and lightning, (5) based on the previous four steps, calculate the annual energy consumption.

BES working principles are mainly based on the laws of thermodynamics and thermal equilibrium. Thermal equilibrium in buildings can be mathematically represented as shown in Eq.15. The heat equilibrium occurs when there is no heat energy flow between the inside and outside of the buildings (i.e. when the sum of all the different types of heat flow into and out of a building is zero (Eq.15)).

$$Q_c + Q_{cv} + Q_s + Q_v + Q_i + Q_e = 0 \tag{15}$$

where Q_c is conduction heat gain or loss (i.e. heat flows from outside or inside through the building envelope), Q_s is solar heat gain (i.e. additional head provided by solar radiation), Q_v is heat gain or loss caused by ventilation, Q_i is internal heat gain or loss (i.e. from people and appliances in the building), and Q_e is heat loss caused by evaporation.

Heat transfer via conduction (Q_c) can be expressed with the Fourier's law of heat conduction, which can be mathematically expressed as in (Eq.16):

$$Q_c = k.A.(\Delta T/L) \tag{16}$$

where Q_c (W) is the rate of heat transfer via conduction, k ($W.m^{-1}.K^{-1}$) is thermal conductivity of the material, A (m^2) is the surface area through which the heat flows, ΔT (K) is the temperature difference between the outdoor and indoor of building, and L (m) is the length or thickness of the material.

Heat transfer via convection (Q_{cv}) can be expressed with Newton's law of cooling, which can be mathematically expressed as in (Eq.17):

$$Q_{cv} = h_c.A.\Delta T \tag{17}$$

where Q_{cv} (W) is heat transfer via convection per unit time, and h_c ($W/m^2\ K$) is convective heat transfer coefficient

The impacts of solar radiation can be mathematically expressed as in (Eq.18):

$$Q_s = A.I.\theta \tag{18}$$

where A (m^2) is the surface area through which the heat flows, I (W/m^2) is radiation heat flow density, and θ (dimensionless) is solar gain factor of the window glass.

In addition, the shaded areas and the areas by which solar rays reach inside the building through windows can be expressed as shown in (Eq. 19) and (Eq. 20). The size of the shaded areas and the areas reached by solar rays reached are calculated according to the position of the sun, the height and width of the windows, and the depth of the outside and inside revealed surfaces (see (Eq.19) and (Eq.20)).

$$A_{1,sh} = \frac{1}{2}\,(d_1 - p_1)^2\,.\tan\alpha \tag{19}$$

$$A_{2,sh} = d_2{}'.L + \frac{1}{2}\,(d_1 + d_2)^2\,.\tan\alpha - \frac{1}{2}\left(d_1 + p + d_2{}''\right)^2.\tan\alpha \tag{20}$$

where $A_{1,sh}$ (m^2) is the shaded area at the outside of the window, $A_{2,sh}$ (m^2) is the shaded area at the inside of the window, d_1 (m) is the depth of outside revealed surface, d_2 (m) depth of inside reveal, L (m) is window height and width, α (degree) is the solar profile angle for shading on revealed surfaces, p_1 (m) is the distance from the outside (inside) surface of frame to glazing midplane, d_1 (m) is depth of shadow cast by top reveal on bottom reveal, or by left reveal on right reveal, or by right reveal on left reveal, and $d_2{}''$ (m) is depth of shadow cast by frame.

Heat exchange caused by ventilation can be expressed as in (Eq.21).

$$Q_v = V.VSHa.\Delta T \tag{21}$$

$$V = (N.RV)/3600 \tag{22}$$

where V (m^3/s) is ventilation rate, $VSHa$ $(Jm^3{}^\circ\mathrm{C})$ is volumetric specific heat of air (1300 $Jm^3{}^\circ\mathrm{C}$), N (m^3/h) is air changes per hour, RV (m^3) is room volume, 3600 is the number of seconds in an hour.

In addition, both wind-driven and buoyancy-driven natural ventilation and infiltration can be expressed as shown in (Eq.23), (Eq.24), and (Eq.25) respectively.

$$Q_w = C_w.A_{opening.}F_{schedule2}.WindS \tag{23}$$

where Q_w is the volumetric air flow rate derived by wind (m^3/s), C_w is opening effectiveness (dimensionless), $A_{opening}$ is opening area (m^2), $F_{schedule2}$ is the open area fraction (dimensionless), and $WindS$ is the local wind speed (m/s).

$$Q_s = C_D.A_{opening}.F_{schedule2}\sqrt{2.\Delta H_{NPL}(|T_{zone} - T_{out}|/T_{zone})} \tag{24}$$

where Q_s is volumetric flow rate due to stack effect (m^3/s), C_D is discharge coefficient for opening (dimensionless), ΔH_{NPL} is height from midpoint of lower opening to the natural pressure level (m), T_{zone} is the zone air dry-bulb temperature (K), and T_{out} is local outdoor air dry-bulb temperature (K).

$$infiltration = (F_{schedule})\frac{A_L}{1000}\sqrt{C_8\,.\Delta T + C_w(WindS)^2} \tag{25}$$

where $infiltration$ is uncontrolled air leakage through building components, $F_{schedule}$ is a value from a user-defined schedule, A_L (cm^2) is the effective air leakage area that corresponds to a 4 Pa pressure differential, C_8 $((L/s)^2/(cm^4.K))$ is the coefficient for stack-included infiltration, *and* C_w $((L/s)^2/(cm^4.(m/s)^2))$ is the coefficient for wind-included infiltration.

Internal heat gain (Q_i) is caused by heat sources inside the building, including humans, appliances, and cookers. Internal gains are represented with pre-defined values mainly reported in the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) guidelines (e.g. the average heat output of human bodies when sitting at rest is 60 W/m^2 (ASHRAE, 2013).

The most five popular energy simulation programs were determined by Boeck et al. (De Boeck, Verbeke, Audenaert, & De Mesmaeker, 2015), and the capabilities of those five energy simulation programs are compared in Table 5 according to the program vendor-supplied information reported by Crawley et al. (Crawley, Hand, Kummert, & Griffit, 2008). Compared to other BES, EnergyPlus has several advantages such as integrated simulation nature, and its capabilities and performance concerning daylighting, infiltration, natural ventilation, flexibility for controlling window opening based on zone or external conditions, and solar gain simulation.

Table 5: Comparison among the most common simulation tools for energy simulations of residential buildings (De Boeck et al., 2015); (Crawley et al., 2008)

	TRNSYS	Energy Plus	DOE-2	IDA ICE	eQUEST
Capabilities for infiltration, ventilation, room and multi-zone airflow					
Single zone infiltration	X	X	X	X	X
Automatic calculation of wind pressure coefficients	-	X	-	-	-
Natural ventilation (pressure & buoyancy driven)	X	X	-	X	X
Multi-zone airflow (via pressure network model)	X	X	-	X	-
Hybrid natural and mechanical ventilation	X	-	-	X	-
Control window opening based on zone or external conditions	X	X	-	-	-
Displacement ventilation	X	X	-	X	-
Mix of flow networks and CFD domains	-	-	-	-	-
Capabilities for building envelope, daylighting and solar					
Inside radiation view factors	-	X	-	X	-
Radiation-to-air component separate from detailed convection (exterior)	X	X	-	X	X
Solar gain and daylighting calculations account for inter-reflections from external building components and other buildings	X	X	-	-	-
Capabilities for interior surface convection - zone loads					
Dependent on temperature	X	X	-	X	-
Dependent on air flow	X	X	-	-	-
Dependent on surface heat coefficient from CFD	-	X	-	-	-
User-defined coefficients (constants, equations or correlations)	X	X	X	X	-
Internal thermal mass	X	X	X	X	X

EnergyPlus is an open source energy analysis and thermal load simulation engine that collects many program modules that work together to calculate the energy required for lighting, heating, and cooling a building under different environmental and operating conditions. In EnergyPlus, the air handling systems, building zones, and central plant equipment are solved simultaneously, while in programs with sequential simulation (e.g. BLAST or DOE-2), all these major parts are simulated sequentially, without feedback from one to the other (EnergyPlus, 2019). The non-user-friendly interface and requirement of advanced expertise for operation are the main shortcomings of EnergyPlus.

In this Ph.D. thesis, the commercial software DesignBuilder was utilised as a BES for three reasons: (1) it combines the advantages of EnergyPlus and Radiance simulation engines. In DesignBuildier, BES are performed based on EnergyPlus simulation engine and lighting simulations are supported with the validated lighting simulation tool Radiance, (2) it has an interface that is designed for ease of use, and it accordingly minimises the possible user error-related simulation accuracy problems, and (3) natural ventilation through windows has a remarkable impact on housing energy demand, and DesignBuilder has a high performance to simulate natural ventilation. The high performance of DesignBuilder in natural ventilation simulations was reported according to a study that compared the simulation results obtained from DesignBuilder and Computational Fluid Dynamics (CFD) simulation programs (Baharvand et al., 2013). The main disadvantage of DesignBuilder is that it cannot provide flexibility and advanced control as much as EnergyPlus on the simulation parameters and settings. However, DesignBuilder was deemed to be sufficient considering the purpose and limitations of this study (i.e. comparison of the impacts of different window parameters on annual energy consumption).

3.4 Symmetry measurement model (SI)

Amongst many other aesthetic parameters (see Section 4.1.2), special importance is attributed to symmetry with a relatively stronger consensus compared to other parameters. The significant impact of symmetry on aesthetic appreciation was reported in previous studies (e.g. (Jacobsen et al., 2006); (Rhodes et al., 2001)) Moreover, there are claims that it is possible to estimate the aesthetics of visual stimuli based on the properties of symmetry and complexity (e.g. Birkhoff's aesthetic measure equation[25] (Birkhoff, 1933); (Emch, 1900)). In addition, the indirect influence of symmetry on buildings' energy efficiency was reported in previous studies (e.g. (Karava, Stathopoulos, & Athienitis, 2011)), and the influence on housings' marketability was determined in the conducted survey (S1, Figure 5) (see Section 6.1.2). According to this, symmetry is considered to be one of the seven window[26] parameters[27] of concern in this thesis (Section 4.1.2).

The desire for symmetry is based on human instincts. Previous studies show that symmetry and asymmetry can even be distinguished by infants, and experiments clearly show that infants prefer symmetric patterns rather than asymmetric ones (Humphrey & Humphrey, 1989). As in facial beauty, even minor and vague variations in symmetry can be detected by individuals. Empirical studies show that more symmetrical faces are stated to be more attractive (Rhodes et al., 2001). Similarly, according to empirical evidence obtained via different methods such as EEG (e.g. (Jacobsen & Höfel, 2003)), fMRI (e.g. (Jacobsen et al., 2006)), and SRM (e.g. (Eisenman & Gellens, 1968)), symmetric visual stimuli are reported to be more attractive than asymmetrical ones.

[25] (i.e. $M = O / C$, the amount of pleasure derived (M) = amount of order (dominated by symmetry) (O) / the amount of complexity (C))
[26] According to conducted pre-studies (PS2 in Figure 5), windows have been identified as the most influential factor, affecting aesthetics, marketability, and energy efficiency. Accordingly, this study is focused on only window parameters (see Section 4.1.2).
[27] Focusing on seven window parameters (width, area, height, position, number, proportion, and symmetry), determined according to the results of the conducted survey (S1in Figure 5) (see Section 6.1.2).

There are two common methods utilised to measure the symmetry level of visual stimuli, including SRM (e.g. (Imamoglu, 2000)) and mirroring method (e.g. (Jacobsen & Höfel, 2003)). Mirroring method, which is based on a vertically and/or horizontally cross-section at the middle of an image and mirroring it, have been utilised to adjust the symmetry of images or to determine whether they are symmetric (e.g. (Jacobsen et al., 2006); (Jacobsen & Höfel, 2003)). Although this symmetry measuring method is simple and efficient, it is limited with non-parametric results, and is not possible to achieve precise projections about the symmetry level comparison of more than one visual stimuli. Inversely, parametric results for symmetry can be obtained with SRM, yet this method requires significant extra time and efforts (i.e. conducting surveys and statistical analyses). Therefore, development of a symmetry index that enables parametric measurement of the symmetry of visual stimuli can be beneficial to measure symmetry with less time, labour, and financial costs.

Development of the symmetry measurement model (symmetry index (SI in Figure 5)) was particularly needed in this thesis because parametric symmetry values were required to develop predictive ANN and decision tree models (PM in Figure 5). In addition, the development of the symmetry measurement model can also support the applicability of YYP. As a parameter that impacts aesthetic judgement, simulating individuals' symmetry perception via mathematical models can be promising with regard to the possibility of simulating other parameters that affect aesthetics in future.

3.4.1 *A mathematical model (symmetry index) to measure the symmetry of building façades parametrically (SI)*

The developed symmetry index (SI in Figure 5) is based on a very simple logic. The notion of symmetry is defined in OED[28] as "*The quality of being made up of exactly similar parts facing each other or around an axis*". Accordingly, the developed models ((Eq. (26) and Eq. (27)) are based on determining the deviation of symmetry according to the linear components' lengths and positions on the XY coordinates.

$$SI = 1 - \frac{\mathrm{DSm} - (\mathrm{DSm}_{\mathrm{min}})}{\mathrm{DSm}_{\mathrm{max}} - \mathrm{DSm}_{\mathrm{min}}} \tag{26}$$

where *SI* is the symmetry index, min and max are the minimum and maximum value amongst the compared values, and *DSm* is the symmetry deviation according to linear components' lengths and position on the XY coordinates, and defined as:

$$DSm = \frac{\left(\left(\left|\sum_{i=1}^{n} PLCXi\right| + \left|\sum_{i=1}^{n} PLCYi\right|\right) 2\right) + \left(\frac{\left|\sum_{i=1}^{n}\left(\left(\frac{PLCXi}{|PLCXi|}\right) LLCi\right)\right| + \left|\sum_{i=1}^{n}\left(\left(\frac{PLCYi}{|PLCYi|}\right) LLCi\right)\right|}{7}\right)}{2} \tag{27}$$

where $| \; |$ is the absolute value, $\sum$ is the summation, n is the upper bound of the summation (i.e. the last linear component (*L*) of the visual stimuli), *PLCX* and *PLCY* are the position of the linear components' centre on the X and Y axes centred on the visual stimuli (negative and/or positive), and *LLC* is the length of the linear components (*L*).

[28] Oxford English Dictionary

Symmetry index (*SI*) (Eq. (26)) is the normalized value of the deviation of symmetry according to the linear components' lengths and position on the XY coordinates (*DSm*) (Eq. (27)), giving a value between 0 and 1. Eq. (26), which is utilised for normalizing the *DSm* value and is the modified version of the standard normalization equation called "feature scaling" or "min-max normalization" is given by Eq. (28):

$$xn = \frac{x - min(x)}{max(x) - min(x)} \tag{28}$$

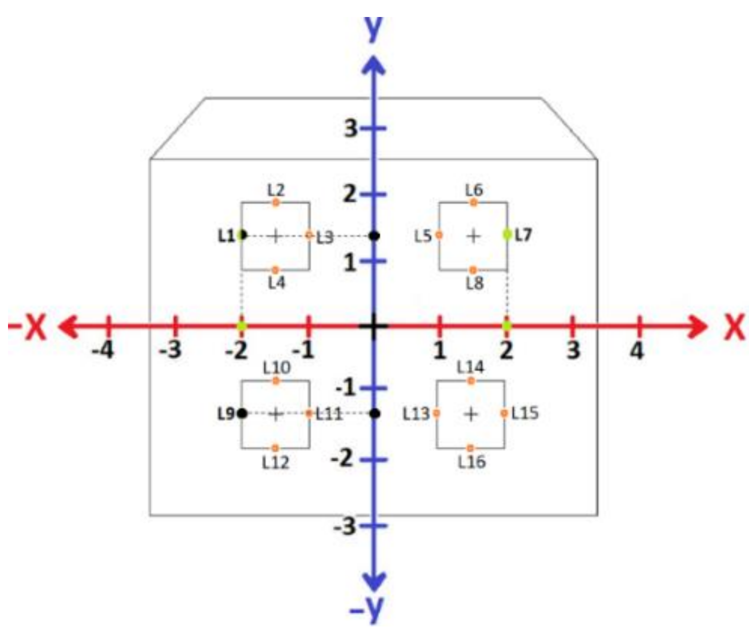
where *xn* is the normalized value, *x* is the original value, min (*x*) is the minimum value amongst the dataset, and max (*x*) is the maximum value amongst the dataset.

The original min-max normalization equation (i.e. Eq. (28)) was modified in symmetry index, as there is a negative relationship between symmetry and the calculated *DSm* value (whereby low symmetry index value indicates more symmetry). In order to achieve a positive relationship between symmetry and the calculated value, the results of the min-max normalization are subtracted from 1 (Eq. (26)). The *DSm* value (Eq. (27)) determines the level of symmetry of visual stimuli. If the result of *DSm* equals 0, then this means visual stimuli are perfectly symmetric. It should be noted that the developed model has a weakness in detecting the impact of angular variations. The weighting values in the *DSm* (i.e. dividing and multiplying by 2 and 7 in Eq. (27)) are related to the studied image, calibrated with trial and error after obtaining the best fit for the results of the conducted survey. Five main steps should be followed in order to apply the developed models:

1. An XY coordinate at the centre of visual stimuli should be established (Figure 8).
2. The linear components of visual stimuli (e.g. L1, L2, etc. in Figure 8) should be labelled.

3. The summation of the distances of the linear components' centre from the X and Y coordinates should be calculated (the first part of (Eq. (27)). When symmetry condition is met, linear components' distances from the X and Y coordinates neutralize each other (see Figure 8 and Appendix H).
4. Each linear components' position should be divided by its absolute value to achieve values between 1 and -1, then the lengths of each linear component should be multiplied by their positions on the X and Y axes (i.e. 1 and -1) (the second part of (Eq. (27)). The aim of this step is to assign a negative or positive value to the length of each linear component. Similar to the previous step when the symmetry condition is met, the lengths of linear components neutralize each other.
5. Once *DSm* (Eq. (27)) values of different visual stimuli are calculated, the symmetry index of those visual stimuli can be calculated with the Eq. (26).

Symmetry index can be utilized for different visual stimuli not only for buildings. A step-by-step example of the application of the developed symmetry index on different visual stimuli can be found in Appendix H.



L: linear components of visual stimuli, *Centre of the linear components*

Figure 8: A visual demonstration of the procedure to calculate the symmetry index (SI)

CHAPTER IV

INVESTIGATING THE APPLICABILITY OF THE PROPOSED NOVEL APPROACH

CHAPTER IV.

INVESTIGATING THE APPLICABILITY OF THE PROPOSED NOVEL APPROACH

This chapter provides the details of two comprehensive surveys (S1 and S2, Figure 5) and eight pre-studies (PS1-PS8, Figure 5) conducted to investigate the applicability of the proposed widespread adoption approach.

4.1 Survey (S1) with real estate agencies

This section contains the details of a survey (S1, Figure 5) and two pre-studies (PS1 and PS2, Figure 5) conducted to develop the main survey and support the existence of the phenomenon of IIBEE.

4.1.1 Pre-study (PS1) about the housing advertisements of estate agents

In the first pre-study (PS1, Figure 5), 12 randomly selected housing advertisements in each of the 30 estate agents' websites were analysed and specific target variables (e.g. nomenclature, highlighted housing exterior features, and EPC) were recorded in order to determine the common nomenclature in housing marketing, the housing exterior features highlighted in advertisements, and the Energy Performance Certificate (EPC) distribution. This information was subsequently used to determine the independent variables and to generate a hypothesis about the phenomenon of IIBEE and the relationship between energy efficiency and marketability. Six estate agents in Inverness (n = 5), Newcastle (n = 5), Sheffield (n = 5), London (n = 5), Cardiff (n = 5), and Bangor (n = 5) were selected, in to have a homogeneous representation of different regions of the UK. The questions and variables of the main survey (S1, Figure 5) were designed based on the results of the first pre-study (PS1, Figure 5).

4.1.2 Pre-study (PS2) to narrow the scope of the study

There are many parameters that have an impact on housing aesthetic and it is not possible to cover all of these in the limited time frame of a Ph.D. study. Therefore, in the second pre-study (PS2, Figure 5), the most critical building parameter for the applicability of the proposed widespread adoption approach was investigated to narrow the scope of the study.

For this purpose, first a pool of 39 parameters (in Table 6 and Table 7) associated with building façade that can affect building aesthetic was generated according to the conducted comprehensive literature review, then a parameter reduction protocol was applied to determine one of the most critical building parameters for the applicability of the proposed widespread adoption approach. There were two steps applied: first, these 39 parameters were reduced to 14 (see Table 7), which have potential to simultaneously affect energy efficiency, aesthetics, and marketability. Due to the nature of the YYP, this study focused particularly on the parameters that simultaneously affect energy efficiency, aesthetics, and housing marketability.

As a second step, the determined 14 parameters were reduced to two according to the comprehensive literature review conducted. In the second step, evidence about the impact of those 14 parameters on energy efficiency, aesthetics, and housing marketability was searched in the previous studies. As a result of the applied parameter reduction protocol, the window and balcony were identified as the final candidates (see Table 7), and the questions and variables of the main survey (S1, Figure 5) were designed accordingly.

Table 6: Literature on parameters associated with building façade that can affect building aesthetic

Parameters	References	Parameters	References
Arches	(Dinc & Yuksel, 2010)	Ornament	(Ozbudak Akca et al., 2015); (Dinc & Yuksel, 2010); (Gifford et al., 2002)
Architectural style	(Erdogan et al., 2010a); (Groat, 1982)	Pattern	(Hassab, 2011); (Devlin & Nasar, 1989)
Balance	(Hassab, 2011); (Dinc & Yuksel, 2010)	Repetition	(Ozbudak Akca et al., 2015); (Hassab, 2011)
Complexity	(Dinc & Yuksel, 2010); (Akalin, Yildirim, Wilson, & Kilicoglu, 2009)	Rhythm	(Hassab, 2011)
Composition	(Hassab, 2011)	Roundness	(Adnan & Yunus, 2012); (Gifford et al., 2002);
Contrast	(Hassab, 2011)	Scale	(Ozbudak Akca et al., 2015); (Hassab, 2011)
Curvature	(Dinc & Yuksel, 2010)	Structure	(Dinc & Yuksel, 2010); (Groat, 1982)
Fullness & emptiness	(Ozbudak Akca et al., 2015)	Texture	(Ozbudak Akca et al., 2015); (Hassab, 2011)
Harmony	(Ozbudak Akca et al., 2015)	Theme	(Hassab, 2011)
Hierarchy	(Hassab, 2011)	Transparency	(Dinc & Yuksel, 2010); (Devlin & Nasar, 1989)
Horizontality	(Ozbudak Akca et al., 2015)	Unity	(Hassab, 2011); (Reis & Lay, 2010)
Massiveness	(Dinc & Yuksel, 2010)	Verticality	(Ozbudak Akca et al., 2015)
Order	(Dinc & Yuksel, 2010)		

Table 7: Literature on identified parameters that have potential to simultaneously affect energy efficiency (EE), aesthetics (AS) and market demand (MD)

Parameters	AS	EE	MD	Parameters	AS	EE	MD
Balconies	(Gifford et al., 2002)	(Chan & Chow, 2010)	(Schnieders & Hermelink, 2006)	Roof	(Gifford et al., 2002)	(Costanzo, Evola, & Marletta, 2016)	
Canopies	(Gifford et al., 2002)	(Kim, Lim, Lim, Schaefer, & Kim, 2012)		Symmetry	(Hassab, 2011)	(Karava et al., 2011)	
Colour	(Cubukcu & Kahraman, 2008)	(Bansal, Garg, & Kothari, 1992)		Windows	(Reis & Lay, 2010)	Tsikaloudaki, Laskos, Theodosiou, & Bikas, 2015)	(Isaksson & Karlsson, 2006)
Material	(Gifford et al., 2002)	(Asan, 2006)		Building form	(Hassab, 2011)	(Depecker, Menezo, Virgone, & Lepers, 2001)	
Proportion	Hassab, 2011)	(Inanici & Demirbilek, 2000)		Number of storeys	(Gifford et al., 2002)	(Depecker et al., 2001)	
Fenestration	(Gifford et al., 2002)	(Susorova, Tabibzadeh, Rahman, Clack, & Elnimeiri, 2013)		Surface roughness	(Dinc & Yuksel, 2010)	(Pires, Silva, & Gonçalves, 2005)	
Reflectivity	(Gifford et al., 2002)	(Hernández-Pérez et al., 2018)		Stepped storeys	(Gifford et al., 2002)	(Y. C. Aydin & Mirzaei, 2017)	

Compared to other building parameters, the window was recognized as the predominant candidate for four reasons: (1) window properties were broadly observed in the first pre-study (PS1), (2) most of the aesthetic properties are directly and indirectly related to windows (e.g. massiveness, reflectivity, transparency, symmetry, contrast, balance, order, verticality, horizontality, etc.), (3) the window is one of the most influential parameters for energy consumption in buildings, e.g. accounting for 45% in the UK (20% via the window itself, and 25% via ventilation) (Palmer & Cooper, 2013), and buyers' willingness to pay for residential buildings (Kwak, Yoo, & Kwak, 2010), (4) according to the results of the first survey (S1, Figure 5) the window was determined as a parameter that affects housing marketability, while in contrast balconies do not have an impact in the UK (see Section 6.1.2). Therefore, one of the survey questions was designed to determine the impact of different window parameters, including the height, width, reflectivity, verticality, horizontality, and etc., which could potentially promote the marketability (Q.4 in Appendix B).

4.1.3 Survey (S1)

Based on the findings of the pre-studies (PS1 and PS2), a comprehensive survey (S1) was conducted with 289 real-estate agents across 26 UK cities to collect data to meet three main goals: (1) to better understand the cause of market failure in EEBs and to develop supplementary strategies and policies to ensure their widespread adoption, (2) to test the validity and applicability of the novel proposed widespread adoption approach (questions 1, 2, and 5 in Appendix B), and (3) to determine the most influential window related parameters that impact the marketability of residential buildings (i.e. question 4). To achieve this, the related parameters on the decision-making process of buyers (i.e. question 1) were investigated. Furthermore, the relation between the energy efficiency of buildings and their selling rates were investigated to observe the current market trends for the EEBs (i.e. question 3). In order to develop alternative strategies to minimize the high initial cost problem of EEBs, the potential average added value (in terms of money) for different factors was investigated (i.e. question 2).

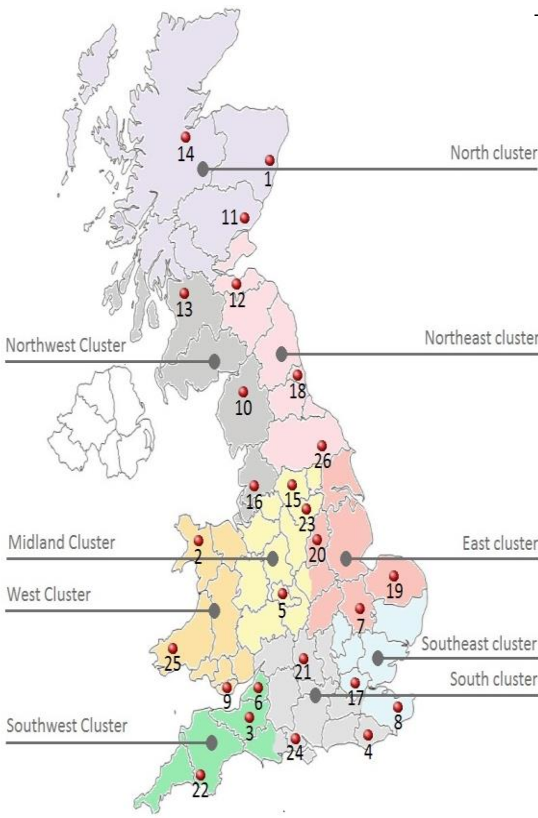
Cluster sampling method was applied in this survey; first, the UK map was divided into nine clusters based on cardinal directions (e.g. north, northeast, etc.), as shown in Table 8. Then, with the exception of the southeast cluster, three cities per cluster were selected with a simple random sampling method. All UK city names belonging to each cluster, were written on a piece of paper, gathered in a box, and mixed. Then, these randomly selected cities in each cluster were marked on the map. A slightly different process was applied to the southeast cluster. London was directly selected as it is the capital of the UK and has the largest population intensity. In order to provide a homogeneous representation between clusters, the southeast cluster was represented by only two cities in total (one directly and one randomly selected).

After running several pre-tests to ensure the consistency, clarity, and content validity of the questionnaire, some modifications were made in the original survey. For example, the maximum values for the questions 2 (i.e. £0 to £30,000 with variation sensitivity of £100) and 3 (i.e. 0 to 15 unit with variation sensitivity of 1 unit) were calibrated accordingly (see Appendix B). In order to encourage participants, the summary of the survey results and the opportunity to receive a monetary incentive was offered to them.

4.1.4 Participants

An invitation email was sent to all accessible residential sales employees (n = 5,760). Their contact details were obtained from the websites of the National Association of Estate Agents (NAEA) and independent estate agents. In order to provide a more realistic representation of the UK cities, efforts were made to get more answers from the cities with more overall real estate employees. Reminder messages were sent with a varying frequency (min: 3, max: 11 iterations) between February and March 2017. 289 responses (85 partially and 204 fully completed) were obtained by the end of March 2017, a 5% response rate. Participants' residential sale experience distribution was 1 to 3 years (18%), 4 to 6 years (15%), 7 to 9 years (7%), and more than 10 years (60%). Participants' cities were as shown in Table 8.

Table 8: Real estate employees' distribution according to 26 selected cities in the UK



No	City	All estate employees *	Accessible population **	Number of responses
1	Aberdeen	5,900	127	3
2	Bangor	-	53	2
3	Bath	3,800	134	3
4	Brighton	5,400	171	5
5	Birmingham	18,900	365	16
6	Bristol	8,200	243	11
7	Cambridge	1,800	222	14
8	Canterbury	-	59	2
9	Cardiff	5,600	201	11
10	Carlisle	1,700	85	3
11	Dundee	2,300	87	3
12	Edinburgh	4,900	133	5
13	Glasgow	10,000	340	7
14	Inverness	-	61	2
15	Leeds	11,600	419	20
16	Liverpool	10,100	370	13
17	London	27,900	1095	82
18	Newcastle	1,300	174	10
19	Norwich	4,200	91	5
20	Nottingham	7,800	283	29
21	Oxford	3,100	222	12
22	Plymouth	6,300	125	5
23	Sheffield	7,700	261	12
24	Southampton	6,300	204	6
25	St David's	-	56	2
26	York	5,300	179	6
	Total:	160,100	5,760	289

* The overall number of all estate employees in cities (includes all departments) (NOMIS, 2017)
** Employees in only residential sales department that have accessible contact details

4.1.5 Measurement tool

An email survey was preferred as the measurement tool for time and financial advantageous, lower social desirability and stereotype bias, and reduced time pressure on participants. Unipolar, fully verbal labelled, five-point Likert scale and numeric slider scale were utilised in this study. Each question was supported by an optional text box to collect participants' additional comments, and to let participants express plausible different answers from the given options. Furthermore, except for demographic questions, the order of the questions and variables were randomized to minimize question order bias. The complete questionnaire can be found in Appendix B.

4.1.6 Survey analysis method

The values for skewness of ±2 are considered to be acceptable in order to meet the assumption of the normality (George & Mallery, 2010); the conducted survey has a normal distribution (skewness: max: 0.732, min: -0.091, kurtosis: max: -1.073, min: -1.100) and a large sample size ($n = 289$), thus parametric models were utilised; two-tailed paired samples T-test and Pearson correlation analysis were utilised as the statistical model via IBM SPSS (Version: 23). In addition, a series of descriptive statistical analysis were presented in order to provide more descriptive information about the results. Considering all questions were independent from each other, pairwise deletion was utilised; the sample size for each question can be found in the given descriptive statistics for each graph. In all statistical calculations, conventional values were chosen for Sig. (2-tailed) value (0.05), with a 95% confidence interval.

Both Cronbach's alpha (α) and test-retest protocol were utilised to better confirm reliability, internal consistency, and longitudinal consistency (in participants' responses over time). For test-retest protocol, the same survey was repeated with the participants who responded to the previous survey (n = 289) at the end of June 2017 (three months after the first survey), in order to minimize the likelihood of recalling the questionnaire and the given answers. 80 responses were obtained, a 28% response rate. Then, the pre-test and post-test responses of those participants were compared with Pearson's correlation to determine the consistency of their answers.

4.2 Survey (S2) with potential housing buyers

This section introduces the details of a survey (S2, Figure 5) conducted to achieve further evidence about the applicability of the proposed widespread adoption approach. In addition, this section contains the details of six pre-studies (PS3-PS8, Figure 5) conducted for developing the surveys (S2-S4, Figure 5) discussed in the rest of the study.

4.2.1 Pre-study (PS3) to determine the parameters affecting aesthetic judgment

In the third pre-study (PS3, Figure 5), the parameters that may affect participants' aesthetic judgments were determined. A high correlation was found between aesthetic judgments from the photographic images and on-site evaluations reported in previous studies (e.g. (Stamps III, 1997)). Despite this fact, extra attention was given to the preference and design of photographic images in the rest of the study due to the fact that aesthetic judgement is sensitive to many variables.

According to the conducted comprehensive literature review, 52 different affecting parameters on aesthetic judgement were grouped under three headings, including building characteristics, environmental characteristics, and photo quality, as shown in Table 9. Hence, efforts were made to ensure that the variations in the participants' judgements are only a result of the configurations being worked on. For this purpose, all other variables were fixed except the configurations of the focused building parameter (i.e. window configurations; see PS2, Figure 5, in Section 4.1.2). In addition, an effort was made to set a balance between minimizing the unwanted impact of those 52 parameters on participants' aesthetic appreciation, and to provide maximum reality to the pictures. For this purpose, surrounding features in the studied illustrations, such as vegetation and background, was kept at the minimum level. In addition, in the rest of the study, black and white photographs were particularly preferred to minimize the influence of colours on participants' aesthetic appreciation (e.g. (Cubukcu & Kahraman, 2008)). Accordingly, in order to obtain fully controlled identical illustrations, a common UK house photograph was adjusted with an open-source photo editing program, GIMP 2.1 Software, to generate all studied building photos in the rest of the study. The common UK housing typology was determined with another pre-study (PS4) as discussed in the next section.

Table 9: Factors influencing aesthetic judgement

	Building features	
1	Architectural typology	(Ibrahim, Abu-Obeid, & Al-Simadi, 2002); (Lindal & Hartig, 2013)
2	Balconies	(Gifford et al., 2002)
3	Building form	(Hassab, 2011)
4	Building height	(Lindal & Hartig, 2013); (Gifford et al., 2002)
5	Canopies	(Gifford et al., 2002)
6	Colour	(Cubukcu & Kahraman, 2008) (Gifford et al., 2002)
7	Mystery	(Ikemi, 2005); (Hanyu, 1997)
8	Facade dirtiness	Brimblecombe & Grossi, 2005)
9	Texture	(Liu et al., 2015)
10	Fenestration	(Gifford et al., 2002)
11	Material	(Gifford et al., 2002)
12	Proportion	(Hassab, 2011)
13	Roof	(Gifford et al., 2002)
14	Surface ornament	(Lindal & Hartig, 2013)
15	Surface Reflectivity	(Gifford et al., 2002)
16	Surface roughness	(Dinc & Yuksel, 2010)
17	Symmetry	(Hassab, 2011)
18	Windows	(Reis & Lay, 2010)
	Surrounding features in the picture	
1	Building dominance	(Stamps & Miller, 1993)
2	Time of the day	(Beute & de Kort, 2013)
3	People	(Cerosaletti & Alexander, 2009)
4	Monuments	(Ferdous, 2013)
5	Openness of surrounding enclosure	(Ferdous, 2013)
6	Roofline silhouette	(Lindal & Hartig, 2013)
7	Shadow patterns	(Beute & de Kort, 2013)
8	Sunny or overcast sky	(Beute & de Kort, 2013)
9	Surrounding enclosure height	(Ferdous, 2013)
10	The architectural characteristic of surrounding buildings	(Lindal & Hartig, 2015)
11	Dominance of urban & nature areas	(Beute & de Kort, 2013)
12	Vegetation	(Lindal & Hartig, 2015); (Chiang, Nasar, & Ko, 2014)
13	Vehicles	(Hanyu, 1997)
14	Water features	(Ferdous, 2013)
	Photo quality	
1	Brightness	(Beute & de Kort, 2013); (Hanyu, 1997)
2	Clarity	(T. O. Aydin, Smolic, & Gross, 2015)
3	Closeness to foreground objects	(Liang, Su, Wang, Wang, & Luo, 2013); (Jin, Wu, & Liu, 2012)
4	Colour harmony	(Lu, Peng, Li, & Wang, 2015)
5	Colourfulness	(T. O. Aydin et al., 2015); (Datta, Joshi, Li, & Wang, 2006)
6	Composition	(Lu et al., 2015); (Zhang, Nefs, Redi, & Heynderickx, 2014); (Chu, Chen, & Chen, 2013)
7	Depth	(T. O. Aydin et al., 2015); (Zhang et al., 2014); (Datta et al., 2006)
8	Focal view	(Arriaza, Cañas-Ortega, Cañas-Madueño, & Ruiz-Aviles, 2004)
9	Focus	(T. O. Aydin et al., 2015)
10	Foreground objects position	(Lu et al., 2015); (Gardner, Fowlkes, Nothelfer, & Palmer, 2008)
11	Image resolution (Pixel)	(Chu et al., 2013); (Liang et al., 2013)
12	Lighting focus	(Ferdous, 2013); (Nikunen & Korpela, 2009)
13	Main object perspective	(Zhang et al., 2014)
14	Main object size	(Cerosaletti & Alexander, 2009)
15	Physical dimensions of illustration	(Chu et al., 2013)
16	Position of the horizon	(Svobodova, Sklenicka, Molnarova, & Vojar, 2014)
17	Saturation	(Datta et al., 2006); (Datta et al., 2006)
18	Sharpness	(T. O. Aydin et al., 2015); (Zhang et al., 2014)
19	Size	(Chu et al., 2013); (Jin et al., 2012); (Liang et al., 2013)
20	Symmetry	(Svobodova et al., 2014)

4.2.2 Pre-study (PS4) to determine focused benchmark buildings

In order to determine the focused benchmark buildings' typology, in the fourth pre-study (PS4, Figure 5), the most common UK building typology and characteristic properties were identified from the literature. Benchmark buildings' features were mainly defined according to the most common housing features in the UK, actual building regulations, and standard features utilised in the Government's Standard Assessment Procedure for Energy Rating of Dwellings calculations (SAP).

Detached (25%) and terraced houses (30%) together represented 55% of UK building stock in 2013 (Department for Communities and Local Government, 2015). The vast majority (80%) of UK dwellings are two-storey buildings (Department for Communities and Local Government, 2010), with an average usable floor area of 94 m^2 (EHS, 2016). A cavity or solid brick wall is the most common building material (98%) (EHS, 2016), and the majority of UK dwellings (51%) have no wall insulation (32% with cavity walls and 91% with solid walls), but most have full double glazing (80%) (EHS, 2016).

Accordingly, the target buildings in this study were two-storey, brick, detached and terraced houses, representing the majority of UK building stock. The window size of the benchmark buildings was determined to be 18.3 m^2 ±25% (for 94 m^2 usable floor area age band A, B, C houses), according to the SAP (the average total glazing area guideline equation in Table S4: Window area) (SAP, 2014). In the light of collected data, black and white terraced and detached benchmark housing illustrations were generated with the photo editing program (GIMP 2.1). Eventually, an original UK housing photo was readjusted according to the most common properties (see Figure 9).

a) b)

Figure 9: Photographs of detached and terraced benchmark buildings

The lack of doors, shutters and other widespread architectural elements on the facade of the utilized building images may emerge the concern that the pictures used in this thesis do not reflect the realistic buildings adequately. However, as shown in Table 9, there are many parameters that have an impact on aesthetic judgement (e.g. parameters related to building characteristics and architectural elements, environmental characteristics, and photo quality of visual stimuli). As discussed in Section 4.1.2, this study is limited with only the impact of windows on detached and terraced housings' aesthetic, marketability and energy efficiency as including the impact of all architectural elements is beyond the scope of this Ph.D. thesis. Hence, efforts were made to ensure that the variations in the participants' judgements are only a result of the configurations applied on focused window parameters (i.e. window height, width, number, area, symmetry, position on X and Y coordinates, and proportion). For this purpose, in all building illustrations utilized in this thesis, an effort was made to minimize the impact of other parameters such as other architectural elements (e.g. door, ornament, balcony, window frame style, rain pipe, etc.) and surrounding features (e.g. vegetation and background) on individuals' judgement. Therefore, it is worth to highlight that this thesis is limited with only the impact of eight window parameters, and further studies are required to consider the impact of other architectural elements.

4.2.3 Pre-study (PS5) to investigate the impact of housing typology on aesthetic judgement

In order to optimize the number of questions in the main survey (S2, Figure 5) and the following studies, a hard copy survey (see Appendix C) was conducted with 35 randomly selected UoN students with different demographic characteristics (see Table 10) to determine the impact of housing typologies (terraced – detached house (see Figure 9)) on individuals' aesthetic judgement. The participants were randomly selected from different parts of UoN Park Campus on different days and at different times. Detached and terraced housings' aesthetic and marketability were measured with a bipolar seven-point semantic differential scale. Cronbach's alpha (α) was utilised to confirm the reliability and internal consistency of the conducted survey.

Table 10: Demographic characteristics of participants

Gender	%	Age	%	Qualification *	%	Income	%	Location	%
Male:	50	Under 18	11	Bachelor's degree:	68	Under £2,500	39	1	4
Female:	50	18-24:	68	Master's degree:	14	£2,501- £10,000	14	2	8
Other:	0	25-34:	18	Ph.D. degree	14	£10,001- £20,000	21	3	8
		35-44:	4	Other:	4	£20,001- £30,000	18	4	19
		45-54:	0			Over £30,001	7	5	39
		55-64:	0					6	8
		65+:	0					7	4
								8	8
								9	4
								10	0

** Completed or currently enrolled*

4.2.4 Pre-study (PS6) to determine the illustrations utilised in the main survey (S2)

In order to identify the illustrations utilised in the main survey (S2, Figure 5) a hard copy survey was conducted with 37 randomly selected UoN students. The complete questionnaire can be found in Appendix D. The demographic characteristics of participants is shown in Table 11. The aesthetics of 33 black and white housing photos in the Figure 13 (not including the five photos belonging to the experimental category) were measured with a bipolar seven-point semantic differential scale, and the most attractive and unattractive housing photos were determined. Further technical details about the utilised 33 housing photos are discussed in detail in Sections 5.3.2 and 5.2.3. Although an unattractive housing photo was determined with sixth pre-study (S2, Figure 5), an attractive housing photo as required level could not be determined among the studied 33 housing photos. The mean of the most attractive one reached only around four (neutral) on the seven-point semantic differential scale (see Section 6.1.4). Therefore, as an additional study, another pre-study (PS7, Figure 5) was conducted to generate attractive housing illustrations.

Table 11: Demographic characteristics of participants

Gender	%	Age	%	Qualification	%	Income	%	Location	%
Male:	51	Under 18	10	Bachelor's degree:	69	Under £2,500	33	1	5
Female:	49	18-24:	69	Master's degree:	16	£2,501- £10,000	30	2	9
Other:	0	25-34:	20	Ph.D. degree	11	£10,001- £20,000	22	3	10
		35-44:	2	Other:	4	£20,001- £30,000	15	4	19
		45-54:	0			Over £30,001	0	5	29
		55-64:	0					6	8
		65+:	0					7	5
								8	8
								9	5
								10	0

4.2.5 Pre-study (PS7) to generate visually attractive housing façades

In order to test the impact of aesthetics on housing marketability, utilisation of an aesthetically attractive housing illustration was necessary. Thus, in the seventh pre-study (PS7, Figure 5), 12 architects with diverse demographic profiles were asked to design an attractive housing façade (according to their own point of view) with the combination of 20 given, pre-identified window typologies (obtained from the generated 33 housing photos) (see Figure 15), without any modification in their dimensions. A blank housing façade and 20 window configurations were sent to participants as a Microsoft Paint file via email, whereby participants could copy and paste windows to generate what they considered to be an attractive housing façade design. The pre-identified 20 window typologies comprised various different heights, widths, areas, and proportions, details of whose spectrum and the reasoning behind their design are discussed in Sections 5.3.2 and 5.2.3. According to the façade designs of the participant architects, 12 fully controlled black and white and identical photographic images were generated with the photo editing program (GIMP 2.1) (see Figure 10). Architecture participants were obtained with snowball sampling method, identifying participants from initial contacts by utilising social circles to recruit secondary participants from the acquaintances of initial recruits. Snowball sampling method was preferred in this study due to the limited time and budget. Accordingly, an invitation email and explanation of the task was sent to some architects who had practical experiences and 12 participants were thus identified. Since this study was not conducted in the form of a questionnaire, the demographic characteristics of the participants were not asked, as the existence of a common aesthetic appreciation for adults with different demographic characteristics was reported in a previous study (Stamps III, 1999).

Figure 10: Building façade designs made by 12 architects via the combination of 20 pre-identified window configurations

4.2.6 *Pre-study (PS8) to identify the most attractive and unattractive housing illustrations*

A hard copy survey was conducted with 30 randomly selected UoN students with different demographic characteristics (see Table 12) to determine an attractive housing photo to be utilised in the main survey (S2, Figure 5), and to develop a general hypothesis. The survey was divided into three sections: in the first section, participants were asked to grade 18 building photos according to their visual aesthetics, to determine the most attractive and unattractive housing photos, using a bipolar seven-point semantic differential scale. These 18 housing photos (see Figure 23) contained the benchmark building photo determined in the fifth pre-study (PS5, Figure 5), five unattractive housing illustrations determined in sixth pre-study (PS6, Figure 5), and 12 housing façades designed by 12 architects in the seventh pre-study (PS7, Figure 5). In the first section, participants could see only one housing illustration on each page. In addition, participants' perceived monetary value of each housing unit was determined with an additional question, in order to develop a hypothesis pertaining to this feature.

In the second section, participants were asked to sequence all 18 given housing photos from most to least attractive. In this section, all housing photos were located on the same page, to let the participants to compare all the given photos, in order to validate the results of the previous section. In the last section, different housing prices and energy bills were assigned to common, attractive, and unattractive housing photos, and participants were asked to choose only one of the buildings to buy. For this stage, the attractive and unattractive housing photos were chosen according to observations obtained in the pre-test process. The order of the illustrations was randomly modified to minimize the question order bias. For this purpose, first, similar pages of hard copy surveys were grouped, then surveys were generated with the randomly selected different ordered pages (except the cover page and introduction page). The complete questionnaire can be found in Appendix E. Cronbach's alpha (α) was utilised to confirm the reliability and internal consistency of both conducted surveys.

Table 12: Demographic characteristics of participants

Gender	%	Age	%	Qualification*	%	Income	%	Location	%
Male:	55	Under 18	25	Bachelor's degree:	73	Under £2,500	41	1	8
Female:	45	18-24:	51	Master's degree:	22	£2,501- £10,000	15	2	5
Other:	0	25-34:	17	Ph.D. degree	5	£10,001- £20,000	22	3	16
		35-44:	7	Other:	0	£20,001- £30,000	16	4	23
		45-54:	0			Over £30,001	5	5	30
		55-64:	0					6	7
		65+:	0					7	4
								8	3
								9	3
								10	1

** Completed or currently enrolled*

4.2.7 Survey (S2)

The main survey (S2, Figure 5) had three main sections. In the first section, the initial impression of participants about the utilised four housing photos[29] were measured to ensure that the housing photos, which are expected to be found attractive and unattractive, are being properly perceived by the participants. For this purpose, participants were asked to rank the given four housing photos from most to least attractive. In the second section, two main points were investigated: (1) the impact of housing properties (i.e. aesthetic, initial cost, energy efficiency) on the buying preference; and (2) the upper limits of the added value that can be reached with the aesthetic enhancement of housing units. For this purpose, the participants were asked to select one of the four house options, with information about appearance, prices, and average annual and monthly energy bills. In total, there were 13 different scenarios, including four different housing façade designs (see Figure 11), four different prices (£200,000, £240,000, £260,000, and £300,000), and three different annual energy bill scenarios (£168, £1,164, and £2,160) (see Table 14).

[29] Two attractive, one benchmark and one unattractive housing photos (Figure 11).

The underlying reasons behind the presences of the utilised housing prices and energy bills are summarised in Table 13. Housing illustrations were obtained from the eighth pre-study (PS8) (See Figure 11), and housing prices and energy bill scenarios were arranged based on the data acquired from the literature. For example, in the UK, an average representative price for a four-bedroom house is £200,000 (UK_Gov, 2018), with average monthly bills of £49 and £48 for electricity and gas (respectively, combining to a total of £97) (UK_Power, 2018). An energy saving of approximately 85% is possible with passive buildings (Schnieders & Hermelink, 2006), while the extra initial cost of EEBs can reach up to 20% of the housing price (Johansson et al., 2012).

Table 13: Summary of applied scenarios and the reasoning behind them

Housing prices	Difference with previous one (%)	Reasoning
£200,000	-	Average house price is £200,000 (UK_Gov, 2018)
£240,000	20%	The extra initial cost of EEBs can reach up to 20% of the housing price (Johansson et al., 2012)
£260,000	20%	The increase in previous step was repeated to provide continuity
£300,000	40%	Although there was an increase of 20% in the previous steps, this step was increased by 40% to minimize the number of questions and maximize the response rate.
Monthly energy bill	**Difference with benchmark value (%)**	**Reasoning**
£14	-85%	Reported highest energy saving possibility has taken in to account; 85% energy saving is possible with passive buildings (Schnieders & Hermelink, 2006)
£97	Benchmark	Average monthly energy bill for this building type in the UK is £97 (UK_Power, 2018)
£180	85%	To provide continuity and generate an extreme energy inefficient building scenario

Table 14: Applied scenarios

		Attractive houses		Common house (benchmark)	Energy effcient house
		A		B	D
Scenarios about the housing appearances					
Scenario 1	Price	£200,000	£200,000	£200,000	£200,000
	Monthly and annual	£97	£97	£97	£14
	energy bill	£1,164	£1,164	£1,164	£168
Scenario 2	Price	£200,000	£200,000	£200,000	£240,000
	Monthly and annual	£180	£180	£97	£14
	energy bill	£2,160	£2,160	£1,164	£168
Scenario 3	Price	£200,000	£200,000	£200,000	£240,000
	Monthly and annual	£97	£97	£97	£14
	energy bill	£1,164	£1,164	£1,164	£168
Scenario 4	Price	£200,000	£200,000	£200,000	£240,000
	Monthly and annual	£14	£14	£97	£14
	energy bill	£168	£168	£1,164	£168
Scenario 5	Price	£240,000	£240,000	£200,000	£240,000
	Monthly and annual	£180	£180	£97	£14
	energy bill	£2,160	£2,160	£1,164	£168
Scenario 6	Price	£240,000	£240,000	£200,000	£240,000
	Monthly and annual	£97	£97	£97	£14
	energy bill	£1,164	£1,164	£1,164	£168
Scenario 7	Price	£240,000	£240,000	£200,000	£240,000
	Monthly and annual	£14	£14	£97	£14
	energy bill	£168	£168	£1,164	£168
Scenario 8	Price	£260,000	£260,000	£200,000	£240,000
	Monthly and annual	£180	£180	£97	£14
	energy bill	£2,160	£2,160	£1,164	£168
Scenario 9	Price	£260,000	£260,000	£200,000	£240,000
	Monthly and annual	£97	£97	£97	£14
	energy bill	£1,164	£1,164	£1,164	£168
Scenario 10	Price	£260,000	£260,000	£200,000	£240,000
	Monthly and annual	£14	£14	£97	£14
	energy bill	£168	£168	£1,164	£168
Scenario 11	Price	£300,000	£300,000	£200,000	£240,000
	Monthly and annual	£180	£180	£97	£14
	energy bill	£2,160	£2,160	£1,164	£168
Scenario 12	Price	£300,000	£300,000	£200,000	£240,000
	Monthly and annual	£97	£97	£97	£14
	energy bill	£1,164	£1,164	£1,164	£168
Scenario 13	Price	£300,000	£300,000	£200,000	£240,000
	Monthly and annual	£14	£14	£97	£14
	energy bill	£168	£168	£1,164	£168

Except the first scenario, in all scenarios, the prices and energy bills of the benchmark house (Figure C in Table 14) and energy efficient house (Figure D in Table 14) were kept constant. The illustration of the energy efficient house (Figure D in Table 14) was preferred to be an unattractive housing image because the unappealing aesthetics of EEBs have been broadly reported in previous studies (see Section 2.2.1). The first scenario was designed to discover whether the initial cost reduction of EEBs is sufficient to enhance their marketability and widespread adoption. For this purpose, the price of all four houses was kept constant, equal to the average representative UK house price (£200,000). Energy bills of the attractive and common housings (Figure A, B, C in Table 14) were adjusted to the common average energy bill (£1,164 per year). Accordingly, in the first scenario, only the appearance of the buildings and the energy bill of the energy efficient building (£168 per year) are different (see Table 14). After the first scenario, the housing price and energy bill of the attractive houses (Figure A and B in Table 14) is gradually increased, and different combinations are generated to discover the impact of aesthetics, price, and energy efficiency on buying preferences and the limits of how much added value can be achieved with aesthetic enhancement in residential buildings. The last section collects information about the demographic characteristics of participants (see Appendix F).

4.2.8 Visual stimuli

According to the results of the six conducted pre-studies (i.e. PS3-PS8, Figure 5), four black and white detached housing photos (identical except for window configurations) were generated with an open-source photo editing program, GIMP 2.1 Software (see Figure 11). The housing photo #1 in Figure 11 is the benchmark building, which is the most common housing typology in the UK according to the results of fourth pre-study (i.e. PS4, Figure 5) and fifth pre-study (i.e. PS5, Figure 5). According to the results of eighth pre-study (i.e. PS8, Figure 5), housing photos #2 and #3 in Figure 11 are determined as the most attractive housing photos, and #4 in Figure 11 is determined as the most unattractive one.

In the main survey (i.e. S2, Figure 5), there are two attractive housing photos (#2 and #3 in Figure 11) for two reasons: (1) the aesthetic ratings of photo #2 (M = 4.37, σ = 0.75) and #3 (M = 4.25, σ = 0.73) are very close to each other; (2) utilising two attractive photos could increase the chance of providing a housing photo found to be attractive by more participants, minimizing potential issues occurring due to aesthetic taste differences among participating individuals. An attractive housing photo as a desired level could not be achieved even in the eighth pre-study. The generated "most attractive" building could only reached just above 4 (neutral) out of the seven-point attractiveness scale.

1 2 3 4

Figure 11: Housing photos utilised in the main survey

4.2.9 Participants

It was initially planned to conduct a comprehensive survey with 7,348 individuals in different occupations in 26 different cities of the UK, but the scope of the participants was limited to only University of Nottingham (UoN) staff due to problems faced in achieving ethical approval. The contact details of 1812 UoN staff were sourced from publicly available data on the UoN website. The participants were randomly selected. In order to provide a more realistic representation of the UK population, efforts were made to determine participants from different departments and occupations (e.g. security, maintenance, academic, administration, and grounds keeping etc.) to ensure demographic variety (e.g. in terms of income, education level, and the cities of origin of participants). An invitation email was sent to UoN staff (n = 1,812) in October 2018 and 183 responses (15 partially and 168 fully completed) were obtained by the end of October 2018, a 10% response rate. Participants' demographic characteristics are shown in Table 15.

Table 15: Demographic characteristics of participants

Gender	%	Age	%	Qualification*	%	Income	%	Location	%
Male:	59	18-24:	4	No schooling	4	£5,001- £15,000	4	1	2
Female:	40	25-34:	20	High school	18	£15,001- £25,000	19	2	3
Other:	1	35-44:	25	Bachelor's degree:	23	£25,001- £35,000	22	3	1
		45-54:	26	Master's degree:	14	£35,001- £45,000	22	4	25
		55-64:	21	Ph.D. degree	33	£45,001- £55,000	15	5	57
		65+:	5	Other:	9	£55,001- £65,000	9	6	5
						£65,001- £75,000	3	7	4
						Over £75,001	6	8	2
								9	1
								10	1

** Completed or currently enrolled*

4.2.10 Measurement tool

An email survey (S2, Figure 5) was conducted in October 2018. Ordering and multiple choice questionnaires were utilised to determine the impacts of the aesthetics, initial cost, and energy efficiency of housing on participants' buying preferences. Participants could see only one question on each page. Each question was supported by an optional text box to collect additional comments. The complete questionnaire can be found in Appendix F.

4.2.11 Survey analysis method

Survey results were analysed with descriptive statistics. IBM SPSS Version-23 was utilised for all statistical analysis. Listwise deletion was applied, and an entire record was excluded from analysis if any missing answer was found for any of the questions. Cronbach's alpha (α) was utilised to confirm the internal consistency of the conducted survey.

CHAPTER V

INVESTIGATING THE APPLICABILITY OF THE PROPOSED NOVEL PARADIGM

CHAPTER V.

INVESTIGATING THE APPLICABILITY OF THE PROPOSED NOVEL PARADIGM

This section discusses the details of the five conducted studies to test the applicability of the YYP. The details of two surveys (S3 and S4, Figure 5), developed symmetry measurement model (symmetry index) (SI in Figure 5), and BES (ES in Figure 5) which were conducted to develop an ANN and decision tree-based predictive models (PM in Figure 5) and multidimensional measurement model (MMM in Figure 5) are discussed. Multidimensional measurement model is the validated predictive model ready to utilise for a new input data set (window parameters) to make predictions about the aesthetics, marketability, and energy efficiency of the UK detached and terraced housings.

5.1 Survey (S3) to validate the developed symmetry measurement model

This section introduces the details of the survey (S3, Figure 5) conducted to validate the developed symmetry index (SI in Figure 5). Symmetry index was necessary to develop predictive models (PM in Figure 5). Further details about the symmetry index can be found in Section 3.4.

5.1.1 Participants

Strong correlations were reported between the aesthetic judgement of students and adults in previous studies (e.g. (Stamps III, 1999)). Therefore, in this study, students were considered as the representative population, so a total of 145 students with different demographic characteristics were recruited for this research from the UoN (UK). The participants were randomly selected from different parts of the UoN Park Campus on different days and times. Participants' ethnic distribution was categorized according to continent of origin. In order to identify the ethnicity distribution in more detail, the Middle East region was separated from Asia and Africa, considering general cultural and ethnic differences (see Appendix G). Participants' demographic characteristics are shown in Table 16. Although this thesis focused on the UK, this survey was conducted with students from different nationalities to achieve a common symmetry perception.

Table 16: Demographic characteristics of participants

Gender (σ = 0.52)	%	Background (σ = 0.47)	%	Qualification* (σ = 0.77)	%	Age (σ = 0.75)	%	Ethnicity (σ = 1.22)	%
Male:	53	Architect:	33	Bachelor's degree:	19	Under 18:	6	North America:	2
Female:	47	Other:	67	Master's degree:	38	18-24:	47	South America:	4
Other:	0.1	No response:	0	Ph.D. degree	43	25-34:	40	Africa:	12
				Other:	0.1	35-44:	6	Europe:	33
						45-54:	1	Middle east:	23
						55-64:	0	Asia:	26
						65+:	0	Australia:	0

** Completed or currently enrolled*

5.1.2 Visual stimuli

Efforts were made to minimize the impacts of parameters that may potentially affect participants' judgement (see Section 4.2.1). Hence, an open-source photo editing program, GIMP 2.1 Software, was firstly utilised to generate a fully controlled and identical photographic images (except window configurations). Then, seven different photographic images (see Figure 12) were generated from a common UK residential building photograph (i.e. the benchmark building in Figure 9 a). In the designed survey, eight[30] similar black and white building photographs were utilized. Except for the demographic questions, the order of the pictures was randomized to minimize the question order bias, while participants could only see one picture at a time to grade the dwellings' symmetry and aesthetics. Further details can be seen in Appendix G

Figure 12: Visual stimuli utilised in the symmetry survey

[30] Benchmark building in Figure 9 a and seven photos in Figure 12.

5.1.3 Measurement tools

A high-resolution hard copy survey was utilised in July 2018 to validate the developed symmetry index (SI in Figure 5) and to determine a correlation between symmetry and aesthetics. A bipolar seven-point semantic differential scale was utilised in this research. Each question was supported by an optional text box to collect participants' additional comments and to let them express a plausible different answer above the given options. The complete questionnaire can be found in Appendix G.

5.1.4 Analysis method

The conducted survey has a normal distribution (skewness: max: 0.565, min: -0.060, kurtosis: max: -1.050, min: -1.366) and a large sample size (n = 145), thus parametric models were utilised. The symmetry of the photos in Figure 12 was measured with the developed symmetry index and the conducted survey. The statistical significance of the difference between two results was investigated with two-tailed paired T-test samples. Moreover, the relationships between symmetry-aesthetic were determined with the Pearson correlation analysis. The impact of demographic differences on participants' symmetry and aesthetic perception was examined with one-way ANOVA; Hochberg GT2 post hoc test was also performed to analyse the details of variances between subgroups. IBM SPSS Version-23 was utilised for all statistical analysis. Since there is no missing data, neither pairwise nor listwise deletion were applied. Cronbach's alpha (α) was utilised to confirm the reliability and internal consistency of the conducted survey. In all statistical calculations, conventional values were chosen for Sig. (2-tailed) value (0.05) with a 95% confidence interval.

In addition, min-max normalization in Eq. (28), was utilised to standardize the range of independent variables of the questionnaire. The data obtained from the questionnaire were normalized to be in the same measurement scale similar to the mathematical model between 0 and 1. The values between 1 and 7 were converted to the same scale as the applied mathematical models (values between 0 and 1). For this purpose, the semantic differential scales were firstly converted to numerical values (i.e. values between 1 for asymmetric and ugly options, and 7 for symmetric and beautiful options). Then, the normalized values (xn) of each numeric semantic differential scale were calculated with Eq. (28).

5.2 Survey (S4) to investigate the impact of different window parameters on aesthetics and marketability of housings

This section introduces the details of the survey (S4, Figure 5) conducted to develop and validate ANN and decision tree-based predictive models (PM in Figure 5) and generate a multidimensional measurement model (MMM in Figure 5).

5.2.1 Survey

A comprehensive email survey (S4, Figure 5) was conducted on October 2018 to investigate the impact of seven window parameters on marketability and the aesthetics of detached residential building façades in the UK. An email survey was preferred in this study. Before conducting the main survey, several pre-tests were conducted to improve the clarity of the survey. Except for the demographic questions and benchmark building (the first picture for the calibration purpose), the order of the pictures was randomized to minimize the question order bias, while participants could only see one picture at a time to grade the dwellings' aesthetic and marketability with a bipolar seven-point semantic differential scale. Each question was supported by an optional text box to collect participants' additional comments, and to let them express a plausible different answer above the given options. In order to minimize misconceptions and to ensure equal conditions for each participant, they were briefly informed with a written instruction about the tasks and working principles of the semantic differential scale. The complete questionnaire can be found in Appendix I.

5.2.2 *Participants*

High correlations between the aesthetic judgement of students and adults were reported in previous studies (e.g. (Stamps III, 1999)). Therefore, in this study, students were considered as a representative population. Invitation emails were distributed to home students (UK nationals) at the UoN (UK) via the UoN IT service. In order to encourage participants, an opportunity to receive a monetary incentive was offered. 1,095 responses were received (288 partially), and only fully completed questionnaires were used. The demographic characteristics of participants are shown in Table 17. Participants' distribution across the UK was categorized according to their regions, defined based on the cardinal directions (e.g. northwest, southwest, etc.) (See Appendix I).

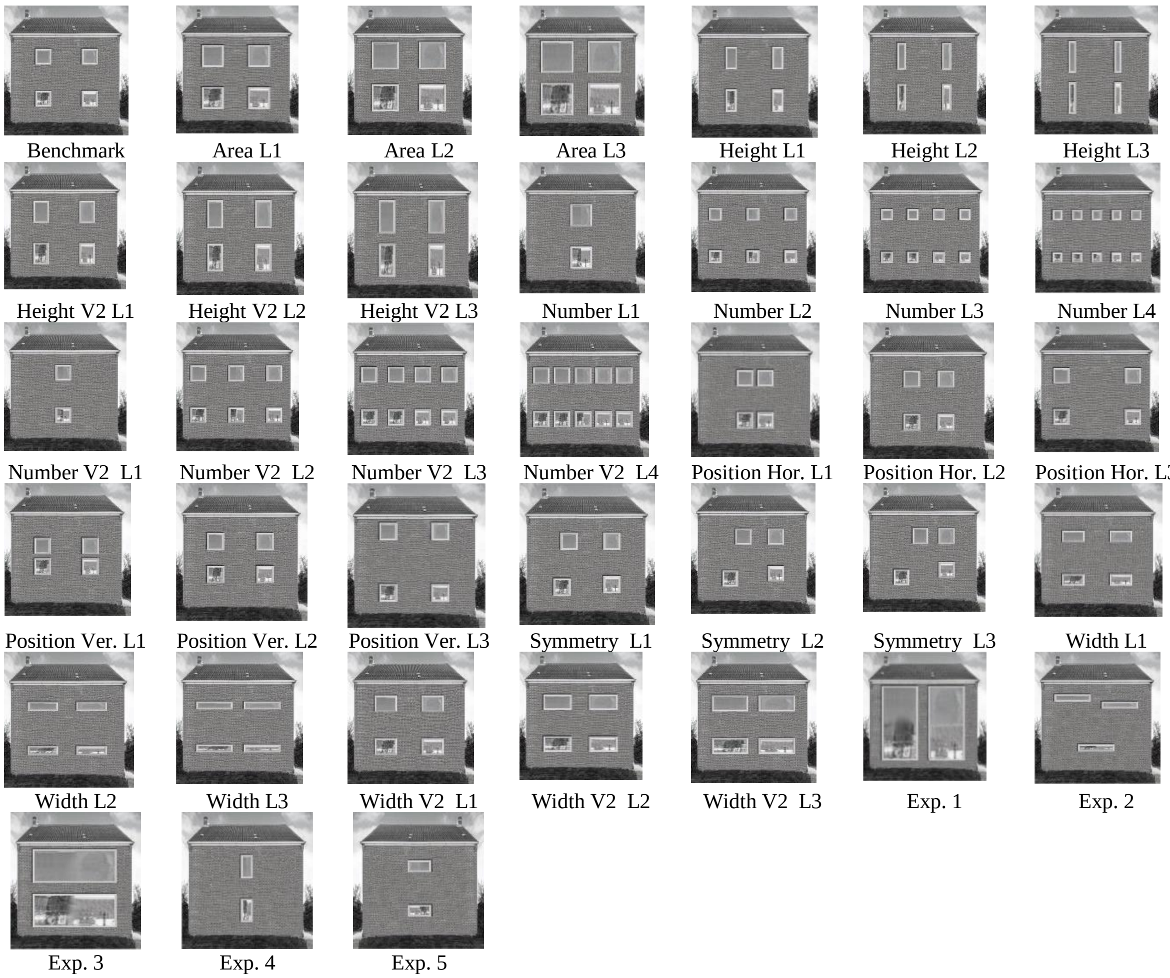
Table 17: Demographic characteristics of participants

Gender		Background		Qualification*		Age		Region ** (σ =1.70)			
(σ = 0.47)	%	(σ =0.48)	%	(σ =1.35)	%	(σ =0.66)	%		%		%
Male:	32	Architect:	3	Bachelor's degree:	47	Under 18:	0	1:	1	6:	17
Female:	67	Art:	6	Master's degree:	16	18-24:	83	2:	7	7:	18
Other:	1	Other:	92	Ph.D. degree	1	25-34:	11	3:	3	8:	2
				Other:	35	35-44:	4	4:	21	9:	3
						45-54:	2	5:	28	10:	1
						55-64:	1				
						65+:	0				

* Completed or currently enrolled,

5.2.3 *Visual stimuli*

A common UK detached house photo was adjusted with the open-source photo editing program GIMP 2.1 Software to generate all other studied building photos. In total, 38 different black and white fully controlled, and identical photographic images were generated (see Figure 13). Parametric details of the applied window configurations can be found in Figure 15.



V2: second version of window configurations, Exp: photos that belong to experimental categories

Figure 13: Visual stimuli utilised in the survey

The generated photos were divided into two categories: training (all images except those between Exp. 1 and Exp. 5 in Figure 13) and experimental (Exp. 1 to Exp. 5 in Figure 13). For the experiment category, five photos were designed to be utilised for provide additional validation of developed predictive models (PM in Figure 5), these photos were not utilised during training. For the training category, 33 photos were designed to be utilised for developing ANN and decision tree models. For photos belonging to the training category, each window parameter was modified under four levels: level (L) 0 (L0) for the benchmark building, and L1, L2, and L3 (see Figure 13). Efforts were made to extract the isolated impact of each of seven window parameters. For this purpose, in each image, only one parameter was changed, and all other parameters were not varied. However, window area, height, width, position, and number, resulted in multiple variations (see Table 18). Accordingly, those parameters were investigated with two variations to extract the isolated impact of each of seven window parameters. For example, in the case of window height configurations, when the window height was modified, window width had to be altered too, in order to keep the window area constant in all window configurations (see Figure 13 and Figure 15). The variations caused by the configuration of window parameters are summarised in Table 18.

Table 18: Variations caused by the configuration of window parameters

Window Parameters	Variations caused by configurations							
	Area	Height	Number	Position X	Position Y	Symmetry	Width	Proportion
Area	X	X					X	
Height		X					X	X
Height Ver.2	X	X						X
Number		X	X	X			X	
Number Ver.2	X		X	X				
Position X*				X				
Position Y*					X			
Symmetry				X	X	X		
Width		X					X	X
Width Ver.2	X						X	X

**Position X and Y refers to the location of windows' centre on the X and Y axis when a coordinate system located at the centre of the building.*

5.2.4 Analysis method

IBM SPSS Version-23 was utilised for all statistical analysis. The conventional values were chosen for Sig. (2-tailed) value (0.05) with a 95% of confidence interval. As the conducted survey had a normal distribution (skewness: *max*: 1.534, *min*: -0.081, kurtosis: *max*: 1.899 -, *min*: -0.804) and large sample size (n = 807), parametric statistical models were utilised. The relationships between the configurations of studied window parameters, aesthetic appreciation, and housings' marketability were determined by Pearson correlation analysis. The impact of demographic differences on participants' aesthetic perceptions were examined with one-way ANOVA. Hochberg GT2 post hoc test was also performed to analyse the details of variances between sub-groups. Moreover, Cronbach's alpha (α) was utilised to confirm the reliability and internal consistency of the conducted survey

5.3 Energy simulations (ES) to investigate the impact of different window parameters on annual energy consumption of housings

This section introduces the details of BES (ES in Figure 5) conducted to develop and validate ANN and decision tree-based predictive models (PM in Figure 5) and generate a multidimensional measurement model (MMM in Figure 5). The impact of seven window parameters (i.e. width, area, height, position, number, proportion, and symmetry) on the annual lighting, heating, and cooling loads of the benchmark buildings was determined with DesignBuilder simulations.

5.3.1 Benchmark buildings

Benchmark buildings' features were mainly defined according to the results of fourth pre-study (PS4, Figure 5) (Section 4.2.2). As illustrated in Figure 14, the benchmark buildings are 94 m^2 (usable floor area – interior wall to interior wall), two-storey, terraced (Figure 14 a), and detached (Figure 14 b) houses, with a wall thickness of 0.22 m (SAP, 2014). Similarly, according to SAP (equation in Table S4: Window area), the average total glazing area for age band A, B, and C houses was calculated as 18.3 m^2 ±25% (for 94 m^2 usable floor area) (SAP, 2014). Most UK building stock consists of buildings constructed pre-1919 (EHS, 2016) (age band B in the SAP (SAP, 2014)). Therefore, most of the thermal and physical properties of benchmark buildings were identified according to age band B buildings. London Gatwick Airport weather data was utilised to model environmental conditions.

In both benchmark buildings, the window areas were kept the same (18 m^2). The east and west walls of the terraced benchmark building are adjacent with the same size blocks; its south and north orientations are exposed façades with four 1.5 m × 1.5 m (length × height) sized square-shaped double-glazing windows (75% openable area, in total 8 windows) (see Figure 14 a). The centres of the windows are located 1.65 m from the floors, and 1.295 m from the building corner edges. The structural properties of the detached building were kept the same as the terraced building, except for two structural differences: (1) detached building has four exposed façades; and (2) the overall window number is 16, with window dimensions reduced to 1.06 m × 1.06 m (length × height) in order to keep the total window area the same as the terraced one (see Figure 14 b).

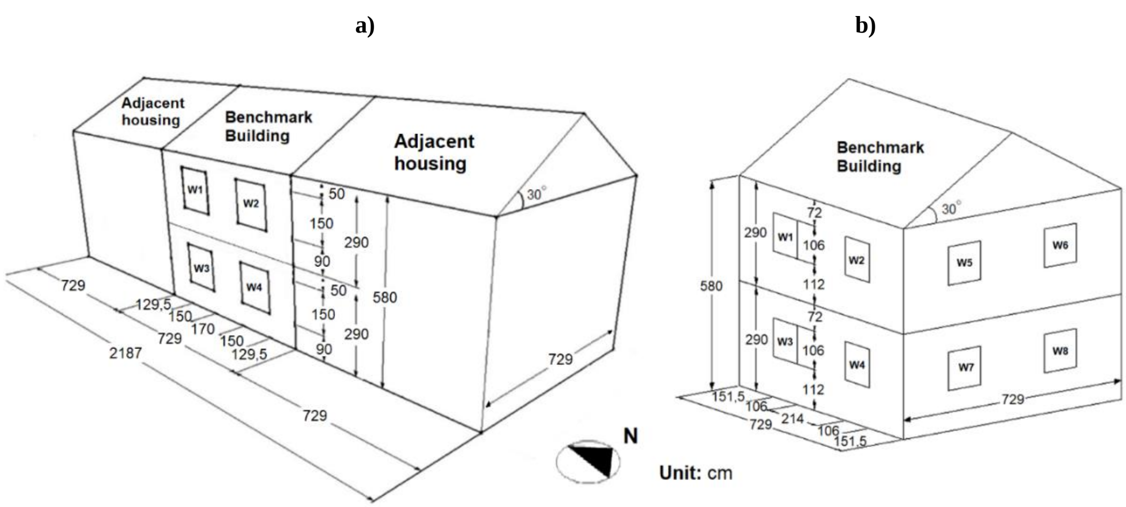


Figure 14: Benchmark buildings (a) terraced house (b) detached house

Taking into account that roofs (e.g. (Kindangen, Krauss, & Depecker, 1997)) and eaves (e.g. (Perén, van Hooff, Leite, & Blocken, 2015)) have an impact on energy efficiency and natural ventilation, a gable roof (30º sloped) was integrated into both benchmark buildings to generate more realistic scenarios. In all simulations, the roof was excluded from the thermal zones and was simulated as a buffer zone. The impact of eaves was disregarded to provide similar environmental conditions for each window configuration. Eaves in particular could be influenced by the results of window position and height configurations, which can cause misleading inferences in the comparison of the impact of different window parameters. In addition, the impact of internal partition walls, doors, and chimneys was not included to simplify the BESs, as those factors do not influence the impact of the focused window parameters on annual energy consumption.

The most common heating system in existing UK building stock is gas central heating (with a gas boiler), which is found in 92% of homes (EHS, 2016). Accordingly, HVAC system, natural gas central heating system, and the electrical cooling system were considered to investigate the annual heating and cooling loads of benchmark buildings. Heating set point temperatures were arranged between 22°C and 23°C. There are two different approaches for natural ventilation and infiltration modelling in DesignBuildier. In one of these approaches (scheduled approach), natural ventilation and infiltration are explicitly defined for each zone by the user. In this study, the calculated approach is utilised, where natural ventilation and infiltration are calculated based on different building and environmental parameters by program, such as window openings, cracks, buoyancy and wind-driven pressure differences, and crack dimensions etc. Window openings were arranged according to a predefined schedule[31] . Most UK housing is occupied by two occupants (Office for national statistics, 2013), thus internal gains were arranged according to this occupancy (123 $W/person$). Lighting and equipment were also included in BES (11,77 W/m^2). Thermal properties of building partitions were as shown in Table 19.

[31] Opening hours are 9:00 to 21:00 for weekends and holidays, and 7:00 to 8:00 then 18:00 to 20:00 for weekdays.

Table 19: Thermal properties of building partitions

Building partition (From outside to inside)	Thickness (m)	U value $(W/m^2 - K)$	R-Value $(m^2 - K/W)$	Total solar transmittance	Light Transmission
<u>Wall - Brickwork</u>	0,22	2,184	0,458		
<u>Ground floor</u>	0,3327	0,250	4,001		
L1: Urea formaldehyde foam	0,1327				
L2: Cast concrete	0,1000				
L3: Floor screed	0,0700				
L4: Timber flooring	0,0300				
<u>Inner floor</u>	0,1300	2,929	0,341		
L1: Cast concrete	0,1000				
L2: Timber flooring	0,0300				
<u>Roof</u>	0,0500	2,930	0,341		
L1: Clay Tile (roofing)	0,0250				
L2: Air gap	0,0200				
L3: Roofing Felt	0,0050				
<u>Window (double glazing)</u>		3,094		0,7	0,781
L1: Clear glass					
L2: Air gap	0,0060				
L3: Clear glass					

L: Layer

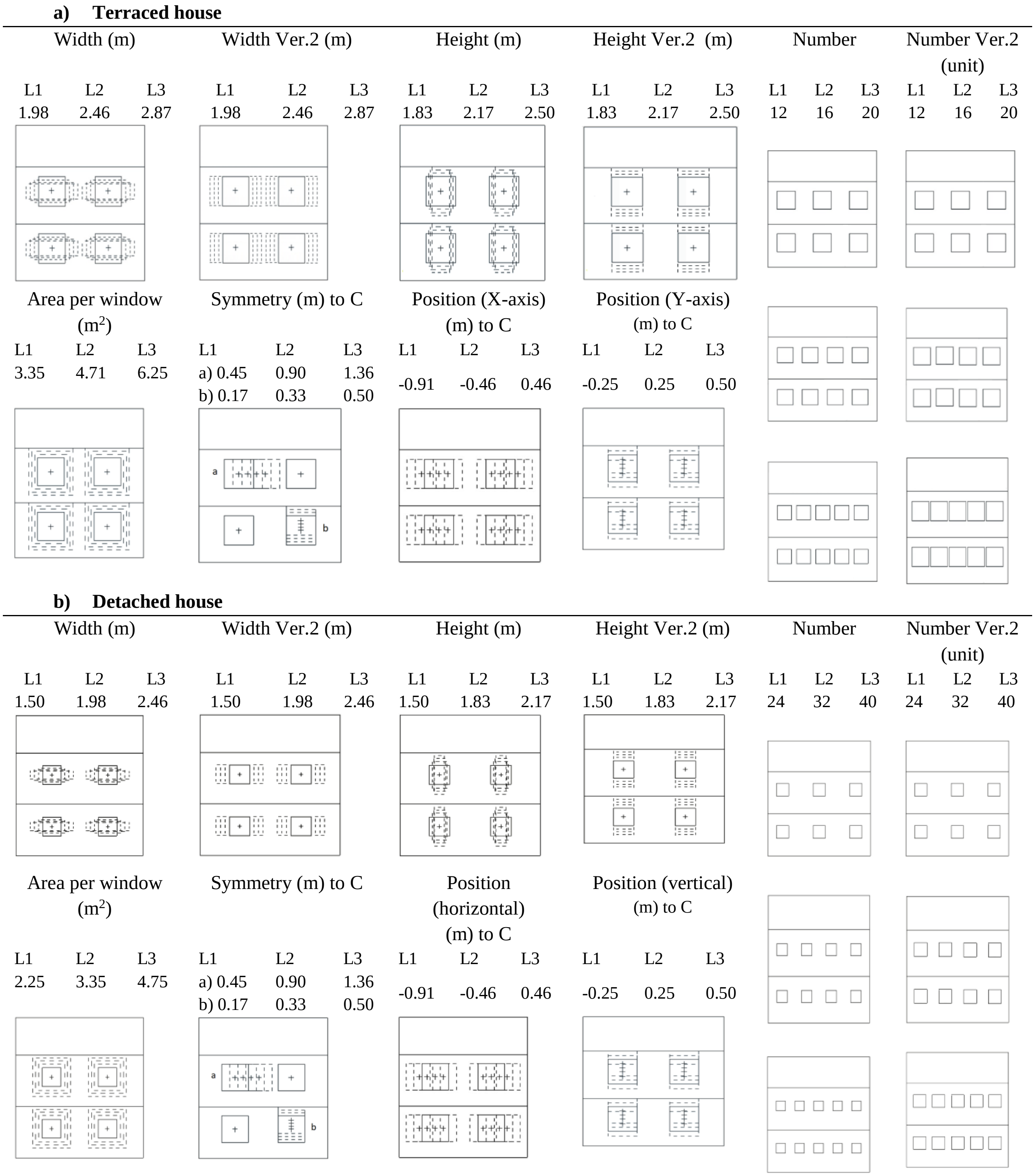
5.3.2 Simulation scenarios

The impacts of seven window parameters on the annual heating, cooling, and lighting loads were investigated with 28 different simulation scenarios, summarised in Table 20.

Table 20: Summary of applied simulation scenarios and utilised variables

Variables	Building typology	Natural ventilation	Window parameters		
Variation	(1) Detached house	(1) With natural ventilation	(1) position	(2) number	(3) area
	(2) Terraced house	(2) Without natural ventilation	(4) width	(5) height	(6) symmetry
			(7) proportion		

Each window parameter was configured for three levels and compared with the original benchmark building's results (four levels in total). The maximum and minimum window configuration levels were adjusted according to four considerations: (1) window areas were kept the same in all configurations except for the case of area configurations and the second versions of the window configurations (Ver.2) (see Figure 15), (2) window centre points were considered to be the same in all configurations except for the case of symmetry and position configurations, (3) minimum distances were limited with the UK building regulations (i.e. the minimum window distance from the building corner is 0.39 m, and the minimum distance between windows is 0,325 m (GOV.UK, 2013), (4) the appropriateness of those window configurations for the images to be used in the aesthetic and market demand survey (S4, Figure 5). The details of each of the window configurations are given in Figure 15. Level 1 (L1) and Level 3 (L3) represent the minimum and maximum configuration levels, respectively. The impacts of the window height, width, position, and energy performance were also investigated with two variations for each parameter, to provide suitable experimental conditions and to examine the isolated impact of those parameters. For example, in the window width configuration version 1, the window width and height were changed to preserve the window area constant, while in version 2 the window height was considered to be the same while the area and width were changed. The distinction between the energy performances when the natural ventilation is applied or not-applied were also considered, to investigate the underlying reasons for energy performance variations with different window configurations.



L: Configuration level, C: distance between benchmark window centre and manipulated window centre

Figure 15: Parametric details of applied window configurations

5.4 Computational predictive models (PM): ANN and decision tree approach

This section introduces the details of a developed computational predictive models (PM in Figure 5), to develop the multidimensional measurement model (MMM in Figure 5). In addition, it discusses the details about the validation process of the developed multidimensional measurement tool.

5.4.1 Development of the predictive models

Computational predictive models (PM in Figure 5) were developed via the normalized results of the conducted survey (S4, Figure 5), BES (ES in Figure 5), and the symmetry values obtained from the developed symmetry index (Eq. (26) and Eq. (27)) (SI in Figure 5).

5.4.1.1 Comparison metrics

Normalization equation, called "feature scaling" or "min-max normalization" (Eq. (28)), was utilised to standardize the range of independent variables, the results of the survey, and the BES. Accordingly, different parameters with different units (e.g. W, m, m^2, and SI) were converted to the normalized values between 0 and 1. In addition, in order to calculate the symmetry of windows parametrically and to provide symmetry data for the input layer of the ANN (see Figure 16) and decision tree-based predictive models (PM in Figure 5), proposed novel symmetry index equations (i.e. Eq. (26) and Eq. (27)) were utilised.

The prediction accuracy of the developed predictive models is determined via two different methods: (1) the total mean square error (MSE) (Eq. (6)), and (2) the consistency percentage when the studied photos are hierarchically ordered; for this purpose, the studied 38 houses in Figure 13 were sequenced from the most to the least attractive, marketable, and energy efficient, according to the results of the conducted survey (S4, Figure 5) and BES (ES in Figure 5) (means); a similar procedure was applied accordingly to ANN and decision tree results, and then the percentage of consistency between the results of conducted studies (S4 and ES in Figure 5) and predictive models (PM in Figure 5) was compared.

5.4.1.2 ANN

A MATLAB Neural Network Toolbox was utilised to develop the ANN model. 70% of the dataset obtained from 33 photos (i.e. training category) (see Figure 13) was allocated to training, 15% to validation, and 15% to testing purposes[32]. Each of the studied photos were defined to ANN and decision-tree models as eight parametric variables (i.e. normalized window position; number; area; width; height; symmetry; proportion; and the impact of window configuration on aesthetics, marketability, and annual energy demand (see Figure 16). The details about input and output variables can be found in Appendix K. The total number of the variations in window configurations is shown in Table 21.

Table 21: Total number of variations of window parameters occurred in utilised window configurations

Area:	19	Number:	6	Position on Y-axis*:	5	Width:	12
Height:	10	Position on X-axis*:	7	Symmetry:	5	Proportion**:	13

** Window position on X and Y axis was calculated according to the centre of windows, ** Proportion was calculated according to aspect ratios (i.e. width/height).*

In this study, a supervised feed-forward backpropagation architecture ANN was utilized to develop the predictive model. In addition, different functions, hidden layer numbers, and neurons

[32] *Training:* These are presented to the network during training, and the network is adjusted according to its error.
Validation: These are used to measure network generalization, and to halt training when generalization stop improving
Testing: These have no effect on training and so provide an independent measure of network performance during and after training.
Note: The mentioned stages above are automatically applied in the ANN tool during the development process.

were tested to improve the performance of the developed ANN model. The best performance was achieved with the model summarised in Table 22. Further technical details about the developed ANN model can be found in Appendix K. The architecture of the developed ANN model is illustrated in Figure 16.

Table 22: Technical details of ANN model

Transfer function:	Tangent sigmoid (TanSig)
Training function:	Levenberg-Marquardt backpropagation
Learning function:	Gradient descent with momentum weight and bias adaptation
Number of hidden layers:	2
Number of neurons:	13

Model of a single artificial neuron can also be seen in Figure 6.

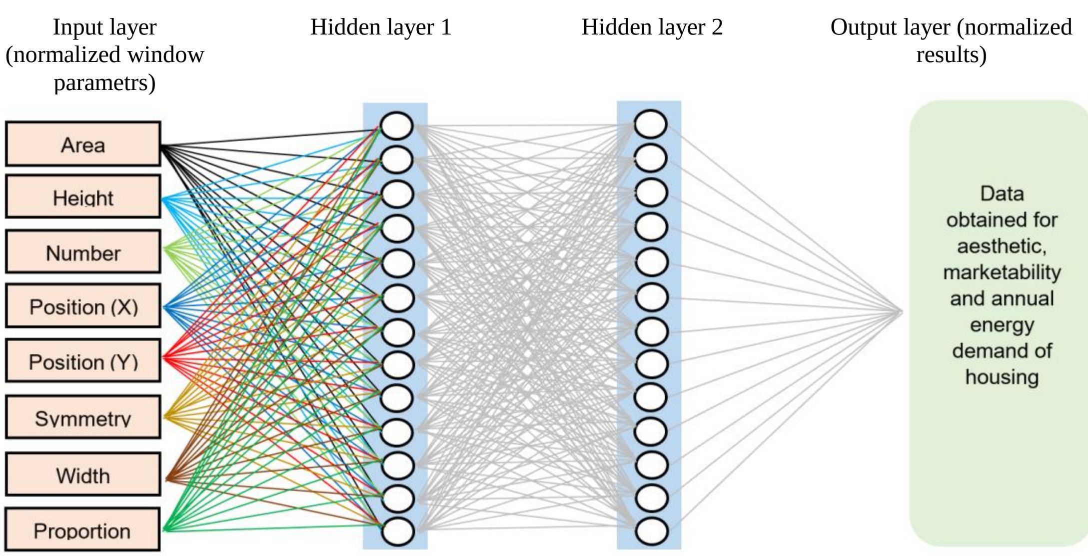


Figure 16: Artificial neural network (ANN) architecture

5.4.1.3 Decision tree method

SPSS Modeler 18.0 was utilised to develop the decision tree model. In order to develop a predictive model in this study, classification and regression trees (CART) model and Gini index

(Eq. 13 and Eq. 14) were performed. 60% and 40% of the total samples obtained from 33 photos were utilised for training and testing purposes, respectively. The details about input and output variables can be found in Appendix K. Different tree depths were tested to improve the performance of the developed predictive model, and the best fit maximum tree depth that specifies the maximum number of levels below the root node was identified as 11 levels. In addition, tree pruning protocol was utilised to simplify the tree, making it easier to interpret and enhance the decision performance. Pruning protocol entails removing bottom-level splits that do not contribute significantly to the accuracy of the tree. This process makes the tree more compact. Further technical details about the developed decision tree model can be found in Appendix K.

5.4.2 Validation of the predicative models

The developed ANN and decision tree-based predictive models (PM in Figure 5) were validated via the results of the conducted survey (S4, Figure 5) and BES (ES in Figure 5). For this purpose, the window parameters of studied 38 photos in Figure 13 were entered as an input to the predictive models developed previously, and their aesthetics, marketability, and energy efficiency predictions were compared with the results of conducted survey and BES. The training category comprised 33 of the 38 photos had utilised during the development process of the predictive models, while five of the 38 photos (experimental category) were used only for validation purposes, and to observe the prediction performance of the developed predictive models with a new and different datasets (i.e. window parameters as input variables, and survey (S4) results as output variables). In order to test the prediction accuracy and performance of the developed predictive models, two methods discussed in Section 5.4.1.1 were utilised.

CHAPTER VI

RESULTS AND DISCUSSION

CHAPTER VI.

RESULTS AND DISCUSSION

Results are discussed under two main sections. In the first section, the applicability of the proposed novel widespread adoption approach is discussed. For this purpose, the results of four pre-studies (PS1, PS5, PS6, and PS8, Figure 5) and two comprehensive surveys (S1 and S2, Figure 5) are discussed. In the second section, the applicability of the YYP is evaluated. For this purpose, the results of two comprehensive surveys (S3 and S4, Figure 5), building energy simulations (BES) (ES in Figure 5), and the validity of developed novel symmetry measurement model (symmetry index) (SI in Figure 5) are discussed. Then, ANN and decision tree based predictive models (PM in Figure 5) are developed and validated with the results of a survey (S4, Figure 5) and BES (ES in Figure 5). Finally, multidimensional measurement tools (MMM in Figure 5) are presented, constituting the validated predictive models ready to use in future studies.

6.1 Investigating the applicability of the proposed widespread adoption approach

This section discusses the results of the two conducted surveys (S1 and S2, Figure 5) and four pre-studies (PS1, PS5, PS6, and PS8, Figure 5), as details explained in Sections 4.1 and 4.2.

6.1.1 Pre-study (PS1) about the housing advertisements of estate agents

Real-estate agencies develop effective marketing strategies based on buyers' interests to sell buildings. Accordingly, advertisements of real-estate agencies can be assumed to be a good starting point to determine the most influential building parameters in the consumer buying decision-making process. Thus, 360 housing advertisements on the websites of estate agents in six different UK cities were investigated. Further details about the first pre-study can be found in Section 4.1.1.

There were 11 dominant parameters frequently highlighted in the studied housing advertisements, including: location (100%), price (100%), number of rooms (100%), building type (e.g. semi-detached, villa, studio, apartment etc.) (70%), finishing (i.e. details about fixed items) (69%), floor area (67%), facilities (e.g. garage, swimming pool, storage area, garden, terrace, balcony etc.) (55%), architectural details (e.g. open plan, separate kitchen, modern bathroom and etc.) (41%), architectural typology (e.g. modern and Victorian, etc.) (23%), window properties (e.g. double glazing, and south oriented large windows) (19%), and EPC (11%). Despite the fact that parameters such as location, price, and number of rooms are crucial factors impacting housing marketability, in this thesis, these parameters are not considered in the conducted studies as this thesis is only focusing on the parameters that simultaneously impact aesthetic, marketability and energy efficiency of detached and terraced housings.

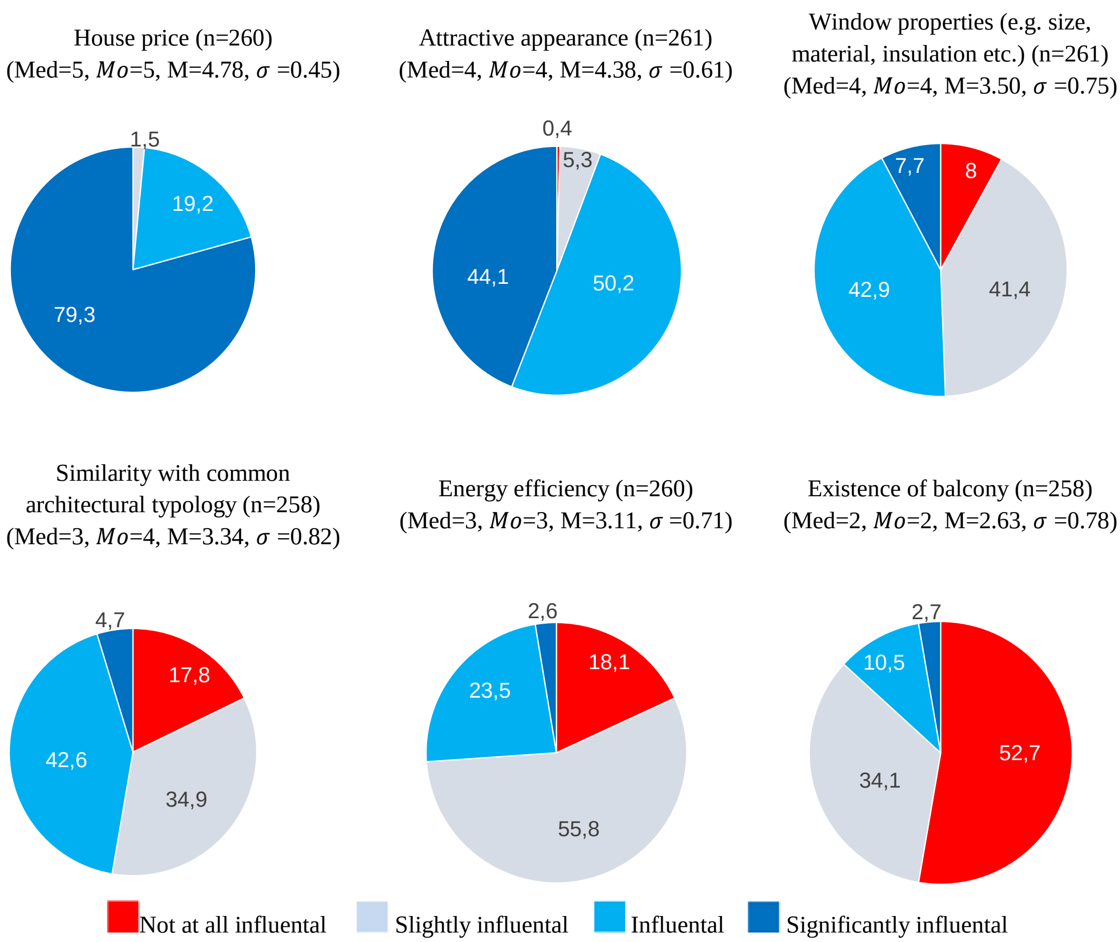
In the real-estate agents' advertisements, it was noteworthy that low EPCs are dominant among the reported EPCs, in addition to the fact that the energy performance of homes is rarely mentioned. The EPC distributions of 360 buildings in the selected advertisements were A (4%), B (9%), C (24%), D (31%), and E (32%). The conducted pre-study was extended with a literature review to form a hypothesis about the inverse relationship between the number of dwellings and energy performances identified in the first pre-study. The conducted pre-study was deemed insufficient to form a hypothesis, since it covered only a limited number of housing advertisements in only six cities. For this purpose, the EPC distribution of buildings in the existing UK building stock reported in the English Housing Survey (EHS) was investigated, and consistent results between the conducted pre-study and EHS were observed. The number of EEBs in the UK is very low; in 2015, 72% of the existing buildings were within EPC: D or below (EHS, 2016), and only 0.2% of them were within EPC: A (EU, 2017). Furthermore, between 2005 and 2015, the number of EEBs with EPC:A to EPC:C increased by only 23% in the UK (EHS, 2016). Accordingly, a hypothesis about an inverse relationship between housing energy efficiency and marketability was generated. The low number of EEBs in the UK could be related to their low marketability and/or a low rate of annual new building construction, which is approximately 0.8% (Higgins, 2017). Accordingly, the first pre-study was extended with a section in the main survey (S1, Figure 5) to investigate the reason behind the low number of EEBs in existing UK building stock in more detail.

6.1.2 Survey (S1) conducted with real estate agencies in the UK

A comprehensive survey (S1, Figure 5) among 289 real-estate agents across 26 UK cities was conducted to collect data for three main goals: (1) to better understand the cause of market failure in EEBs and to develop supplementary strategies and policies to ensure their widespread adoption; (2) to test the validity and applicability of the proposed widespread adoption approach in practice; and (3) to determine the most influential window parameters affecting the marketability of residential buildings. The rationale behind why this study focuses on window parameters was discussed in Section 4.1.2. According to conducted reliability analyses, a high internal consistency ($\alpha = 0.77$) and consistency of participants was achieved, with a strong correlation between pre-test and post-test responses (r = between 0.73 to 0.66, $p = 0.00$) in the test-retest protocol. Further details about the conducted survey can be found in Section 4.1.

6.1.2.1 Important building parameters in the consumer decision-making process

As shown in Figure 17, among six different factors, there is a 100% agreement that the house price is the most influential parameter in the decision-making process of buyers ($t(259) = 9.233$, $p = 0.000$). 79% of the participants described the house price as a significantly influential parameter on buyers' decision-making process ($M = 4.78$, $Mo = 5$, $\sigma = 0.45$). Results clearly show that the price of EEBs is a critical factor to achieve a better marketability. However, as discussed in Section 6.1.4.4 in detail, the results of the second survey (S2, Figure 5) clearly showed that, even if the initial cost of EEBs can be reduced to the price of ordinary housing, which is not possible due to additional extra expenses such as insulation, this alone will not be sufficient to enhance the marketability of EBBs. Therefore, in addition to the efforts for price reduction of EEBs, increasing the monetary worth of EEBs via different new marketing motivations in the eyes of buyers would be a more effective strategy to enhance the marketability of EEBs.



Med: *Median,* ***Mo****: mode,* ***M****: mean,* ***σ:*** *standard deviation,* ***2:*** *not at all influential,* ***3:*** *slightly influential,* ***4:*** *influential,* ***5:*** *significantly influential*

Figure 17: Impact level (%) of various building parameters on decision-making process of buyers

Attractive appearance (aesthetic) is determined as the second most influential factor (t (260) = 16.240, p = 0.000); almost all of the participants (99.6%) agreed to varying degrees that appearance is an influential parameter in buyers' decision-making process. Almost half of participants (44%) declared that an attractive appearance is significantly influential (M = 4.38, *Mo*

= 4, σ = 0.61). In addition to survey results, some of the frequently written feedback in the optional text boxes was scrutinized to further elaborate on the decision-making process of buyers. In the written feedback, aesthetic properties were broadly emphasised as important features to be competitive in the housing market; buyers initially focus on the location, size, and appearance of a house, and then they tend to see the interior and other features of housings. In other words, houses without attractive appearances are eliminated by buyers before considering other details such as energy performance and even price. Furthermore, supportive results about the impact of aesthetic on the housings' marketability and added value (price according to consumer perceptions) were also obtained in the eighth pre-study (PS8, Figure 5) (see Section 6.1.4.3), and second survey (S2, Figure 5) (see Section 6.1.4.4). The results about the impact of aesthetic on housings' marketability are clearly in favour of the applicability of the proposed widespread adoption approach. In other words, the aesthetic enhancement of EEBs can be a key strategy to enhance their marketability and number in the UK.

Window properties, which also have big potential to affect building aesthetics and energy efficiency, are ranked as the third important parameter for housing marketability (t (257) = 2.361, p = 0.019). Almost all of the participants (92%) agreed to varying degrees that window properties are influential in the decision-making process of buyers (M = 3.50, Mo = 4, σ = 0.75). In addition, the importance of windows for the marketability of housings is also emphasised in the frequently written feedback in optional text boxes. Many different general functions considered important for marketing a house are attributed to windows by the participants (e.g. interaction with the environment, natural light, privacy, and attractiveness (aesthetic)).

Despite the fact that the similarity with the common architectural typology is ranked as the fourth most important parameter (t (257) = 2.284, p = 0.001), it can shed light on a better understanding of one another potential cause of the market failure of EEBs that is barely discussed in previous studies. Almost all of the participants (82%) agreed (at different levels) that similarity with the common architectural typology is influential on the decision-making process (M = 3.34, Mo = 4, σ = 0.82). Taking into account these results, it is reasonable to claim that avoiding energy efficiency-oriented remarkable differentiation, which would significantly impact common housing outlooks, can be another strategy to enhance the EEBs' marketability in the UK.

Among the studied housing features, energy efficiency is determined as the least important factor for the decision-making process of buyers (t (257) = 7.758, p = 0.000). Although 82% of the participants agreed to varying degrees that energy efficiency is influential on the decision-making process, the majority (56%) ranked it as slightly influential (M = 3.11, Mo = 3, σ = 0.71). In addition, in the frequently written feedback in the optional text boxes, the participants were broadly reported that they pay little attention to EPC ratings in their marketing strategy, as they believe that it has no considerable effect on the sale of a house. Furthermore, many of them reported that high EPCs and passive houses have several marketing disadvantages, such as high price, less attractive appearance, long payback period, and negative perceptions (e.g. the perception of imprisonment due to high insulation levels). Furthermore, supportive results about the low market value of energy-efficiency features were also obtained in the first pre-study (PS1, Figure 5) (see Section 6.1.1), eighth pre-study (PS8, Figure 5) (see Section 6.1.4.3), and second survey (S2, Figure 5) (see Section 6.1.4.4). Accordingly, overall, although energy efficiency features contribute to housing marketability slightly, it is not enough alone to convince buyers to purchase an EEB. Therefore, it is clear that other motivations must be found to promote the marketability of EEBs, and the aesthetic enhancement of EEBs is determined as the one of the most promising motivations to achieve marketability enhancement and widespread EEB adoption.

The existence of a balcony is seen to be a non-influential factor in the decision-making process of buyers; 53% of the participants described the existence of balcony as "not at all influential" (M = 2.63, Mo = 2, σ = 0.78). The reason was frequently reported by the participants in their written feedback in the optional text boxes; most of the residential buildings in the UK are low-rise dwellings with their own gardens, so it is not necessary to have a balcony. However, it is also widely noted that, depending on the height of a building and its location (near a busy road or garden), the existence of balcony is quite influential in the marketing of multi-storey apartments, particularly in the big cities such as London.

To sum up, the energy performance enhancement of EEBs is not enough alone to promote EEB marketability. If any attempt to increase energy efficiency overlaps with price, aesthetic quality, and harmony with the local architectural texture of residential buildings, strong opposition can arise to EEB in the current UK residential building market. Therefore, during the development and design of EEBs, extra attention is required to be given to the aesthetic quality, price, and harmony with the local architectural texture.

6.1.2.2 The monetary added value of different parameters

In order to identify whether it is possible to enhance the worth of EEBs in the eyes of buyers with alteration in their certain features, the amount of extra money that an intermediate-income buyer[33] would potentially spend for a benchmark house worth £200,000[34] with better housing features[35] compared to ordinary houses was investigated (Figure 18). According to the mean of responses, more attractive appearance (aesthetic) is the feature providing the greatest added value for a residential building (M = £14,026, Mo = £10,000, σ = 832.036), which is almost two times higher than better window properties[36] (M = £7,389, Mo = £5,000, σ = 567.149) (t (237)

[33] £31,800 per year (Reuben & Price, 2017).
[34] An average house price in the UK (UK_Gov, 2018).
[35] e.g. better appearance, window properties, and energy efficiency.
[36] e.g. size, material, insulation, etc.

= 12.638, p = 0.000), and almost three times higher than energy efficiency enhancements (M = £5,617, Mo = £0, σ = 567.417) (t (238) = 5.062, p = 0.000).

According to the most frequently given answers (modes), the added value for an attractive appearance, better window properties, and energy efficiency enhancements are £10,000 (11%), £5,000 (16%), and £0 (13%), respectively. The mode and the mean for the appearance (M = £14,026, Mo = £10,000) and better window properties (M = £7,389, Mo = £5,000) are found to be close, yet these differences are found to be huge for energy efficiency enhancements (M = £5,617, Mo = £0). This is because, despite the fact that most frequent answers were £0 for energy efficiency enhancement, some participants (0.4%) claimed that the added value can be up to £30,000. However, it is not rational to claim that the added value can be up to £30,000 via energy performance enhancement for two reasons: (1) the energy performance of housings has very low market value and low monetary added value according to valid evidences obtained in the first pre-study (PS1, Figure 5) (see Section 6.1.1), eighth pre-study (PS8, Figure 5) (see Section 6.1.4.3), first survey (S1, Figure 5) (see Section 6.1.2), second survey (S2, Figure 5) (see Section 6.1.4.4) and the results of the conducted comprehensive literature review (see Section 2.1.1.1), (2) there is a huge difference between the mean and mode (i.e. most frequently given answer) (M = £5,617, Mo = £0) of the given answer for the potential added value obtaining with energy efficiency enhancement. Accordingly, it is reasonable to claim that in practice, the added value that can be achieved with energy performance enhancement of housing would be below even the determined value in this question (i.e. £5,617).

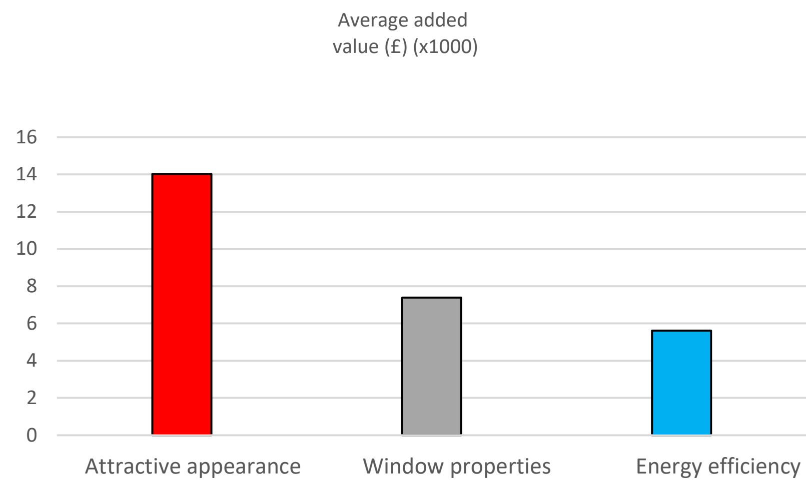


Figure 18: Average added financial value of different factors

To sum up, it is possible to increase a house value from £200,000 in the eyes of an intermediate-income buyer by 7% with an aesthetic enhancement, 4% with better window properties, and 3% with energy efficiency enhancements. In other words, it is possible to obtain approximately 14% added value enhancement with a better EEB design. Accordingly, the reported high initial cost of EEBs (i.e. 20%) (see Section 2.1.1.2) can be mostly compensated with a proposed widespread adoption approach (i.e. aesthetic enhancement of EEBs). It should also be noted that, as discussed in detail with regard to the results of the studies conducted with potential housing buyers (i.e. PS8 (Figure 5) (see Section 6.1.4.3) and S2 (Figure 5) (see Section 6.1.4.4)), it is possible to increase the monetary added value of a house worth £200,000 by up to 50%. Therefore, it is clear that increasing the added value of EEBs in eyes of buyers via aesthetic enhancement can be a practical and valid approach to minimize existing market resistance for EEBs.

6.1.2.3 *Market demand for EEBs*

In order to identify the relation between the energy efficiency of housings and their selling rates in the existing UK market, and further explore the underlying reason behind the low number of EEBs in existing building stock, the numbers of EEBs from EPC A to C categories sold by the participants over the past one year were investigated. According to the outcomes, there is a significant negative correlation between energy efficiency and the number of sold housing units ($r = -0.694$, $p = 0.000$). The average number of sold houses within EPC category C (M = 9 house, Mo = 15 house, σ = 4.82) is almost two times higher than category B (M = 4 house, Mo = 0 house, σ = 3.55) ($t(164) = 16.948$, $p = 0.000$). The houses within EPC A category are the least sold houses in the past year (M = 1 house, Mo = 0 house, σ = 1.72) ($t(164) = 10.956$, $p = 0.000$) (Figure 19). It is worth highlighting that most of the participants did not sell any EEBs with the EPC A (66%) and B (22%) over the last year.

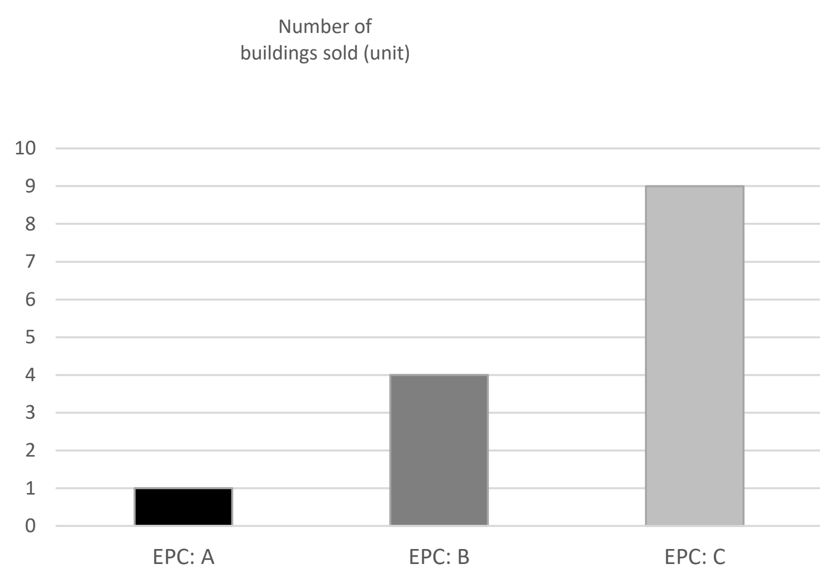
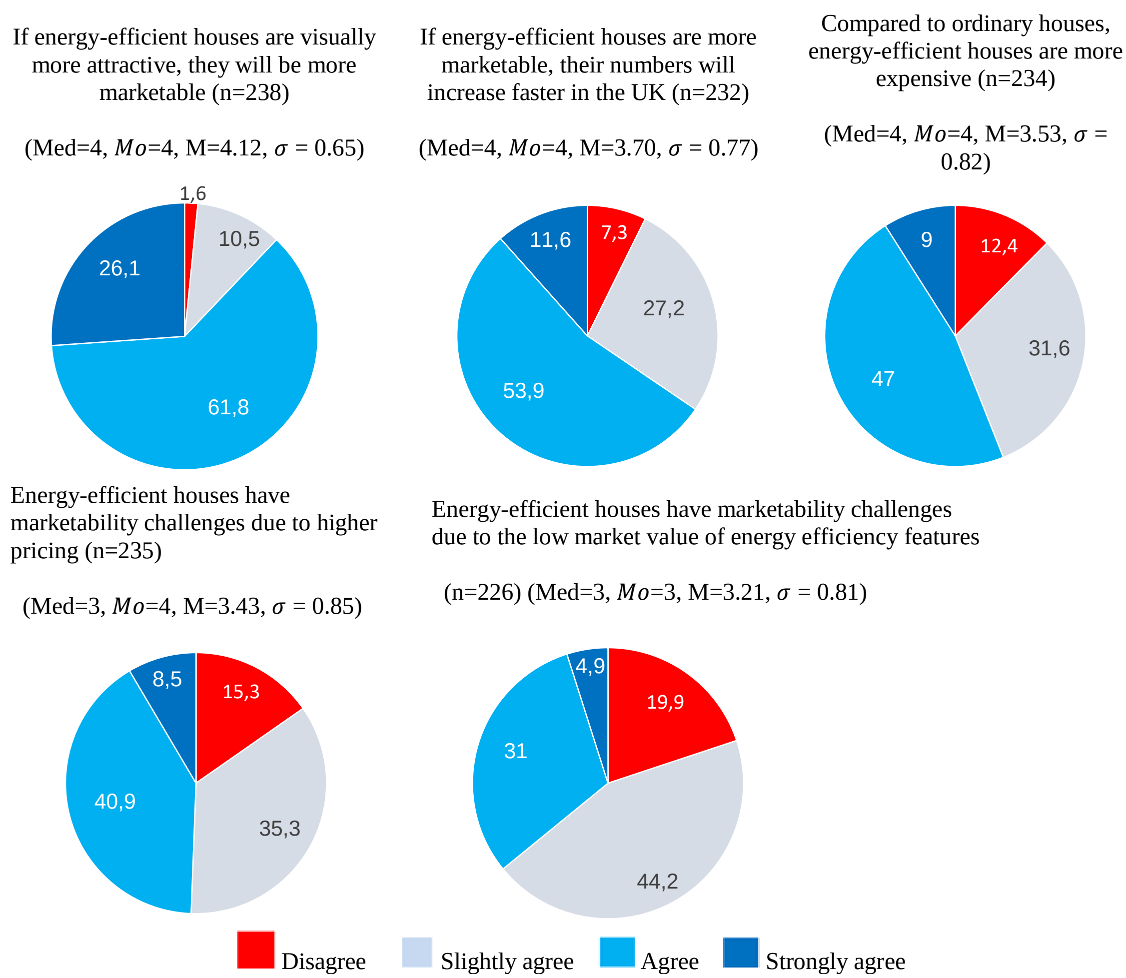


Figure 19: Average number of houses sold by the participants over the last year within EPC categories A to C

The low selling rates of EEBs can be related to the low number of EEBs in the existing UK building stock. Nevertheless, two important points of the market economy should be taken into account: (1) there is a direct relation between the demand and supply, whereby more demand for a product (e.g. EEBs) triggers more supplies of that product, (2) according to the law of supply, if the quantity of a product in the market remains the same and the demand increases, the price of that product will increase, thus the greater the profit, which will trigger an increase in the supplied quantity (which will then subsequently lead to a reduction in prices over the long term if demand does not continue to increase concomitantly with increased supply).This means, despite the low rate of reconstruction in the UK (i.e. 0.8%) (Higgins, 2017), if there was a strong market demand for EEBs, the current building stock would naturally adapt itself, at least with refurbishment, even if not with the construction of new units. Accordingly, also considering the empirical evidences found for the low market value of energy efficiency features in conducted other studies (as discussed in Section 2.1.1.1, 6.1.1, 6.1.4.3, 6.1.2, and 6.1.4.4), the low market demand for the EEBs is more likely to be the main reason for the low sales rates of those buildings, rather than the low number of EEBs in the UK and/ or the low new construction rate.

6.1.2.4 Opinions about the current marketing barriers to EEBs and potential solutions

The empirical evidence so far shows clearly that the enhancement of housings' aesthetic can be an effective approach to overcome current market barriers, such as a high initial cost, low market value, and a lack of market demand for EEBs. The opinions of the participants with regard to the current marketing barriers of EEBs and the applicability of the proposed widespread adoption approach were investigated with another question. The agreement level of the participants about several statements is also shown in Figure 20.



***Med:** Median, **Mo**: mode, **M**: mean, **σ:** standard deviation, **2:** disagree, **3:** slightly agree, **4:** agree, **5:** strongly agree*

Figure 20: Agreement level of the participants about the market barriers and potential solutions

Almost all of the participants (88%) agreed to varying degrees (M = 3.53, Mo = 4, σ = 0.82) that energy-efficient houses are more expensive than ordinary ones. There is also a strong consensus that the higher initial cost of EEBs (85%) (M = 3.43, Mo = 4, σ = 0.85) and low market value of energy efficiency features (80%) (M = 3.21, Mo = 3, σ = 0.81) are the underlying reasons behind the market failure of EEBs. With a very strong consensus, almost all participants (98%) agreed that EEBs will become more marketable when they have become more aesthetic (M = 4.12, Mo = 4, σ = 0.65). It is worth highlighting that the aesthetic enhancement of EEBs, as a solution to their marketability challenge, has the strongest agreement level compared to other statements. With the second-highest agreement level, 93% of the participants agreed to varying degrees that if EEBs were more marketable, their numbers would increase faster in the UK (M = 3.70, Mo = 4, σ = 0.77). To sum up, real-estate sales department employees, who are the most knowledgeable group on the dynamics of the UK housing market, strongly agree on the underlying reasons of the phenomenon of IIBEE and applicability of the proposed widespread adoption in the UK.

6.1.2.5 *Impact of window parameters on market demand for residential buildings*

In order to identify the impact of window parameters on market demand for UK housing, the hierarchical order of the importance of eight window parameters was investigated with another question; the results are illustrated in Figure 21. Window position (M = 3.59, Mo = 4, σ = 0.73), number (M = 3.55, Mo = 4, σ = 0.74), and area (M = 3.52, Mo = 4, σ = 0.82) were identified as the most important parameters that influence the marketability of housings. Most of the participants declared that the window depth (51%) and the glass reflectivity (68%) have no importance for the marketability of housings (See Figure 21).

In general, the hierarchical order of the importance ranking of the window related parameters on the housing marketability can be presented as: position > number > area > width > height > symmetry > depth > reflectivity. Nonetheless, it should be noted that the inferential statistics results suggest that there is no statistically significant difference between the following four parameter pairs: (1) window position–number (t (203) = 0.768, p = 0.443), (2) number–area (t (201) = 0.264, p = 0.792), (3) width–height (t (203) = 0.464, p = 0.643), and (4) height–symmetry (t (197) = 0.861, p = 0.390). In contrast, there is a significant difference between the following three parameter pairs: (1) area–width (t (202) = 4.573, p = 0.000), (2) symmetry–depth (t (192) = 5.932, p = 0.000), (3) depth–reflectivity (t (194) = 3.604, p = 0.000). Therefore, the hierarchical ranking order of the mentioned parameters can be revised as position = number = area > width = height = symmetry > depth > reflectivity. In brief, the data obtained from the extensive survey shows that the window position, number, area, width, height, and symmetry are the parameters that substantively affect market demand for residential buildings in the UK.

Considering the results of this study, the remainder of this Ph.D. thesis focuses on the impact of the following six window parameters: position, number, area, width, height, and symmetry. In addition, window proportion (aspect ratio (i.e. width/height)) was included in the focused window parameters, due to its special importance in the fields of art and architectural aesthetics. Accordingly, this thesis focused on the impact of these seven window parameters on housings aesthetic, marketability, and energy efficiency.

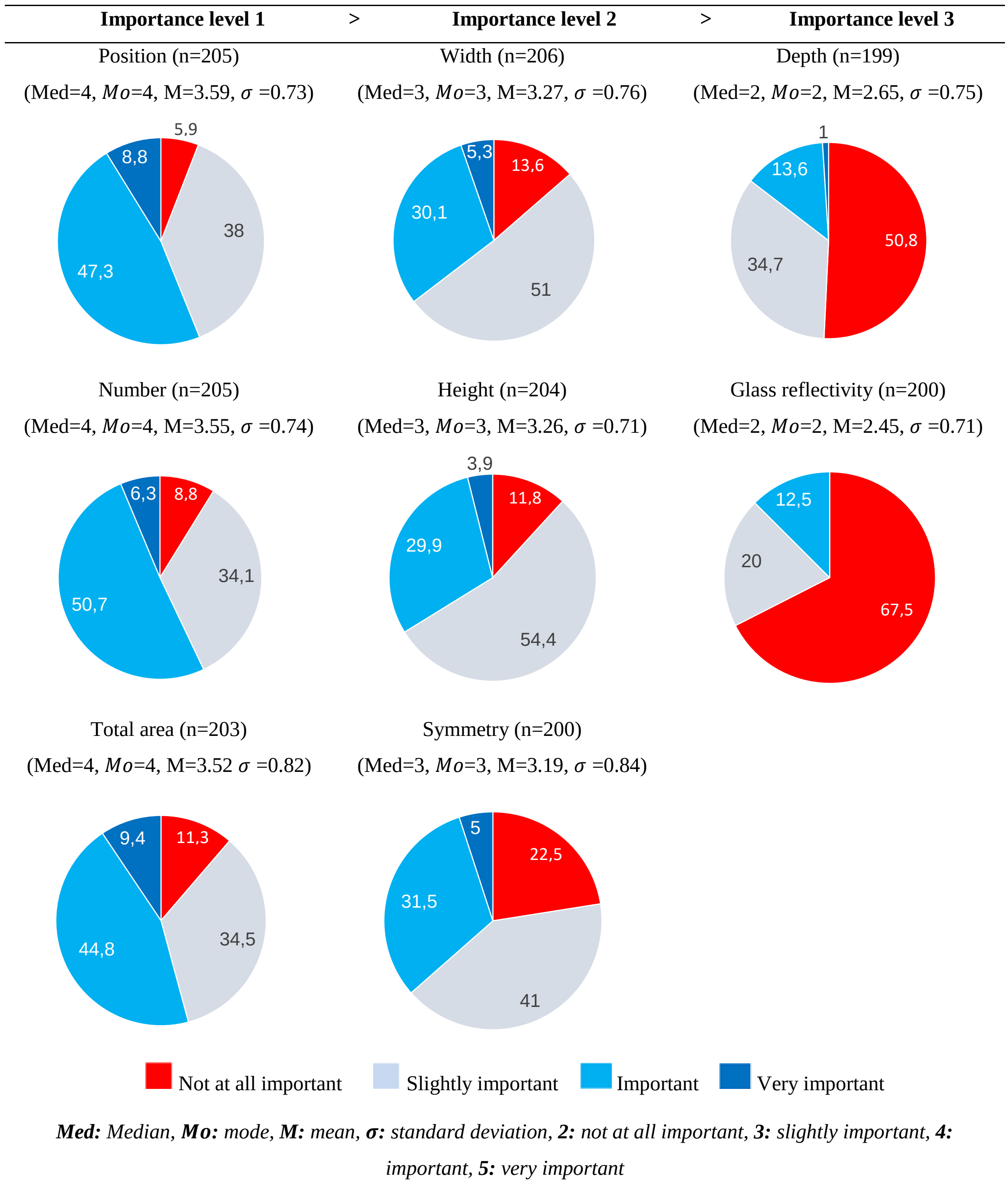


Figure 21: Importance level of window related parameters on marketability of housings (%)

6.1.3 Summary

- Housings' location, price, number of rooms, type, finishing, and facilities are the most frequently highlighted features in the advertisements of real-estate agencies in the UK.

- The high price of EEBs, and the low market value of energy efficiency features, are the underlying reasons behind the market failure of EEBs in the UK real-estate sector.

- Energy performance of housings has a low market value; its added value (3%) is considerably lower than its extra cost (up to 20%), and it even has negative impacts on marketability due to several factors, such as higher initial cost and prejudice among buyers about EEBs. Accordingly, it is reasonable to claim that any extra initial cost of EEBs over 3% is likely to face strong market resistance in the existing UK housing market.

- A significant negative correlation was determined between energy efficiency and the marketability of housings. The low number of energy-efficient houses in the UK is more likely related to the market failure of EEBs rather than to the low rate of annual new building construction in the UK.

- Energy efficiency-oriented remarkable differentiation, which would affect common housing outlooks, should be avoided, in order to enhance the EEBs' marketability in the UK.

- It is possible to obtain approximately 14% more added value with a better EEB design, and the greatest added value (7%) can be achieved via aesthetic enhancement.

- The impact ranking of various factors on the decision-making process of buyers can be presented as house price > attractive appearance (aesthetic) > window properties > similarity with common architectural typology > energy efficiency.

- There is a strong consensus among the participants that proposed widespread adoption approach has a strong basis for wider deployment in the UK residential building market. EEBs would become more marketable when they have a more attractive appearance (98% agreement), and if EEBs were more marketable, then their numbers would become more prolific in UK building stock (93% agreement).

- Window depth and reflectivity have no influence on market demand. The configurations of window positions, number, and area are among the strongest candidates to make EEBs more marketable. The impact ranking of various window factors' impacts on housing marketability can be represented as: position = number = area > width = height = symmetry > depth > reflectivity.

6.1.4 *Further evidences about the applicability of the proposed widespread adoption approach*

Once promising results for the applicability of the proposed widespread adoption approach in the UK were achieved in the first survey (S1, Figure 5), the study was extended with another survey (S2, Figure 5) conducted with potential housing buyers (183 UoN staff with different demographic characteristics) to obtain further evidence for the applicability of the proposed novel approach in the UK. This section also introduces the results of the three conducted pre-studies (PS5, PS6, and PS8, in Figure 5) to develop the main survey (S2, Figure 5) and generate the housing illustrations utilised in the rest of the study. Further technical details about the conducted surveys can be found in Section 4.2. In addition, the results about five different points are discussed in this section in order to: (1) determine the impact of housing typology (detached terraced houses) on aesthetic appreciation and marketability of housings (PS5, Figure 5), (2) generate attractive and unattractive housings illustrations (PS6 and PS8, Figure 5), (3) investigate the relationship between aesthetic appreciation and the monetary worth of focused housings in eyes of the participants, (4) discover the dynamics of participants' decision-making process to buy a house, (5) discovering whether the initial cost reduction of EEBs can be sufficient to enhance their marketability and widespread adoption.

6.1.4.1 *Pre-study (PS5) to investigate the impact of housing typology on aesthetic judgement*

A pre-study was conducted with 35 randomly selected UoN students with different demographic characteristics to determine the impact of housing typology on the aesthetics and marketability of housings and to minimize the number of questions in conducted surveys in the rest of study. Cronbach's alpha (α) criterion was initially investigated and the convenient reliability and internal consistency was observed ($\alpha = 0.71$). Further technical details about the conducted pre-study can be found in Section 4.2.3.

According to the results of Pearson correlation analysis, a significantly high positive correlation was found between individuals' aesthetic judgement and housings' marketability ($r = 0.897$, $p = 0.000$) in this pre-study, and consistent supporting results were yielded by subsequent studies (see Section 6.1.4.4 and 6.2.2). This implies that the results obtained on the aesthetic of housings can be extended to their marketability results. Therefore, in the remainder of the study, only the results of aesthetic judgement are discussed.

According to the paired samples T-test results, no meaningful statistical differences were determined in individuals' aesthetic judgments for the detached (Figure 9 a) ($M = 2.50$, $Mo = 2$, $\sigma = 1.05$) and terraced houses (see Figure 9 b) ($M = 2.30$, $Mo = 2$, $\sigma = 1.23$) ($t(29) = -0.972$, $p = 0.339$). This implies that the results obtained from the detached houses can be extended to the terraced houses. Accordingly, the main survey (S2, Figure 5) and the following studies were conducted with only the detached house photos, to reduce the volume of questions and maximise the response rate. According to ANOVA analysis results, the demographic differences of individuals do not affect their aesthetic perception ($p > 0.05$).

6.1.4.2 Pre-study (PS6) to determine the illustrations utilised in the main survey (S2)

A survey was conducted with 37 UoN students to identify the illustrations utilised in the main survey (S2, Figure 5), and convenient reliability and internal consistency was observed ($\alpha = 0.68$). The aesthetics of 33 housing photos in Figure 22 were measured with a bipolar seven-point semantic differential scale, and the most attractive and unattractive housing photos were determined according the mean of the participants' responses. The details and rationales behind the design of the utilised 33 housing photos were discussed in detail in Section 5.2.3 and 5.3.2. Further technical details about the conducted pre-study can be found in Section 4.2.4.

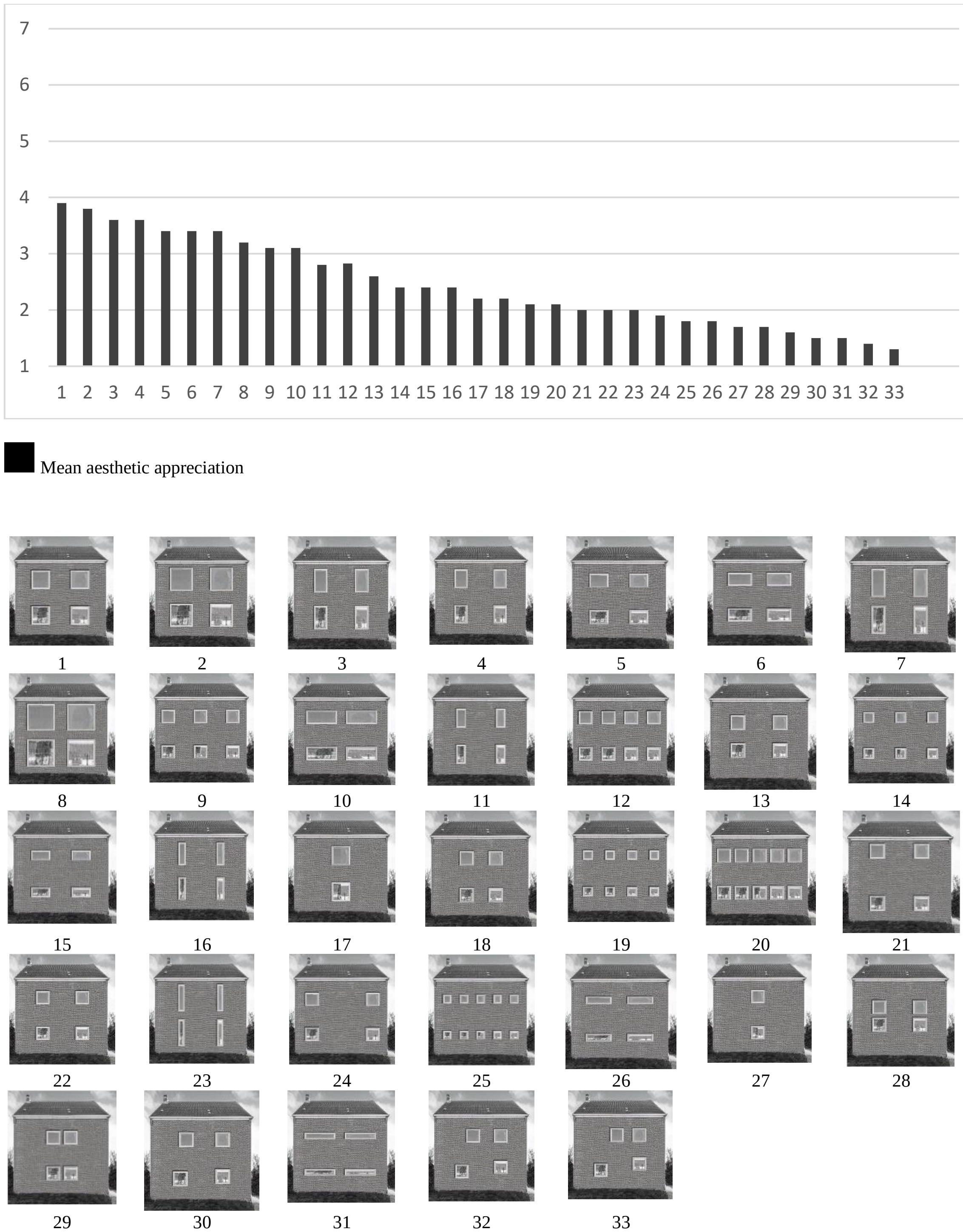


Figure 22: Mean of the aesthetic judgement of participants for the housing photos

The mean distribution of the aesthetic appreciation of participants for the studied housing photos were as shown in Figure 22. The housing photos were sequenced from the most to least attractive, to allow easier interpretation. According to the results, photo #1 (M = 3.91, Mo = 5, σ = 1.63) and #33 (M = 1.33, Mo = 1, σ = 1.07) were determined as the most and least attractive houses, respectively. Although unattractive housing photos (close to 1 in the seven-point scale) were determined in this pre-study, an attractive housing photo as a required level could not be determined among the studied 33 housing photos. The mean of the most attractive one (i.e. photo #1) reached only around 4 in the seven-point scale, which represents the mid-point or neutral response. In other words, technically there were no attractive buildings among the studied 33 buildings. In order to define a photo as attractive, the mean of the aesthetic judgement of participants should be above 4 on the seven-point scale. In order to test the impact of aesthetics on housing marketability and develop the main survey (S2, Figure 5), an aesthetically attractive housing illustration was necessary. Therefore, another pre-study (PS7, Figure 5) was conducted to generate attractive housing illustrations; 12 architects were asked to design attractive housing façades (see Section 4.2.5), and the study was extended with the eighth pre-study (PS8, Figure 5).

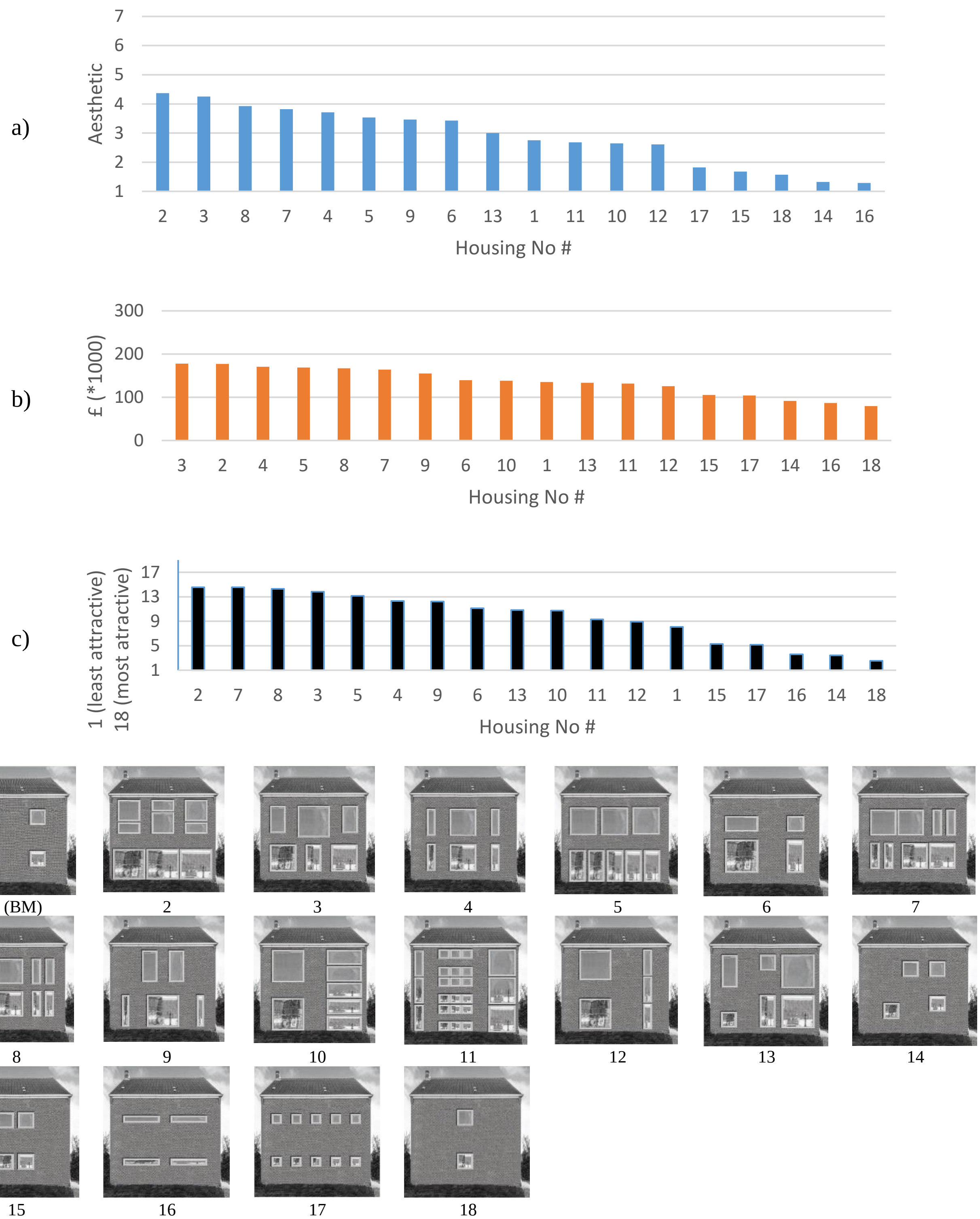
6.1.4.3 Pre-study (PS8) to identify the most attractive and unattractive housing illustrations

A hard-copy survey was conducted with 30 randomly selected UoN students with different demographic characteristics (see Table 12) to determine attractive and unattractive housing photos utilised in the main survey (S2, Figure 5) and to investigate the relationship between aesthetics, marketability, and the monetary worth of housings in the eyes of buyers. According to the investigated Cronbach's alpha (α) criterion, significantly high reliability and internal consistency of the conducted survey was observed (α = 0.93). Further technical details about the conducted pre-study can be found in Section 4.2.6.

The survey was divided into three sections: in the first section, participants were asked to grade 18 building photos according to their visual aesthetic. The details of 18 housing photos (see Figure 23) was discussed in Section 4.2.6. In the first section, participants could see only one housing illustration on each page. In addition, the monetary worth of each housing unit in the eyes of participants was determined with an additional question.

The plain outcomes of the survey are shown in Figure 23. According to the descriptive statistics results, photos #2 (M = 4.37, Mo = 5, σ = 0.75) and #3 (M = 4.25, M = 5, σ = 0.73) in Figure 23 were deemed to have the most attractive housing façades, and photo #16 (M = 1.29, M = 1, σ = 0.45) was determined as the most unattractive (see Figure 23 a). When the participants were asked how much money they would spend to buy those houses if they had £300,000 of capital, participants emphasised photos #2 (M = £177,482 (Min: £50,000, Max: £300,000), σ = 75.67), #3 (M = £177,778 (Min: £50,000, Max: £300,000), σ = 61.73), and #16 (M = £87,111 (Min: £0, Max: £160,000) (see Figure 23 b). According to Pearson's correlation analysis, a very strong positive correlation (r = 0.989, p = 0.000) between aesthetics and monetary worth was determined (see Figure 23 a and b), and consistent results were also found in conducted other studies (see Section 6.1.2.2 and 6.1.4.4).

In the second section, participants were asked to sequence all 18 given housing photos in Figure 23 from the most to least attractive. In this section, all housing photos were located on the same page, to let the participants to compare all the given photos, to obtain more data to determine attractive and unattractive housing illustrations. The sequence of 18 given housing photos from most to least attractive was as shown in Figure 23 c.



a) Aesthetic judgement, b) monetary worth according to consumer perceptions, and c) sequence from most to least attractive

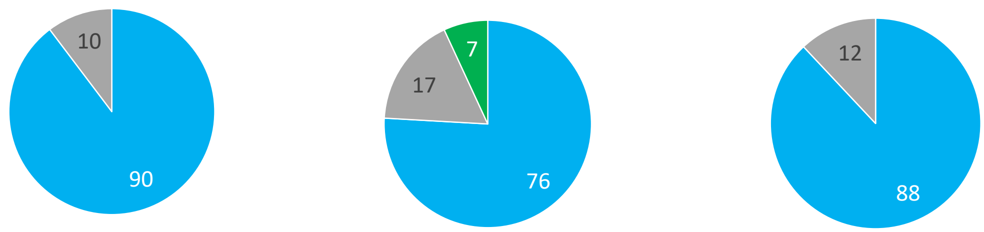
Figure 23: *Plain results of the pre-study survey*

The sequences of 18 housing photos from the most to least attractive show differences between the first and second sections of the conducted pre-study (see Figure 23 a and c). Accordingly, it is reasonable to claim that individuals' aesthetic judgement differs when visual stimuli are not isolated buildings. Other buildings in the field of view may have a magnifying or declining impact on the aesthetic perceptions of the focused building. In order to understand the level of deviation between the sequences of 18 housing photos obtained in the first and the second sections of the conducted pre-study, another study was conducted. The sequences of 18 housing photos in Figure 23 a and c were divided into half, and two clusters were generated: the first nine photos represent the more attractive cluster, and the other nine represent the less attractive cluster. Despite the orders of photos in each cluster being different in Figure 23 a and c, photos # 2, # 3, # 4, #5, #6, #7, #8, #9, #13 were in the cluster that represents more attractive housing photos, and the rest of photos were in the cluster that represents less attractive ones. This means participants' aesthetic judgment is consistent, as there was no dramatic difference between the sequences of 18 housing photos in the first and the second sections of conducted pre-study.

In the main survey (S2, Figure 5), photos # 2 and # 3 in Figure 23 were utilised as the attractive housing illustrations, and photo # 16 was utilised as the unattractive housing illustration. During the decision for the preference of attractive and unattractive housing illustrations, the results obtained in the first sections of the conducted pre-study were considered, rather than the results obtained in the second section. The reason for this is that the results obtained in the first section were from insulated buildings, which was considered more reliable. The reason why two attractive housing photos were utilised in the main survey (S2, Figure 5) is explained in Section 4.2.8.

In the last section, different housing price and energy bills were assigned to common, attractive, and unattractive housing photos, and participants were asked to choose only one of the buildings to buy. For this stage, the attractive and unattractive housing photos were chosen according to observations obtained in the pre-test process of the conducted pre-study. The dynamics of the house-buying decision making of the participants were explored in six different scenarios, as shown in Figure 24. Participants were asked to choose one of the housings with a different appearance, price, and annual energy bills (see Figure 24). EEBs were represented with an unattractive housing illustration, as their unappealing aesthetics were broadly reported in previous studies (see Section 2.2.1). However, in Cases 3, 6, 9, and 12 in Figure 27, the attractive houses were also presented as energy efficient in order to observe the participants' buying decision making.

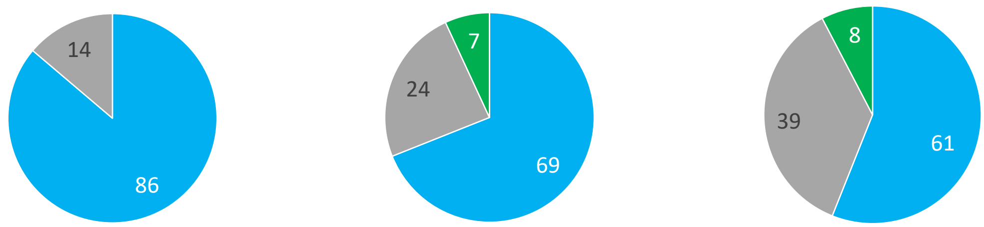
In the first scenario, only annual energy bills differed. EEB annual energy bills are up to 90% cheaper than other housing options, yet none of the participants preferred to buy EEBs; they preferred to buy attractive (90%) or ordinary (10%) houses. This clearly shows that energy performance has low market value in the eyes of buyers, and even a significant reduction of EEBs' initial cost would be insufficient to enhance their marketability, without the contribution of other marketing motivations such as aesthetics; in addition, consistent and supplementary results were yielded by subsequent studies ((S2, Figure 5) (see Section 6.1.4.4)). In the second scenario, the annual energy bill of the attractive house was increased by 72% compared to the previous scenario, and the rest of the parameters were kept constant. Despite a 72% rise in the annual energy bill, the vast majority of participants (76%) preferred to buy the attractive houses, while only 17% and 7% of them preferred to buy ordinary and energy-efficient houses, respectively. In the rest of the scenarios, ordinary and energy efficient house prices (£160,000 and £240,000) and annual energy bills (£1,164 and £168) were kept constant, and only the attractive housing's price and energy bill were modified. Attractive houses reached the highest price (50% higher than the ordinary houses) and highest energy bill (1,090% higher than EEB) in the last scenario. Even under the highest energy bill and price conditions, the vast majority of participants (61%) preferred to buy attractive houses (see Figure 24). Results clearly showed that housings' aesthetic are the predominant parameter affecting buying decisions, and have a great potential to make EEBs more marketable, and can also help to overcome existing market barriers of EEBs, such as suspending their higher initial cost while increasing the monetary worth of EEBs according to consumer perceptions.



CASE 1	Price	AEB
Attractive	£160,000	£1,164
Ordinary	£160,000	£1,164
EEB	£160,000	£168

CASE 2	Price	AEB
Attractive	£160,000	£2,000
Ordinary	£160,000	£1,164
EEB	£160,000	£168

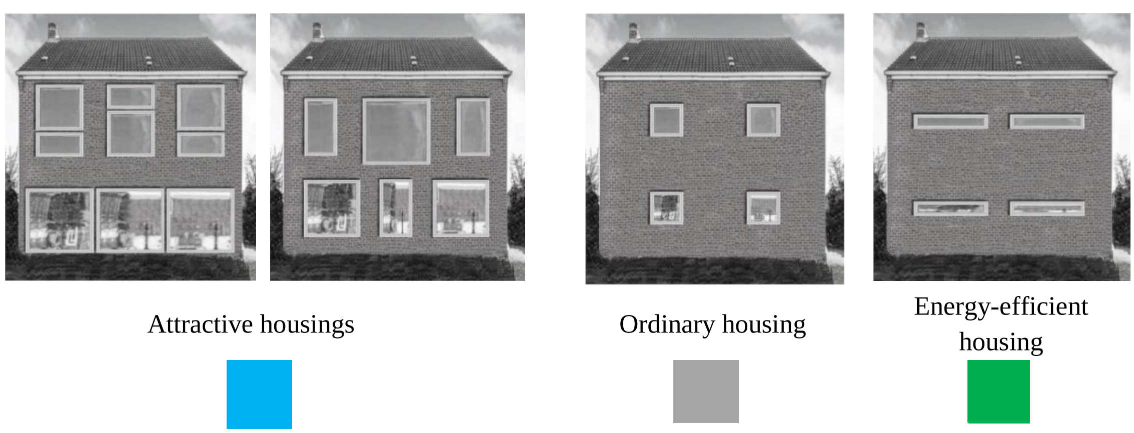
CASE 3	Price	AEB
Attractive	£200,000	£1,164
Ordinary	£160,000	£1,164
EEB	£240,000	£168



CASE 4	Price	AEB
Attractive	£200,000	£2,000
Ordinary	£160,000	£1,164
EEB	£240,000	£168

CASE 5	Price	AEB
Attractive	£240,000	£1,164
Ordinary	£160,000	£1,164
EEB	£240,000	£168

CASE 6	Price	AEB
Attractive	£240,000	£2,000
Ordinary	£160,000	£1,164
EEB	£240,000	£168



EEB: Energy efficient housing, AEB: Annual energy bill

Figure 24: Housing buying preferences of participants under different scenarios

6.1.4.4 Survey (S2) conducted with potential housing buyers

A comprehensive email survey (S2, Figure 5) was conducted with potential housing buyers (183 UoN staff with different demographic characteristics) to: (1) obtain further evidence about the applicability of the proposed widespread adoption approach; (2) discover whether the initial cost reduction of EEBs would be sufficient to enhance their marketability; and (3) investigate the potential added value of aesthetic enhancement of housings. Cronbach's alpha (α) indicated the conducted survey's significantly high reliability and internal consistency (α = 0.95). Further technical details about the conducted survey can be found in Section 4.2.7.

There were three sections of the conducted survey. In the first section, the initial impression of participants about the four utilised housing photos was measured to ensure the housing photos, which are expected to be found attractive and unattractive, are properly perceived by the participants. Therefore, the participants were asked to rank the photos from most attractive (i.e. 4) to least attractive (i.e. 1) (Figure 25). The results confirm that the utilised housing photos were perceived by the participants as they should be.

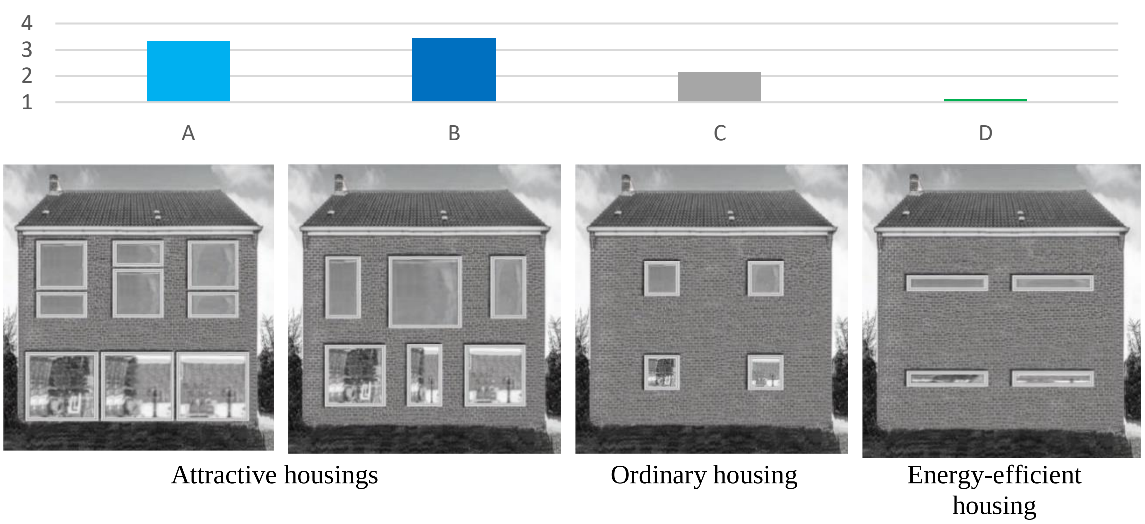
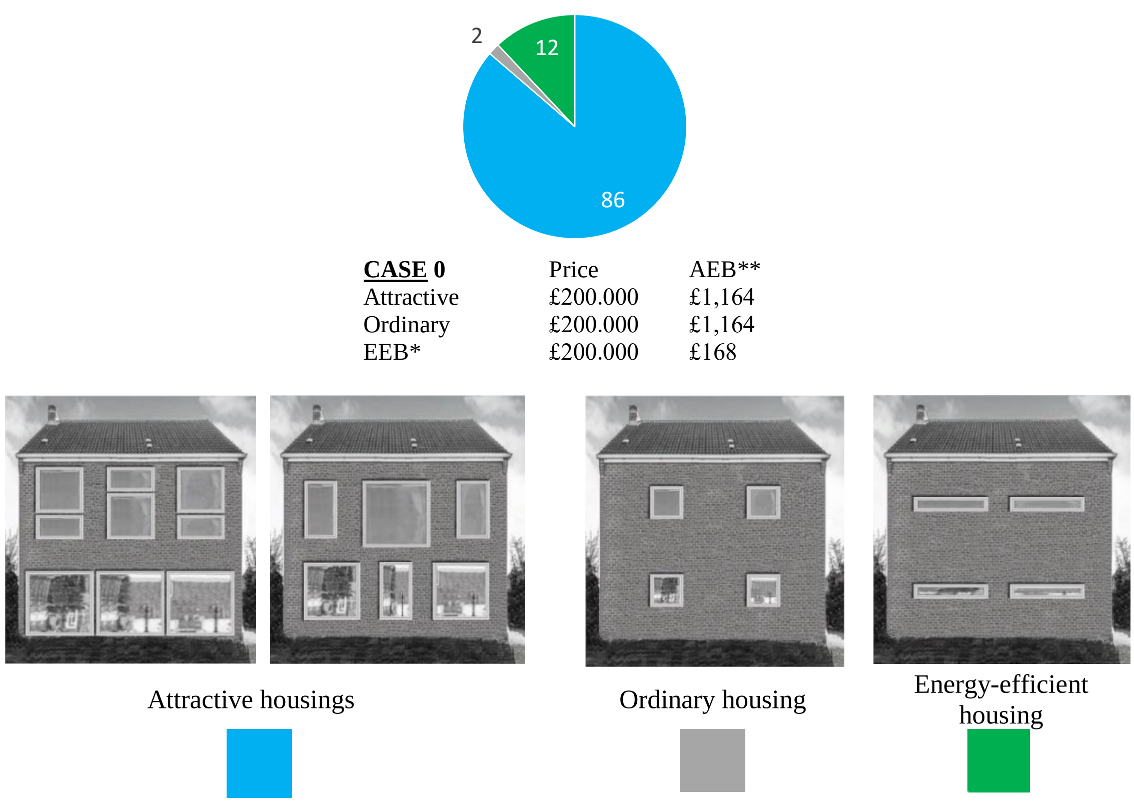


Figure 25: Comparison of aesthetic appreciation for studied housing photos

In the second section of the survey, a question was designed to discover whether the initial cost reduction of EEBs would be sufficient to enhance their marketability and widespread adoption. As discussed in Section 2.1.1.2, the high initial cost of EEBs is one of their main marketing barriers, thus the price reduction of EBBs can be an alternative approach to proposed widespread adoption approach. To test the practicality of this alternative approach (i.e. price reduction of EBBs), the price of all four houses in Figure 26 was kept constant equal to the average representative UK house price (£200,000), and the annual energy bill of EEB was set 85% less compared to attractive and ordinary housing options. Accordingly, in the first scenario, only the appearance of the buildings and energy bill of the EEB (£168 per year) differed (see Figure 26).

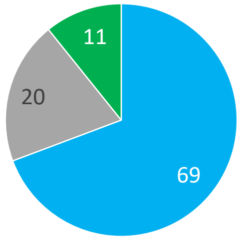


EEB: Energy efficient housing, AEB: Annual energy bill

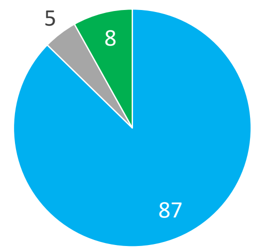
Figure 26: Results for testing the potential of a EEBs' price reduction strategy to enhance their marketability

Results illustrated in Figure 26 clearly show that even if EEBs' initial cost would be reduced up to the ordinary house price, which is not possible due to additional expenses such as insulation, they have no chance in the building market without aesthetic enhancement or other motivations that enhance marketability; 86% of the participants preferred to buy attractive houses and only 12% of them preferred to buy energy efficient ones. In summary, empirical evidence clearly shows that the aesthetic enhancement of EEBs must be considered for enhancing their marketability and to ensure their widespread adoption. This highlights the importance of the proposed widespread adoption approach to overcome the phenomenon of IIBEE and the insufficiency of price reduction of EEBs.

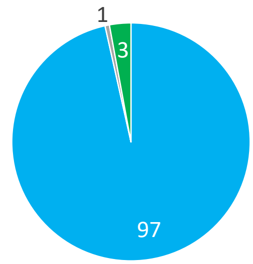
In the third section of the conducted survey, the impact of aesthetics, energy efficiency, and initial cost on housing buyers' buying preference was investigated with 12 different scenarios (see Figure 27). The price and energy bill of attractive houses (see figure Figure 26) were gradually increased with different combinations (see Figure 27). According to the results, if an EEB (in passive house standards) is designed to be attractive, it can be sold with a price of up to 50% higher compared to ordinary houses (see case 12 in Figure 27), which is more than double the reported higher initial cost (20%; see Section 2.1.1.2). As seen in case 12 (see Figure 27), 63% of participants prefer to buy an attractive house costing £300,000 with a £168 annual energy bill. In other words, the marketability of EEBs can be significantly enhanced with their aesthetic improvement. Another important point that should be highlighted is related to case 7, as shown in Figure 27; the majority of participants (53%) prefer to buy an attractive house with a 30% higher price and 86% higher energy consumption (bill) compared to ordinary houses. More surprisingly, a considerable number of participants (39%) still preferred to buy an attractive house even if it has a 50% higher price and 86% higher energy consumption (bill) compared to ordinary houses (see case 10 in Figure 27).



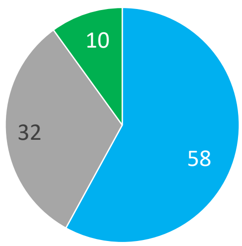
CASE 1	Price	AEB
Attractive	£200.000	£2,160
Ordinary	£200.000	£1,164
EEB	£240.000	£168



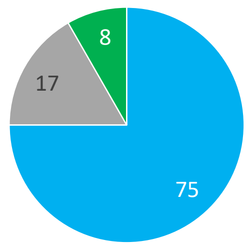
CASE 2	Price	AEB
Attractive	£200.000	£1,164
Ordinary	£200.000	£1,164
EEB	£240.000	£168



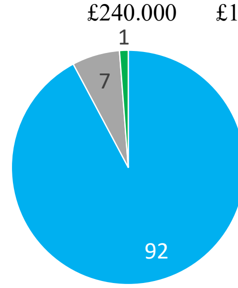
CASE 3	Price	AEB
Attractive	£200.000	£168
Ordinary	£200.000	£1,164
EEB	£240.000	£168



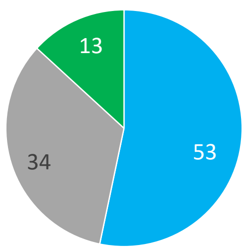
CASE 4	Price	AEB
Attractive	£240.000	£2,160
Ordinary	£200.000	£1,164
EEB	£240.000	£168



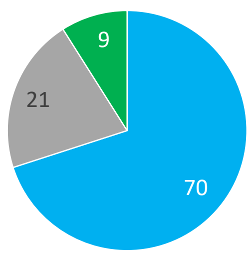
CASE 5	Price	AEB
Attractive	£240.000	£1,164
Ordinary	£200.000	£1,164
EEB	£240.000	£168



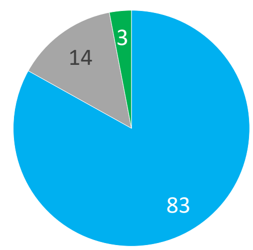
CASE 6	Price	AEB
Attractive	£240.000	£168
Ordinary	£200.000	£1,164
EEB	£240.000	£168



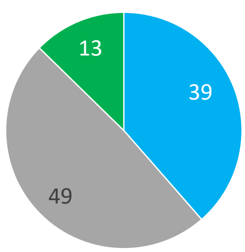
CASE 7	Price	AEB
Attractive	£260.000	£2,160
Ordinary	£200.000	£1,164
EEB	£240.000	£168



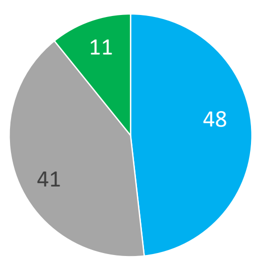
CASE 8	Price	AEB
Attractive	£260.000	£1,164
Ordinary	£200.000	£1,164
EEB	£240.000	£168



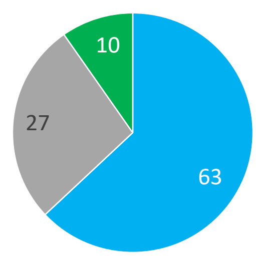
CASE 9	Price	AEB
Attractive	£260.000	£168
Ordinary	£200.000	£1,164
EEB	£240.000	£168



CASE 10	Price	AEB
Attractive	£300.000	£2,160
Ordinary	£200.000	£1,164
EEB	£240.000	£168



CASE 11	Price	AEB
Attractive	£300.000	£1,164
Ordinary	£200.000	£1,164
EEB	£240.000	£168



CASE 12	Price	AEB
Attractive	£300.000	£168
Ordinary	£200.000	£1,164
EEB	£240.000	£168

Attractive housing

Ordinary housing

Energy-efficient housing

EEB: Energy efficient housing, AEB: Annual energy bill

Figure 27: Housing buying preferences of participants under different scenarios

It is worth to highlight that participants particularly prefer to buy attractive (aesthetic) low-price and energy-efficient buildings. Cases 1, 2, 3, 10, 11 and 12 in Figure 27 can be given as examples to support this claim. In Figure 27, 69% of the participant preferred to buy the attractive house in Case 1 (Price: £200.000, AEB: £2,160). This gradually increased to 87% in Case 2 (Price: £200.000, AEB: £1,164), and to 97% in Case 3 (Price: £200.000, AEB: £168). Similarly, 39% of the participant preferred to buy the attractive house in Case 10 (Price: £300.000, AEB: £2,160) while it gradually increased to 48% in Case 11 (Price: £300.000, AEB: £1,164), and to 63% in Case 12 (Price: £300.000, AEB: £168). According to these results, it is clear that in order to increase the number of EEBs, strategies should be developed to decrease the housing price and to enhance their energy efficiency and aesthetics. Even though energy efficiency features have an added value for the housings marketability, yet energy efficiency is not enough alone to compensate the EEBs' extra price and the existing market barriers without additional motivations such as aesthetic (similar results were also found in Section 6.1.2).

It is important to emphasise that the attractive housing photos utilised in this survey are not attractive at the adequate level (i.e. 6 and above on the seven-point scale). The mean aesthetic appreciation of participants for utilised attractive housing illustrations (i.e. photo #2 ($M = 4.37$) and #3 ($M = 4.25$) (see Figure 23) barely passed the mid-point or neutral response (i.e. 4 on the seven-point scale) (see Section 6.1.4.3). Accordingly, it is reasonable to expect that, if more attractive housing illustrations had been utilised in this survey, then compared to achieved results (i.e. with monetary added value enhancement of up to 50%), a much greater monetary added value and buying preference could have been observed.

6.1.5 Summary

- There are no meaningful differences between individuals' aesthetic judgments of detached and terraced houses.

- Individuals' aesthetic judgements differ when housing illustrations are shown in isolation (one at a time) and on pages with multiple other housing units.

- There is a significantly high positive correlation between housings' aesthetic and marketability. Housing aesthetic is the most dominant parameter that affects buying decision, and the energy efficiency features of the housings have very low market value.

- There is a very strong positive correlation between the aesthetic and monetary worth (according to consumer perceptions) of housings. Participants prefer to buy attractive houses even if they have higher initial costs (up the 50%) and annual energy bills (up to 86%) compared to ordinary ones.

- In order to increase the number of EEBs, strategies should be developed to decrease price and enhance their energy efficiency and aesthetics.

- The reduction of EEBs' initial cost is not enough to enhance their marketability, thus aesthetic enhancement of EEBs' seems the one of the most practical approach to enhance their marketability. Existing market barriers of EEBs, such as higher initial cost and low market value according to consumer perceptions, can easily be overcome with aesthetic enhancement.

- Energy efficiency features have an added value for housings marketability, yet energy efficiency is not enough alone to compensate the EEBs' extra price and existing market barriers without additional motivations such as aesthetic

- Proposed novel widespread adoption approach has strong applicability in the practice.

6.1.6 Conclusion

In this section, strong empirical evidence was presented about the existence of the phenomenon of IIBEE. There is a significant market resistance for the EEBs in UK; the low market value of energy efficiency features, high initial cost, and buyers' prejudgements about the EEBs are the underlying reasons behind this market resistance. Results clearly show that most of the existing market barriers of EEBs that cause the phenomenon of IIBEE, such as high initial cost and low market value of energy, can be overcome via the aesthetic enhancement of EEBs. There is a significant positive correlation between the aesthetic of housings and their marketability and monetary worth according to consumer perceptions, which clearly indicate that EEBs would become more marketable with a more attractive appearance, and if EEBs would be more marketable, then their number would increase faster in the UK building stock due to natural supply-and-demand dynamics. In conclusion, significant empirical evidences were found indicating that the proposed widespread adoption approach has very strong grounds and applicability in the UK housing market.

This section demonstrates the applicability of the proposed widespread adoption approach in the UK; the following section considers how the aesthetic enhancement of EEBs can be implemented.

6.2 Investigating the applicability of the proposed novel paradigm (YYP)

The ambiguity about how EEBs' aesthetic can be enhanced is the main obstacle to the applicability of the proposed widespread adoption approach. Therefore, a novel paradigm (YYP) was introduced in this thesis. This section discusses the applicability of YYP in practice; for this purpose, a multidimensional measurement model was developed to ensure applicability. In addition, this section discusses four main points: (1) the relationship between window configurations and housing aesthetic, marketability (S4, Figure 5), and energy efficiency (ES in Figure 5), (2) the relationship between symmetry and individuals' aesthetic judgement, (3) the validity of the developed symmetry measurement model (symmetry index) (SI and S3, Figure 5) and ANN and decision tree based predictive models (PM Figure 5), and (4) the performance of the developed multidimensional measurement model (MMM in Figure 5).

6.2.1 Survey (S3) to validate the developed symmetry measurement model

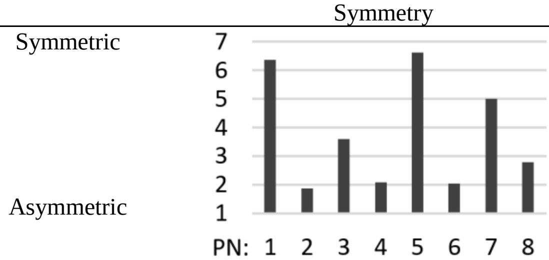
This section introduces the results of a comprehensive survey (S3, Figure 5) conducted with 145 UoN students with diverse demographic characteristics. This survey was conducted to investigate: (1) the relationship between symmetry and individuals' aesthetic judgement; (2) the demographic impact on symmetry and aesthetic judgement; and (3) to validate and testing the performance of the developed symmetry index (SI in Figure 5), which was needed to develop the predictive models (PM Figure 5). Convenient reliability and internal consistency of the conducted survey was observed according to the investigated Cronbach's alpha (α) criterion (α = 0.73).

Further technical details about the conducted survey and symmetry measurement model can be found in Sections 5.1 and 3.4 respectively.

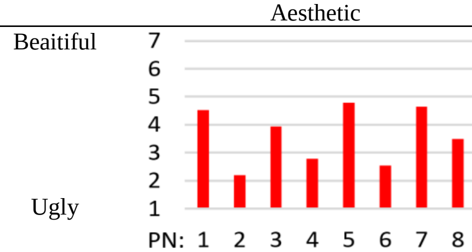
6.2.1.1 *Relationship between symmetry and individuals' aesthetic judgement*

The plain outcomes of the survey are shown in Figure 28. The mean distributions of the symmetry and aesthetic value of the eight studied building photos were compared, as shown in Figure 29. Both descriptive statistics and Pearson's correlation results clearly show that there is a strong positive correlation between the symmetry and aesthetics of residential buildings (r = 0.526, n = 1160, p = 0.000); when symmetry increases, aesthetic appreciation increases.

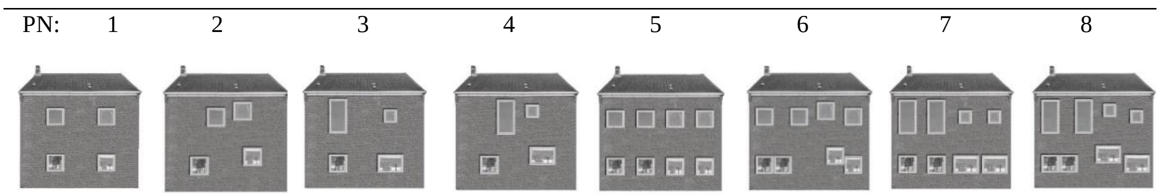
Symmetry



Aesthetic

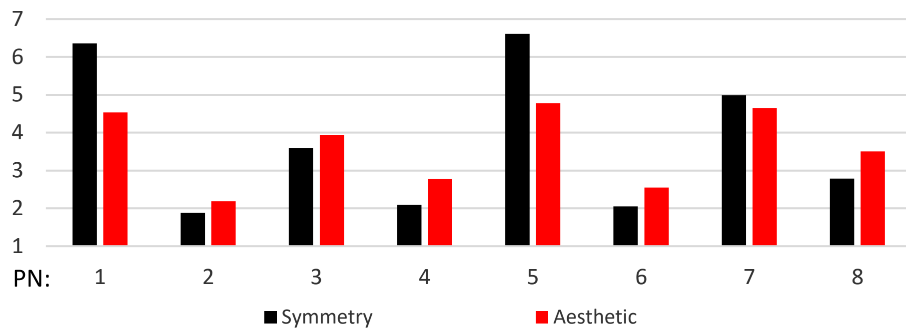


	Symmetry								Aesthetic							
PN:	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
M=	6.4	1.9	3.6	2.1	6.6	2.1	5.0	2.8	4.5	2.2	3.9	2.8	4.8	2.6	4.7	3.5
Mo=	7.0	1.0	3.0	2.0	7.0	1.0	6.0	2.0	4.0	1.0	4.0	3.0	6.0	2.0	5.0	4.0
σ =	1.1	1.1	1.7	1.1	0.8	1.2	1.7	1.6	1.4	1.2	1.6	1.4	1.6	1.3	1.6	1.7
SI=	1.0	0.0	0.5	0.0	1.0	0.0	0.7	0.2								



PN: photo no., Mo: mode, SI: Symmetry index, 1: asymmetric, ugly, 7: symmetric, beautiful

Figure 28: Plain results of the survey



PN: photo no., 1: asymmetric, ugly, 7: symmetric, beautiful

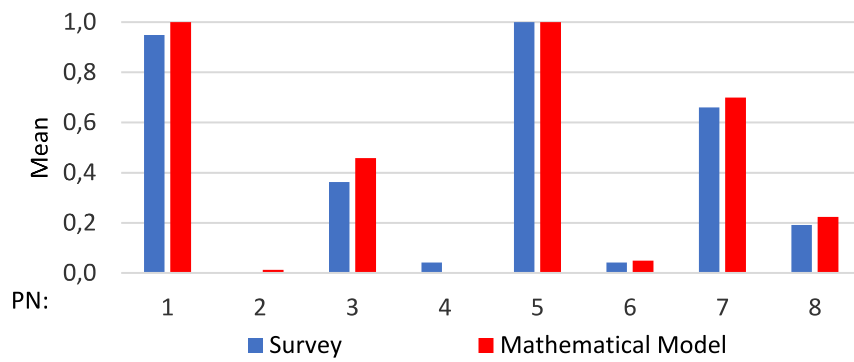
Figure 29: Mean distribution of the symmetry, and aesthetic level of eight studied building photos

Interestingly, it was observed that, compared to a horizontal-symmetry (when visual stimuli are cut in X-axis), the vertical-symmetry (when visual stimuli are cut in Y-axis) can be more dominant in individuals' symmetry perceptions for housings. As seen in Figure 28, the studied housings have no horizontal symmetry, because they only have a gable roof on top. Nevertheless, the vast majority of the participants described photos #1 (M = 6.4, Mo = 7) and #5 (M = 6.6, Mo = 7) as symmetric.

Another interesting observation is that photos #1 and #5 are not entirely vertically symmetric, as there is a chimney on the left side of the gable roof. However, the mode (the most common given answer) for the symmetry of photos #1 (61%) and #5 (73%) are seven, which is the highest possible symmetry grade (see Figure 28). This may be due to low impact of small details on the symmetry perception.

6.2.1.2 Validity of the proposed symmetry measurement model

A comparison of normalized symmetry data obtained from the survey and symmetry index can be seen in Figure 30. In general, the symmetry index slightly overestimates symmetry in almost all cases (see Figure 30). The average difference between the symmetry index and survey results is 9% (min: 0%, max: 26%). The statistical significance of the similarities between the survey results and the mathematical model is investigated with paired samples T-Test, and there is no statistical difference between the results obtained from the survey (M=0.40, σ =0.42) and mathematical model (M=0.40, σ =0.42) (t (7) = -1.53, p=0.17). In summary, it has been determined that the developed symmetry index is successful in the prediction of individuals' symmetry perception, with a high level of accuracy.



PN: photo no

Figure 30: Comparison of the normalized means of symmetry data extracted from the survey and mathematical model

It is worth highlighting that, as an abstract parameter affecting aesthetic judgment, measuring the symmetry perception of individuals via computational approaches gives hope for the possibility to predict other factors that impact on aesthetic judgment, and for the applicability of YYP. The investigation of symmetry perception clearly shows that there is a rationale behind it; furthermore, as discussed in more detail in the following sections (see Section 6.2.2), empirical evidence about the existence of a rationale behind the aesthetic judgments of individuals was also found in this thesis. In predicting the perception of symmetry, if there is a rationale behind aesthetic judgement then it can be predicted with computational approaches; the following sections also provide strong empirical evidence in favour of this claim (see Section 6.2.4).

6.2.1.3 Demographic impact on symmetry and aesthetic judgement

ANOVA results indicate that demographic differences among individuals do not affect their symmetry or aesthetic perceptions in most cases. However, it is determined that ethnicity has a slight influence on aesthetic perceptions ($F(5, 1154) = 2.789$, $p = 0.016$). Hochberg GT2 post hoc test was performed to analyse the impact of ethnicity on the symmetry and aesthetic perception. Although the rest of the ethnic groups have high similarities, participants from the Middle East had different judgment ($p < 0.05$) compared to those from Asia. It is worth to highlight that Middle East is a part of Asia continent, in this study it was separately investigated due to ethnic and cultural differences. Accordingly, in general, results show that the proposed symmetry index can be utilised to simulate the symmetry perception of individuals that belong to most of the different demographic groups.

6.2.1.4 Summary

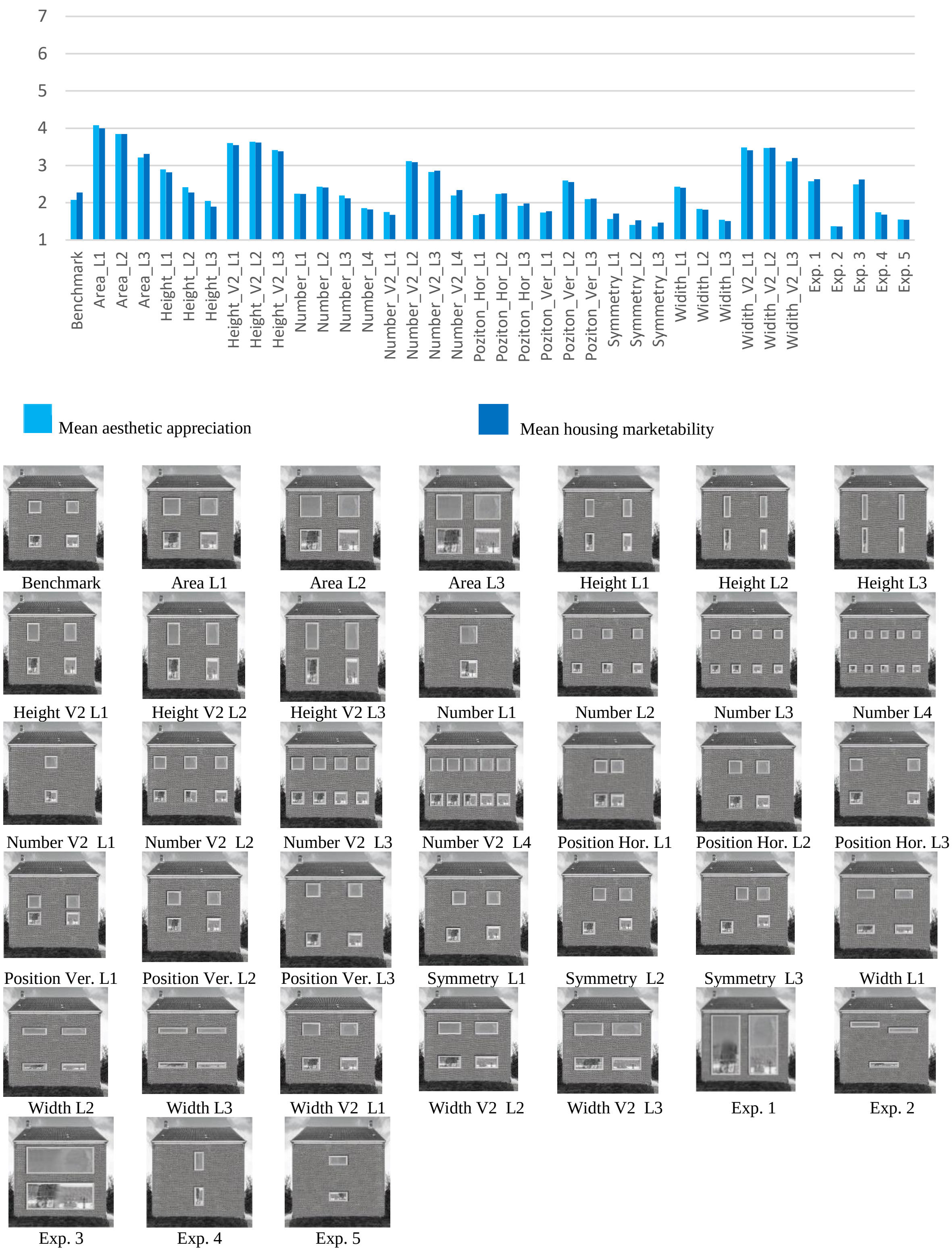
- There is a strong positive correlation between symmetry and aesthetic value.
- Vertical symmetry tends to predominate in individuals' symmetry perceptions than horizontal symmetry in housing illustrations.
- The developed symmetry measurement model is highly successful in simulating individuals' symmetry perceptions.
- Demographic differences among individuals have no considerable impact on their symmetry and aesthetic perceptions.

6.2.2 *Survey (S4) to investigate the impact of different window parameters on the aesthetics and marketability of housings*

This section introduces the results of a comprehensive survey (S4, Figure 5) conducted with 807 native UoN students. The survey was conducted to investigate: (1) the impact of different window configurations on the marketability and aesthetic of housings, (2) the relationship between marketability and aesthetic of housings, (3) the demographic impact on aesthetic judgment, and (4) to provide data for the development of predictive models (PM in Figure 5). According to Cronbach's alpha (α) criterion, significantly high reliability and internal consistency of the conducted survey was observed ($\alpha = 0.95$). Further technical details about the conducted survey can be found in Section 5.2.

The plain outcomes of the survey are shown in Figure 31. A significantly high positive correlation ($r = 0.876$, $p = 0.000$) between housing aesthetic and marketability was observed. Similar results were also obtained in the three previously conducted surveys (see Sections 6.1.4.1, 6.1.4.3, and 6.1.4.4). This implies that the results of aesthetic judgement for detached house photos can be extended to their marketability. Accordingly, in the remainder of this thesis, only aesthetic results are discussed. In addition, in this survey only the detached house form was evaluated, for the rationale discussed in the fifth pre-study (PS5, Figure 5) in Section 6.1.4.1.

Despite housing photos being shown to participants via random order, in almost all window configurations, a clear trend (i.e. upward, downward, and U-shape) can be observed for the impact of each window configuration on housings' aesthetic (see Figure 31). This clearly shows that there is a rationale behind the aesthetic judgment of individuals. Certain window parameters gradually modified in each level of configuration resulted with gradual changes in individuals' aesthetic appreciation.



V2: second version of window configurations, Exp: photos that belong to experimental categories, 1: unattractive, 7: attractive

Figure 31: Mean aesthetic appreciation and housing marketability distribution for each housing photos

The configurations of window area and symmetry were determined as two extreme samples that have the greatest magnifying and attenuation impacts on housing aesthetic. In the Figure 31, a clear reverse U-shape relationship can be observed between housing aesthetic and window area. Participants' aesthetic appreciation for the benchmark housing (M = 2.08, Mo = 2.00, σ = 1.08) is almost doubled in the window area configuration level 1 (M = 4.08, Mo = 5.00, σ = 1.64), then it gradually reduces at the window area configurations of level 2 (M = 3.84, Mo = 5.00, σ = 1.67) and level 3 (M = 3.22, Mo = 3.00, σ = 1.69) (see Figure 31). Despite housing aesthetic having a downward trend in the window area configurations from level 1 (M = 4.08, Mo = 5.00, σ = 1.64) to level 3 (M = 3.22, Mo = 3.00, σ = 1.69), in general, the reinforcing effect of the window area on houses' aesthetic was observed. The highest aesthetic scores (i.e. around 3 to 4 on a seven-point scale) can be observed in the housing photos that have a relatively higher window area, such as the second versions (V2) of window configurations, area configurations, and photos (Exp1 and Exp3[37] in Figure 31).

In the window symmetry configurations, the symmetry of the windows was decreased from level 1 to level 3 (see Figure 31), because the other window configurations were symmetric, and in order to test the impact of symmetry on aesthetic, asymmetric housing photos are required. In general, window symmetry configurations (i.e. asymmetric housing photos) have the lowest aesthetic appreciation mean. Participants' aesthetic appreciation for the benchmark housing (M = 2.08, Mo = 2.00, σ = 1.08) was significantly attenuated in window symmetry configuration level 1 (M = 1.57, Mo = 1, σ = 0.89), and gradually reduced in level 2 (M = 1.40, Mo = 1.00, σ = 0.77) and level 3 (M = 1.36, Mo = 1.00, σ = 0.81). Similarly, photo Exp 2 in Figure 31 has one of the

[37] The details and the rationale behind the second version of window configurations and the experimental and training categories for studied photos can be found in Section 5.2.3.

lowest aesthetic scores. Accordingly, it is reasonable to claim that symmetry has a positive effect on aesthetic appreciation.

It should be noted that an interpretation only based on the mean aesthetic distribution can result in a misleading conclusion; Figure 31 shows the overall judgment about each of the housing photos. The aesthetic judgment for each photo is the result of the combination of all visible components of the photos, not only the focused window configuration. For example, in the window height configurations (see Figure 31), window height gradually increased from level 1 (1.50 m) to level 3 (2.17 m), yet when participants were evaluating their aesthetics they simultaneously perceived other window parameters, such as window area, width, number, position, proportion, and symmetry. In other words, the aesthetic appreciation for each photo is the result of the simultaneous combination of seven previously identified window parameters, which have mutual impacts on each other, affecting the overall aesthetic judgement. For example, despite the fact that the window width and height configurations have a downward aesthetic appreciation trend from level 1 to level 3, this trend evolves to a slight reverse U-shaped relationship in the second versions of the window width and height configurations (see Figure 31). This implies that different window parameters (e.g. window width – height, and width – area) have a mutual impact on each other. Accordingly, the relation between window parameters and housings aesthetic should be investigated in greater depth.

For this purpose, a more detailed graph that illustrates the normalized values of all seven window parameters (i.e. width, height, area, position, symmetry, proportion, and number) and aesthetic appreciation for each housing photo was generated. In order to generate the graph, first, survey results (aesthetic appreciation) and window parameters for each of the studied housing photos were normalized via Eq. (28), then the studied photos were ordered from the most to least attractive, to investigate whether there is any obvious linear relation between aesthetic and window properties (see Figure 32).

As can be seen in Figure 32, no visible meaningful linear relationship can be observed between aesthetic and window parameters. Despite a clear trend between aesthetic and window configurations in Figure 31, the absence of any linear relation in Figure 32 clearly indicates that the descriptive models are inadequate to understand the dynamics of aesthetic appreciation. Therefore, the study was extended via inferential static models. For this purpose the correlation between aesthetics and the seven studied window parameters were investigated with Pearson's correlation analysis. According to results, a meaningful positive correlation was found only between aesthetics and window area ($r = 0.330$, $p = 0.031$), height ($r = 0.337$, $p = 0.027$), and position on X-axis ($r = 0.351$, $p = 0.053$). Nonetheless, no meaningful correlation was observed between aesthetics and window number ($r = 0.005$, $p = 0.997$), position on Y-axis ($r = 0.055$, $p = 0.748$), symmetry ($r = 0.071$, $p = 0.652$), width ($r = 0.070$, $p = 0.653$), and proportion ($r = -0.288$, $p = 0.061$).

It is worth to highlight that the results about the correlation between symmetry and aesthetic achieved in this study (i.e. forth survey (S4)) contradict the results of the third survey (S3 see in Section 6.2.1.1). This contradiction may be occurred due to two reasons: (1) the number of symmetry variations (four) may not be enough to determine an accurate relationship between symmetry and aesthetic as there were eight symmetry variations utilized in the third survey (S3), and (2) different window configurations applied in the S4 may have an unexpected impact on the symmetry perception. Hence, considering the contradiction between these two studies (i.e. S3 and S4), further studies are necessary as the future work to determine rationale behind such mismatches.

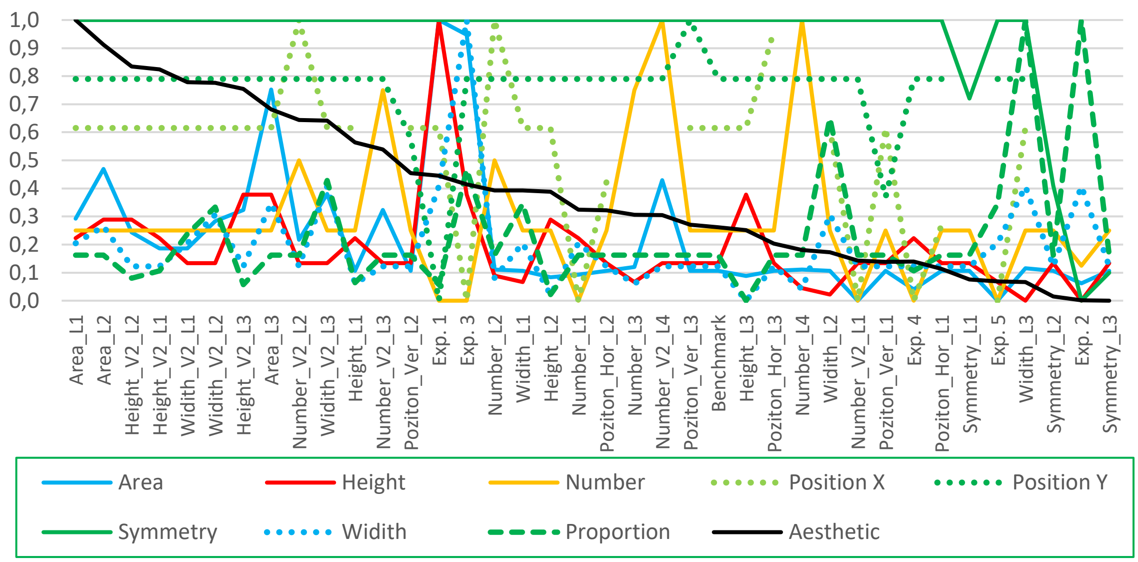


Figure 32: Normalized values for all dependent (aesthetic) and independent variables (window parameters)

6.2.2.1 Demographic impact on aesthetic judgement

According to ANOVA results, there is a noticeable impact of demographic features on aesthetic judgment, including gender (F (2, 26631) = 4.802, p = 0.008), age (F (6, 26631) = 2.598, p = 0.035), qualifications (F (3, 26631) = 12.660, p = 0.000), background (F (2, 26631) = 35.919, p = 0.000), and location (F (9, 26631) = 26.837, p = 0.000)). According to post-hoc test results, in background demographics, all subgroups' aesthetic judgements differed from each other ($p < 0.05$). This was an expected result, as an aesthetic judgment difference between architects and non-architects was broadly reported in previous studies (see Section 2.2.1). In the gender and qualification demographics, the subgroup labelled as "other" differs from other subgroups ($p < 0.05$). Similarly, in the age and location demographics, the subgroups labelled as "55-64" and "5, 8, and 10" respectively differ to other subgroups in related demographics ($p < 0.05$). It should be noted that all of the differing subgroups have the lowest number of participants. For example, the subgroup labelled as "other", and "55-64" in the gender and age demographics respectively were represented by only 1% of participants. In other words, the deviation of aesthetic judgement between these subgroups may probably due to the fact that they are not adequately representative due to their small number of participants, particularly considering that the results of previous studies showed that demographics do not have an impact on aesthetic judgement (see Section 6.1.4.1, and 6.2.1.3), thus it would be misleading to infer that demographic features have an impact on aesthetic judgment based on these results.

6.2.2.2 Summary

- There is a significantly high positive correlation between residential building aesthetics and marketability.

- There is a rationale behind the aesthetic evaluation of individuals. Certain window parameters gradually modified in each level of configuration resulted in a gradual change in individuals' aesthetic appreciation.

- Window area is the predominant parameter that affects aesthetic judgement. In general, the elevation of the window area has a reinforcing impact on aesthetic judgement. There is a reverse U-shape relationship between aesthetics and window area.

- There is a meaningful positive correlation between aesthetic judgment and window area, height, and position on X-axis.

- Symmetry has a reinforcing impact on housings' aesthetic.

- There is an aesthetic judgment difference between architects and non-architects.

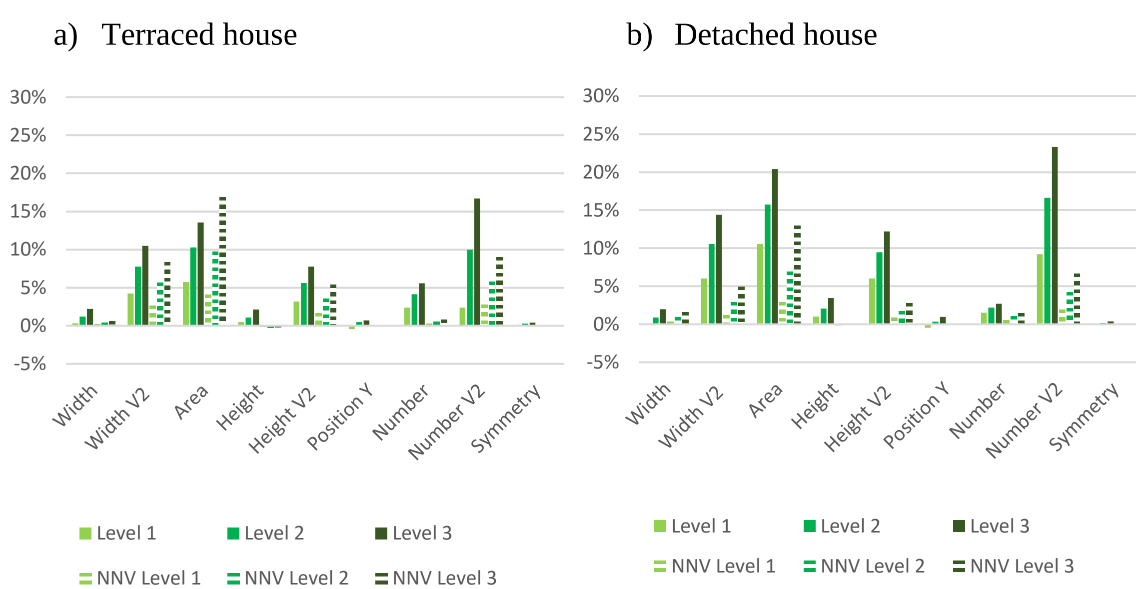
6.2.3 Energy simulations (ES) to investigate the impact of different window parameters on annual energy consumption of housings

This section introduces the results of a BES (ES in Figure 5). This study was conducted to: (1) investigate the impact of different window configurations on the annual energy consumption of housings and (2) obtain data for the development and validation of predictive models (PM in Figure 5). Further technical details about the conducted BES can be found in Section 5.3.

The impacts of each applied window configuration on the annual total energy demand, including heating and cooling loads of the terraced and detached benchmark houses, are given in Figure 33, Figure 34, and Figure 35, respectively. Since no change in the annual lighting loads was observed in any of the window configurations, this parameter is not discussed in the rest of the study. The minimum total window area (18 m^2) is found to be enough to compensate the target illuminance (300 lux). Similarly, the horizontal window position configurations caused no change in the annual energy demand.

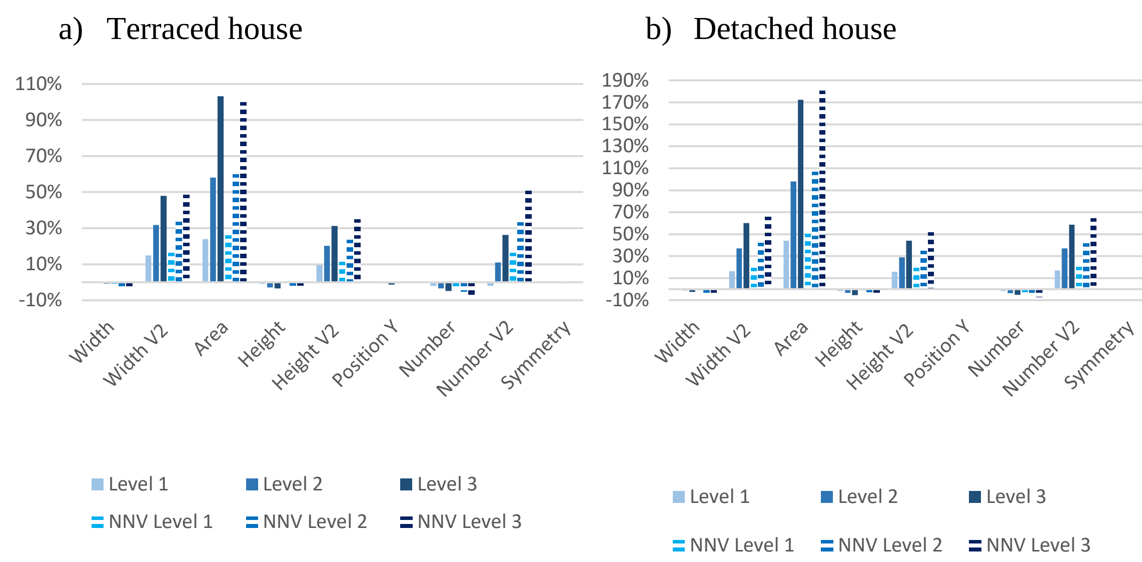
In comparison with benchmark housings' annual energy consumption, the detached house has more annual energy consumption than its terraced counterpart when natural ventilation is included (29% (18.99 kWh)) or excluded (33% (6.57 kWh)). Heating loads were significantly dominant in annual energy consumption of both benchmark buildings, particularly when natural ventilation was included; heating loads of detached and terraced houses were responsible for up to 85% (71.06 kWh) and 80% (51.75 kWh) of annual energy consumption, respectively. When natural ventilation is included, the detached house has 37% (19.31 kWh) more heating loads and 3% (0.03 MWh) less cooling loads compared to the terraced house. The detached house has more heating loads compared to the terraced house due to two reasons: (1) the window number of the detached house is two times more than that of the terraced house, and it has windows on four façades facing the four different cardinal orientations, while the terraced house has windows on only two façades (see Figure 14 and Section 5.3.1), which increases heat loos through natural ventilation and infiltration, and (2) the terraced house has a 100% (4.5 m^2) larger window area on the south façade compared to the detached house, and accordingly has 3% (0.47 MJ) more solar heat gain from the south oriented windows.

Overall, it is observed that terraced and detached houses have similar energy consumption trends in all applied window configurations (see Figure 33, Figure 34, and Figure 35). In general, window configurations have a more pronounced impact on annual energy consumption at the detached house due to the greater number of windows. Accordingly, in the rest of this study, the impact of the window configurations on energy consumption is discussed only for the detached houses, as similar interpretations can be extended to the terraced houses due to terraced and detached houses have similar energy consumption trends.



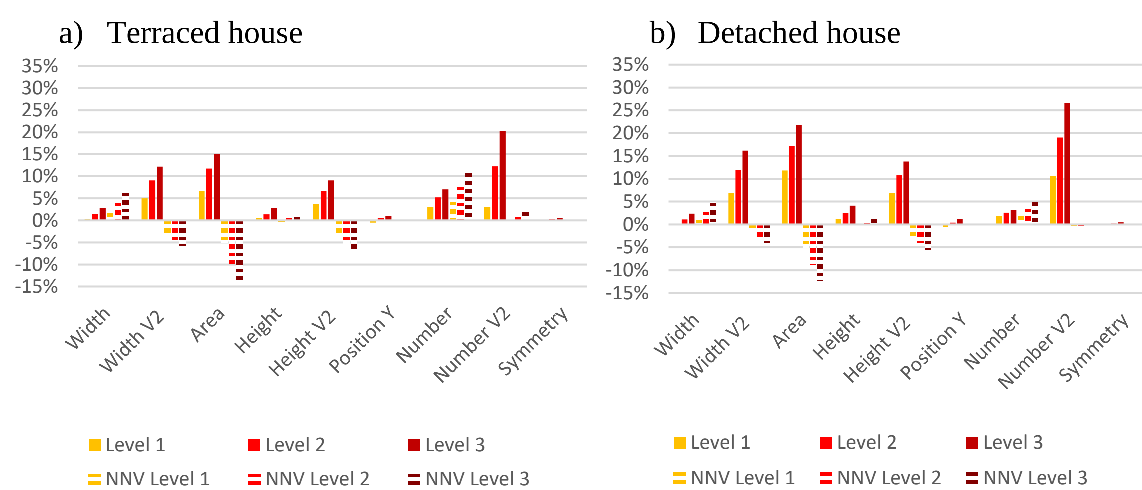
NNV: No natural ventilation, V2: Version 2

Figure 33: Percentage of the difference between all window configuration levels and benchmark building annual energy demand, (a) terraced house, (b) detached house



NNV: No natural ventilation, V2: Version 2

Figure 34: Percentage of the difference between all window configuration levels and benchmark building annual cooling load, (a) terraced house, (b) detached house



NNV: No natural ventilation, V2: Version 2

Figure 35: Percentage of the difference between all window configuration levels and benchmark building annual energy demand, (a) terraced house, (b) detached house

Window area was determined as the most influential parameter affecting annual energy consumption. Despite the fact that each window configurations have a clear impact trend (i.e. upward or downward) on annual energy consumption, other window configurations, except window area, have no considerable impact on annual energy consumption (see Figure 33); their impact was below 4% change in annual energy consumption. Larger window areas, such as the window area configurations and the second versions (V2) of window width, height, and number, caused significantly more annual energy consumption compared to other window configurations (up to 24%) (see Figure 33 and Figure 36). Compared to the benchmark building's annual energy consumption, the highest annual energy consumption alteration was achieved in the second version of window number configuration level 3 when natural ventilation is included (24% 103.00 kWh) and excluded (7% 28.25 kWh) (see Figure 33), as the window area was increased to 45 m^2 in this configuration.

The window area is the most influential parameter on the housing units' annual energy consumption, because it simultaneously influences housings' natural ventilation, infiltration, and direct solar gain. Natural ventilation is mainly related to the opening area, local wind speed, indoor and outdoor dry-bulb temperature difference, and the height from the midpoint of the opening to natural pressure level (see Eq. 23 and Eq. 24). The window area is also influential on the amount of solar beam reaching inside houses; it is in accordance with the position of the sun, the height and width of the windows, and the depth of the outside and inside reveal surfaces (see Eq. 19 and Eq. 20). In addition, the window area has an indirect influence on infiltration, which is generally caused due to the cracks around windows and building elements. The infiltration rate depends on the effective air leakage area, the absolute temperature difference between zone air and outdoor air, and the local wind speed (see Eq. 25).

In order to observe the impact of window parameters on the housings' annual energy consumption in more detail, normalized annual energy consumption and window parameters for each window configuration (with Eq. (28)) are compared in Figure 36. For this purpose, window configurations were sequenced from the highest annual energy consumption value to the lowest one (see Figure 36). Accordingly, a clear linear relationship can be observed only between the window area and annual energy consumption. Pearson's correlation analysis was also utilised to investigate these relationships in more detail. According to the results, there is a positive correlation between the annual energy consumption and window area (r = 0.495, p = 0.000), and number (r = 709, p = 0.000). No meaningful correlation was observed between the annual energy consumption and the rest of the studied window parameters (p>0.05).

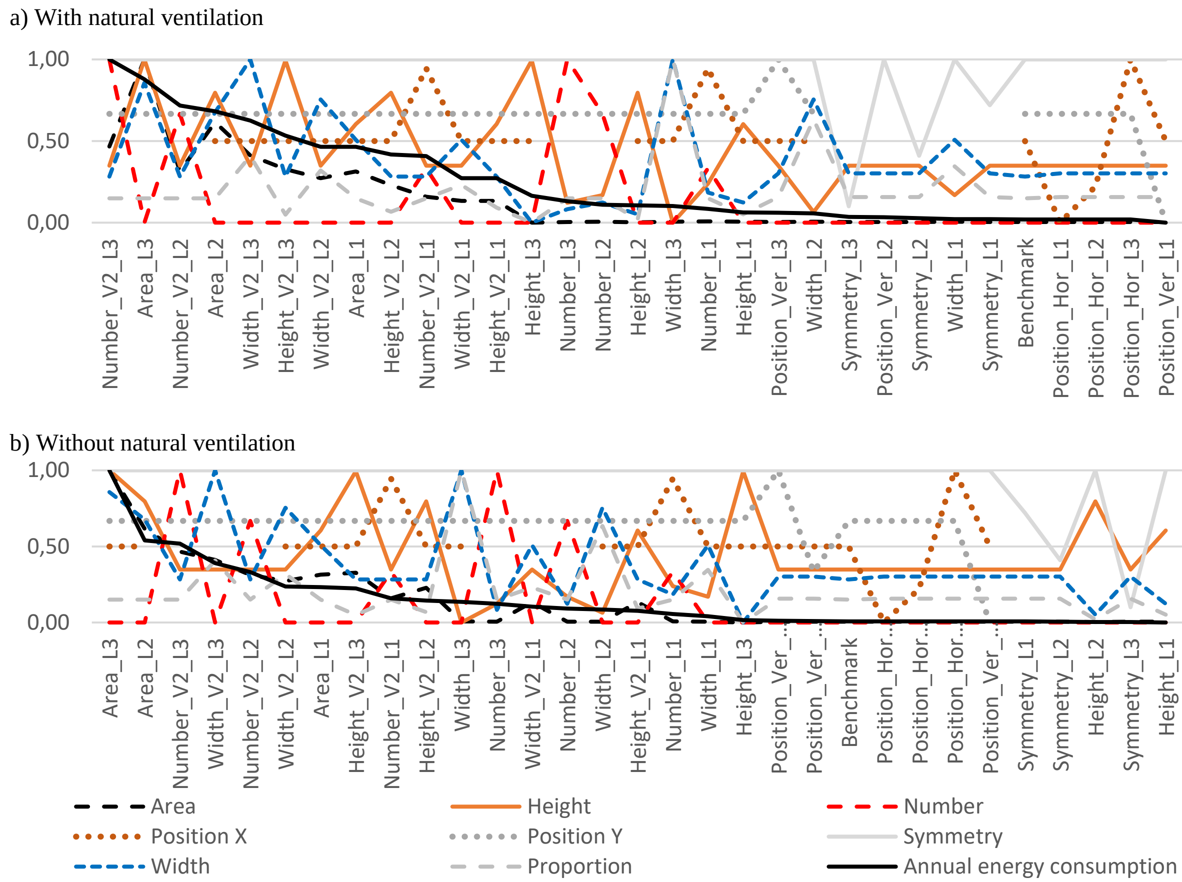


Figure 36: Normalized values for all window parameters and annual energy consumption in detached house.

6.2.3.1 Summary

- Housing typology (detached-terraced) does not influence energy consumption trends in applied window configurations. In general, window configurations have a more pronounced impact on annual energy consumption in detached houses, due to their greater number of windows.

- Detached houses consume more energy compared to terraced houses.

- In London weather conditions, heating load is responsible for the major portion of annual energy consumption.

- Window area is the most influential parameter affecting annual energy consumption; in contrast, other window configurations have no considerable impact on annual energy consumption.

- There is a positive correlation between the annual energy consumption and window area and number. There is no meaningful correlation observed between the annual energy consumption and the rest of the studied window parameters.

6.2.4 Multidimensional measurement model (MMM) developed via computational predictive models (PM)

This section discuss the performance of the developed multidimensional measurement model (MMM in Figure 5), which is a validated ANN and decision tree-based predictive model (PM in Figure 5). Predictive models were developed via the data obtained from the results of the fourth survey (S4, Figure 5), BES (ES in Figure 5), and symmetry data obtained from the developed symmetry index (SI in Figure 5). The ANN and decision tree models were developed via aesthetic and annual energy consumption results for detached houses (including natural ventilation scenarios), based on the rationale discussed in previous sections (see Section 6.2.2, 6.1.4.1, and 6.2.3). Utilised BES data was based on the natural ventilation-included scenario to reproduce more realistic scenarios. Further technical details about the development and validation procedure of the predictive models can be found in Section 5.4.

6.2.4.1 Prediction of housings' aesthetic and marketability

The comparison of the normalized survey results and predictive models' predictions are given in Table 23. Both ANN (MSE: 1.73E-04), and decision tree (MSE: 4.23E-04) models predict the aesthetic appreciation for all housing photos (see Table 24) with high accuracy (See Table 23). Surprisingly, the ANN model showed better performance to predict aesthetic appreciation for housings photos in the experimental (Exp.) category[38] (MSE: 3.46E-05), compared to housings photos in the training category (MSE: 1.94E-04). Despite there being no significant difference, compared to the training category (MSE: 4.10E-04), the aesthetic appreciation prediction performance of the decision tree model was slightly lower in the experimental category (MSE: 5.09E-04) (see Table 23).

[38] The rationale and details behind the experimental and training categories for studied buildings was discussed in the Section 5.2.3.

Table 23: Performance of ANN and decision tree predictions

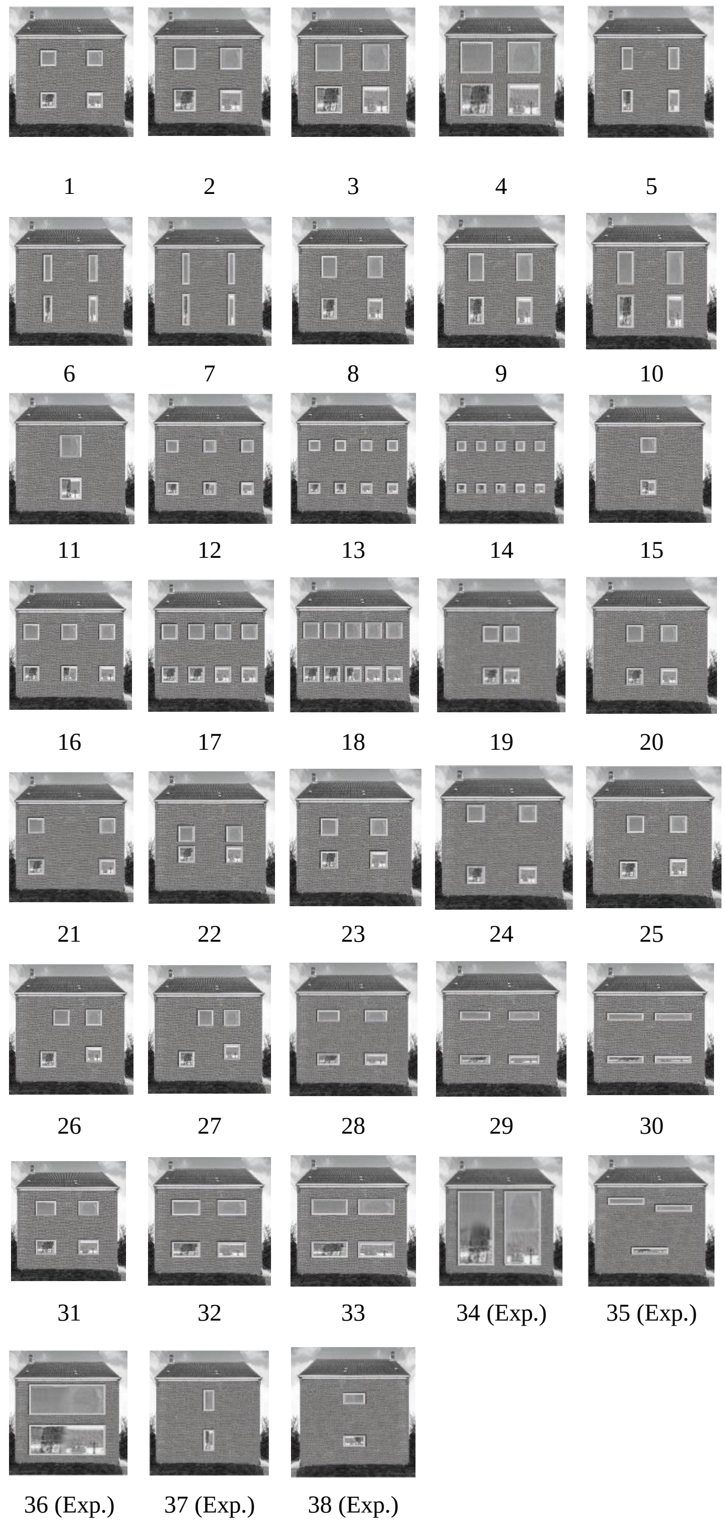
Housing No	Housing name	Normalized Survey mean	Normalized ANN prediction	ANN-Survey Squared error (SE)	Normalized Decision Tree (DT) prediction	DT- Survey Squared error (SE)
1	Benchmark	0.262	0.260	4.00E-06	0.289	7.29E-04
2	Area_L1	1.000	1.000	0.00E+00	0.958	1.76E-03
3	Area_L2	0.912	0.910	4.00E-06	0.958	2.12E-03
4	Area_L3	0.681	0.680	1.00E-06	0.724	1.85E-03
5	Height_L1	0.564	0.560	1.60E-05	0.560	1.60E-05
6	Height_L2	0.388	0.384	1.60E-05	0.390	4.00E-06
7	Height_L3	0.251	0.250	1.00E-06	0.250	1.00E-06
8	Height_V2_L1	0.824	0.820	1.60E-05	0.825	1.00E-06
9	Height_V2_L2	0.835	0.830	2.50E-05	0.825	1.00E-04
10	Height_V2_L3	0.754	0.750	1.60E-05	0.724	9.00E-04
11	Number_L1	0.325	0.320	2.50E-05	0.320	2.50E-05
12	Number_L2	0.393	0.390	9.00E-06	0.390	9.00E-06
13	Number_L3	0.306	0.310	1.60E-05	0.310	1.60E-05
14	Number_L4	0.181	0.190	8.10E-05	0.175	3.60E-05
15	Number_V2_L1	0.142	0.140	4.00E-06	0.109	1.09E-03
16	Number_V2_L2	0.644	0.640	1.60E-05	0.640	1.60E-05
17	Number_V2_L3	0.538	0.550	1.44E-04	0.540	4.00E-06
18	Number_V2_L4	0.305	0.310	2.50E-05	0.310	2.50E-05
19	Poziton_X_L1	0.113	0.110	9.00E-06	0.109	1.60E-05
20	Poziton_X_L2	0.322	0.320	4.00E-06	0.289	1.09E-03
21	Poziton_X_L3	0.203	0.200	9.00E-06	0.200	9.00E-06
22	Poziton_Y_L1	0.139	0.140	1.00E-06	0.140	1.00E-06
23	Poziton_Y_L2	0.455	0.450	2.50E-05	0.450	2.50E-05
24	Poziton_Y_L3	0.270	0.270	0.00E+00	0.289	3.61E-04
25	Symmetry_L1	0.075	0.000	5.63E-03	0.023	2.70E-03
26	Symmetry_L2	0.015	0.000	2.25E-04	0.023	6.40E-05
27	Symmetry_L3	0.000	0.008	6.40E-05	0.023	5.29E-04
28	Width_L1	0.392	0.390	4.00E-06	0.390	4.00E-06
29	Width_L2	0.172	0.170	4.00E-06	0.175	9.00E-06
30	Width_L3	0.066	0.069	9.00E-06	0.070	1.60E-05
31	Width_V2_L1	0.779	0.780	1.00E-06	0.780	1.00E-06
32	Width_V2_L2	0.776	0.780	1.60E-05	0.780	1.60E-05
33	Width_V2_L3	0.641	0.640	1.00E-06	0.640	1.00E-06
		Survey-ANN MSE for training photos:		1.94E-04	Survey-DT MSE for training photos:	4.10E-04
34	Experiment 1	0.445	0.440	2.50E-05	0.428	2.89E-04
35	Experiment 2	0.001	0.012	1.21E-04	0.023	4.84E-04
36	Experiment 3	0.415	0.410	2.50E-05	0.428	1.69E-04
37	Experiment 4	0.139	0.140	1.00E-06	0.140	1.00E-06
38	Experiment 5	0.069	0.070	1.00E-06	0.109	1.60E-03
		Survey-ANN MSE for experiment photos:		3.46E-05	Survey-DT MSE for experiment photos:	5.09E-04
			Overall Survey-ANN MSE:	1.73E-04	Overall Survey-DT MSE:	4.23E-04

In order to test the performance of the developed predictive models in detail, another study was conducted. Firstly, the results of survey and the predictions made by the ANN and decision tree models were normalized via Eq. (28), then all studied housing photos were sequenced from the most to least attractive based on the results of the survey and the predictive models' predications. Finally, the consistency between the sequences obtained from the survey and predictive models were compared (see Table 24). The mispredicted and potentially mispredicted sequenced photos are represented with red and blue colours, respectively (see Table 24). In the blue coloured numbers, the sequence of the housing numbers can be either mispredicted or accurate, because aesthetic values belonging to blue-coloured numbers have the same aesthetic values as the previous or next housings. For example, according to the normalized survey results, the housing photo of #31 (0.779) is more attractive than #32 (0.776) (see Table 23 and Table 24). However, according to the normalized ANN prediction results, the housing photo #31 (0.780) and #32 (0.780) have the same aesthetic value, so when sequencing the housing photos, the order of the housing photos #31 and #32 can be either mispredicted or accurate. It was observed that both predictive models are insufficient in determining minor differences between the aesthetics of some photos, and accordingly computing the same aesthetic level for those photos (e.g. photo #31 and #32).

Overall, both the ANN and decision tree models have consistent performance in sequencing the housing photos, with accuracy compared to the survey results varying between 63-95% and 24-92%, respectively (Table 24). Using ANN and decision tree models, the numbers of photos mispredicted were 2 and 3, and the numbers of potentially mispredicted photos were 12 and 26, respectively. Accordingly, in the estimation of the sequence of 38 photos (from most attractive to least atractive), correct sequences of 63-95% can be achieved with ANN, and 24-93% with decsion tree. Both ANN model and decision tree models were successful to predict the sequence of five experimental photos, which are the new dataset utilized for validation of the developed predictive models (see Section 5.4.2 and Table 24).

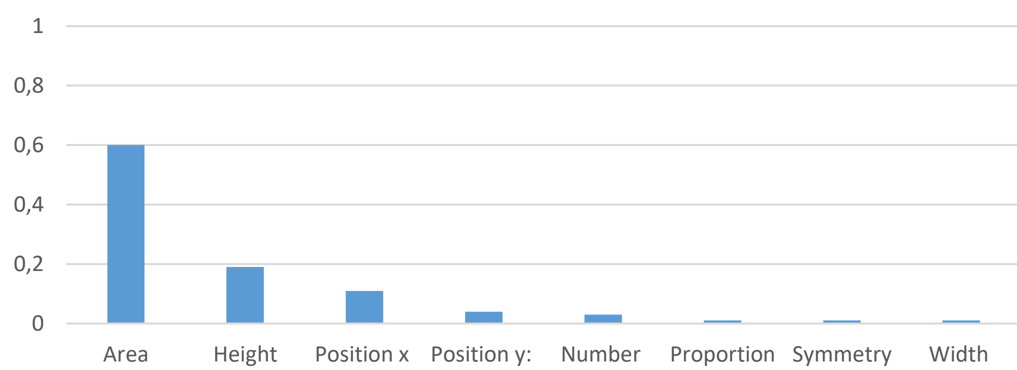
Table 24: Comparison of hierarchical order when photos were sequenced from the most attractive to the least one

	Survey	ANN	Decision tree
Prediction accuracy		%95-63	%92-24
	2	2	2
	3	3	3
	9	9	9
	8	8	8
	31	31	31
	32	32	32
	10	10	10
	4	4	4
	16	16	16
	33	33	33
	5	5	5
	17	17	17
	23	23	23
	34	34	34
	36	36	36
	12	12	12
	28	28	28
	6	6	6
Housing No	11	11	11
	20	20	13
	13	13	18
	18	18	24
	24	24	1
	1	1	20
	7	7	7
	21	21	21
	14	14	14
	29	29	29
	15	15	22
	22	22	37
	37	37	15
	19	19	19
	25	38	38
	38	30	30
	30	35	26
	26	27	35
	35	25	27
	27	26	25



* Red and blue coloured numbers represent the mispredicted sequence and potential mispredicted sequence photos, respectively

Considering the fact that, statistically, the probability to achieve correct sequence for the aesthetic level of the studied 38 photos is 9.29E-61, both predictive models have shown very high prediction performance. Overall, ANN model shows better prediction performance (63-95% prediction accuracy, MSE: 1.73E-04) compared to decision tree (24-92% prediction accuracy, MSE: 4.23E-04), as it is a more flexible approach (see Table 23 and Table 24). While the decision tree model has limited levels of tree depth for the predictions (i.e. nine levels (see Figure 38)), the ANN calculates suitable weights for each of the individual parameters (see Figure 16 and Section 5.4.1.2). The developed decision tree based predictive model is illustrated in Figure 38. The decision tree has nine levels, beginning with the window area in its root, which is the most influential parameter that affects aesthetic of housings (see Figure 38). Predictor importance is illustrated in Figure 37. Decision tree approaches target the predictors that matter most, and target dropping or ignoring those that matter least, to achieve simplicity and compactness in the developed tree (See Eq. 11, and Eq. 13). The predictor importance chart (generated by SPSS) illustrates this by indicating the relative importance of each predictor in the developed predictive model. The importance of each predictor to predict the aesthetic appreciation of participants in all utilised housing photographs can be summarized as: area > height > position on X-axis > position on Y-axis > number > proportion = symmetry = width (see Figure 37).



*1 most important, 0 least important

Figure 37: Predictor importance obtained from the decision tree approach

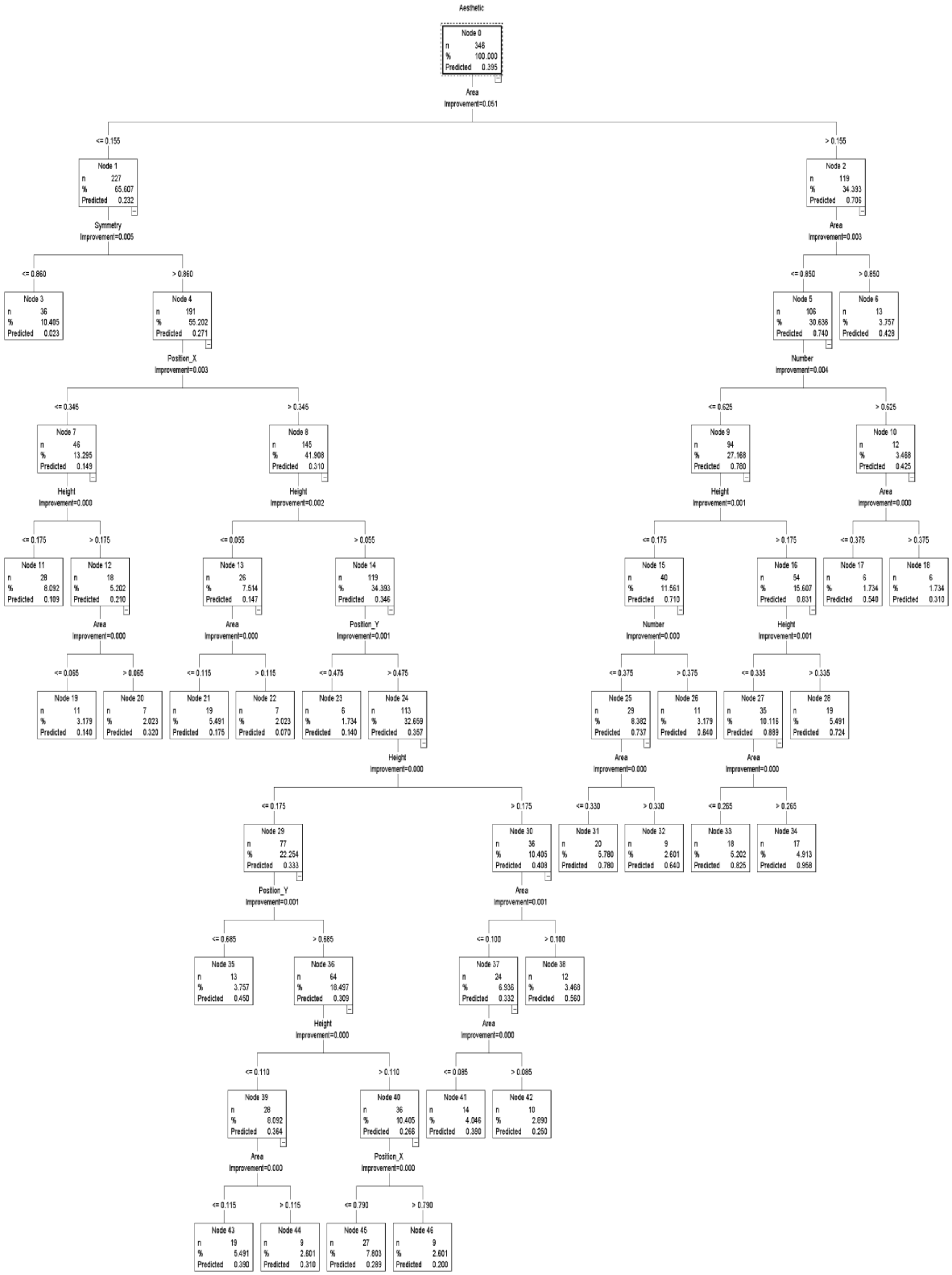


Figure 38: Housing aesthetic and marketability prediction model (decision tree) for window parameters (see Appendix L for larger illustration)

In order to use the developed decision tree in the future studies to compare the housings' aesthetic, the window parameters of the housings should be first normalized, then the pattern from the root toward the leaves of the decision tree should be followed based on the values obtained from the normalized window parameters. For example, as the window area is determined as the most important predictor, the root of the decision tree begins with the window area values. If the window area of a focused housing unit is smaller than or equal to 0.115, then the left branch will be followed. If the window area is bigger than 0.115, then the right branch will be followed (see Figure 38). The same process should be repeated for each branch until reaching the end of that pathway (leaf), where the predicted aesthetic value on that leaf can be accordingly found.

6.2.4.2 Prediction of housings' annual energy consumption

The comparison of the normalized BES results and predictive models' predictions are illustrated in Table 25. ANN model predicts the annual energy consumption of all housing photos with reasonable accuracy (MSE: 5.88E-03). Comparable predictions cannot be made with the decision tree approach (MSE: 9.07E-02) (See Table 25). The consistency between the sequences obtained from the BES and predictive models are compared in Table 26. Compared to the sequence obtained from BES results, the accuracy of predictive models to sequence the studied housings from the least to most energy efficient one was 52% in ANN, and varied from 15-82% in the decision tree model. The numbers of mispredicted housings by ANN and decision tree models were 16 and 6, respectively. There were no potentially mispredicted houses by ANN, but decision tree models generated 22 potentially mispredicted houses (see Table 26).

The predictor importance is illustrated in Figure 39. Window area is determined as the most and only predominant predictor in annual energy consumption prediction (See Figure 39). Predictor importance for the housings' annual energy consumption can be summarized as area > height =

number = position on Y-axis = proportion > position on X-axis = width = symmetry (see Figure 39). The developed decision tree is illustrated in Figure 40.

**1 most important, 0 least important*

Figure 39: Predictor importance for housings energy efficiency

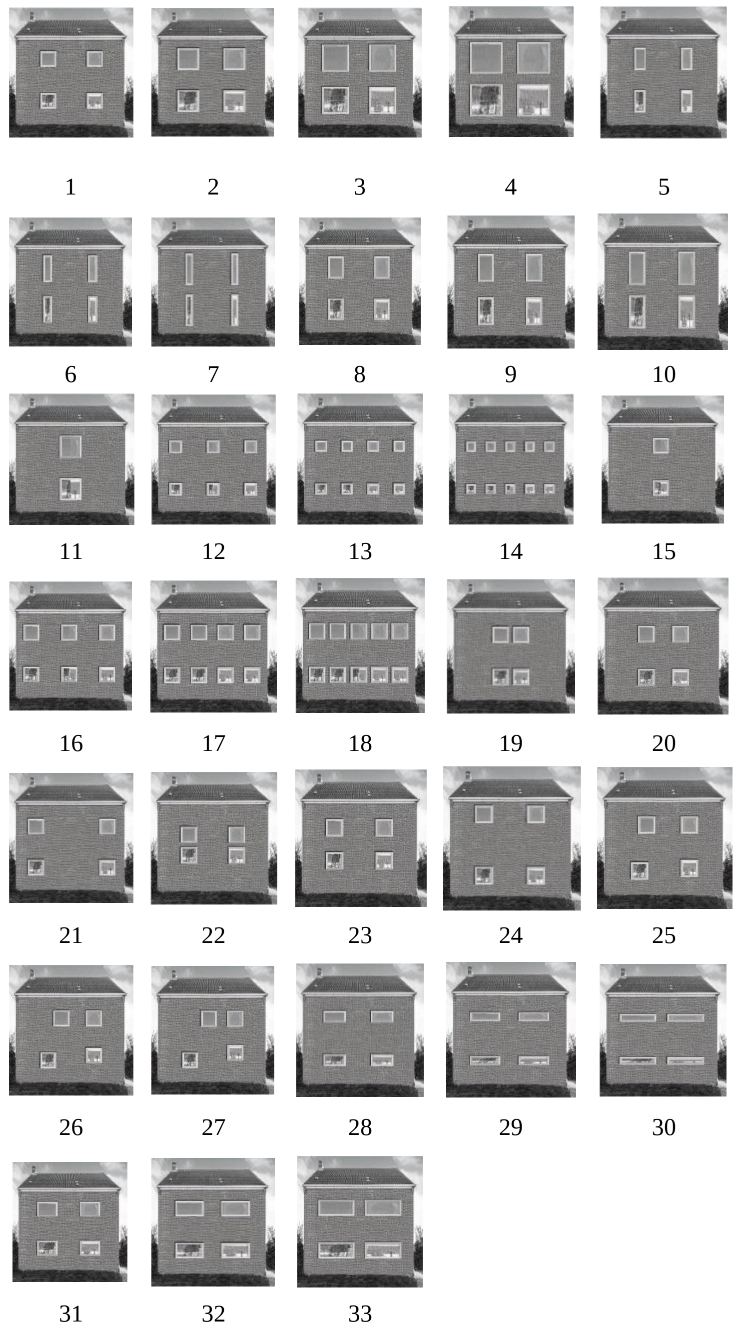
Surprisingly, overall, the annual energy consumption prediction performance of ANN and decision tree models (i.e. MSE of ANN: 5.88E-03, MSE of decision tree: 9.07E-02) were considerably lower when compared with their aesthetic prediction performance (i.e. MSE of ANN: 1.73E-04, MSE of decision tree: 4.23E-04). This was surprising because a model that can predict an abstract phenomenon which has complex dynamics with high accuracy, such as aesthetic appreciation, was expected to show much better performance to predict annual energy consumption of housings based on physical laws, quantifiable phenomena, and mathematical models. In addition, in the previous studies, ANN models have shown high performance to estimate the energy consumption and better performances of ANNs compared to other models such as regression models was reported (Tso & Yau, 2007). The reason for this unpredicted result can be explained by the number of predictors that impact predictions. Four parameters (i.e. area, height, position, and number) affected aesthetic predictions, and the differences in the importance levels of those parameters were reasonable (see Figure 37). In contrast, in annual energy consumption predictions, there was only one dominant parameter (i.e. area) affecting predictions, and the difference of the impact level between window area and other parameters on annual energy consumption predictions (i.e. height, position, number and proportion) was tremendously high (see Figure 39). Accordingly, predictions were mainly based on one parameter in annual energy consumption predictions, which limited the sensitivity of predictions to the fluctuations caused by other window parameters. As discussed in more detail in Section 6.2.4.3, in the context of YYP, developing predictive models for predicting housings' annual energy consumption is not practical. Therefore, coupling the aesthetic and marketability measurement model with one of the existing user-friendly BES programs via plug-in can be proposed as a more pragmatic strategy to ensure the applicability of YYP. Yet, this was not the focus of this work and further research on this is recommended.

Table 25: Performance of decision tree predictions for aesthetic appreciation and energy efficiency of detached housing

Housing name	Normalized annual energy consumption of detached house with natural ventilation	ANN Energy simulation prediction	ANN Energy simulation Squared error	DT Energy simulation prediction	DT Energy simulation Squared error
Benchmark	0.019	0.020	1.00E-06	0.410	1.53E-01
Area_L1	0.464	0.624	2.56E-02	0.720	6.55E-02
Area_L2	0.682	0.681	1.00E-06	0.660	4.84E-04
Area_L3	0.878	0.880	4.00E-06	0.880	4.00E-06
Height_L1	0.062	0.061	1.00E-06	0.410	1.21E-01
Height_L2	0.106	0.110	1.60E-05	0.410	9.24E-02
Height_L3	0.165	0.160	2.50E-05	0.410	6.00E-02
Height_V2_L1	0.272	0.269	9.00E-06	0.038	5.48E-02
Height_V2_L2	0.418	0.415	9.00E-06	0.270	2.19E-02
Height_V2_L3	0.534	0.547	1.69E-04	0.446	7.74E-03
Number_L1	0.083	0.077	3.60E-05	0.410	1.07E-01
Number_L2	0.111	0.129	3.24E-04	0.410	8.94E-02
Number_L3	0.132	0.516	1.47E-01	0.410	7.73E-02
Number_V2_L1	0.408	0.374	1.16E-03	0.038	1.37E-01
Number_V2_L2	0.718	0.753	1.23E-03	0.720	4.00E-06
Number_V2_L3	1.000	0.999	1.00E-06	1.000	0.00E+00
Poziton_X_L1	0.019	0.048	8.41E-04	0.410	1.53E-01
Poziton_X_L2	0.019	0.026	4.90E-05	0.410	1.53E-01
Poziton_X_L3	0.019	0.026	4.90E-05	0.410	1.53E-01
Poziton_Y_L1	0.000	0.002	4.00E-06	0.410	1.68E-01
Poziton_Y_L2	0.033	0.005	7.84E-04	0.410	1.42E-01
Poziton_Y_L3	0.060	0.101	1.68E-03	0.410	1.23E-01
Symmetry_L1	0.021	0.000	4.41E-04	0.410	1.51E-01
Symmetry_L2	0.027	0.000	7.29E-04	0.410	1.47E-01
Symmetry_L3	0.036	0.001	1.23E-03	0.410	1.40E-01
Width_L1	0.022	0.025	9.00E-06	0.410	1.51E-01
Width_L2	0.057	0.063	3.60E-05	0.410	1.25E-01
Width_L3	0.103	0.114	1.21E-04	0.410	9.42E-02
Width_V2_L1	0.273	0.277	1.60E-05	0.038	5.52E-02
Width_V2_L2	0.465	0.473	6.40E-05	0.270	3.80E-02
Width_V2_L3	0.626	0.642	2.56E-04	0.446	3.24E-02
	Mean squared errors (MSE):	ANN:	5.88E-03	Decision tree:	9.07E-02

Table 26: Comparison of the hierarchical order when houses were sequenced from least to most energy efficient

	BES	ANN	Decision tree
Prediction accuracy		%52	%82-15
Housing No	18	18	18
	17	17	17
	4	4	4
	16	16	2
	3	3	16
	33	14	3
	10	33	33
	32	2	10
	2	10	7
	9	13	14
	15	32	13
	31	9	12
	8	15	6
	7	31	30
	14	8	11
	13	7	5
	12	12	24
	6	30	29
	30	6	27
	11	24	23
	5	11	26
	24	29	28
	29	5	25
	27	19	1
	23	20	19
	26	21	20
	28	28	21
	25	1	22
	1	23	32
	19	22	9
	20	27	31
	21	25	15
	22	26	8



* Red and blue coloured numbers represent the mispredicted sequence and potential mispredicted sequence photos, respectively

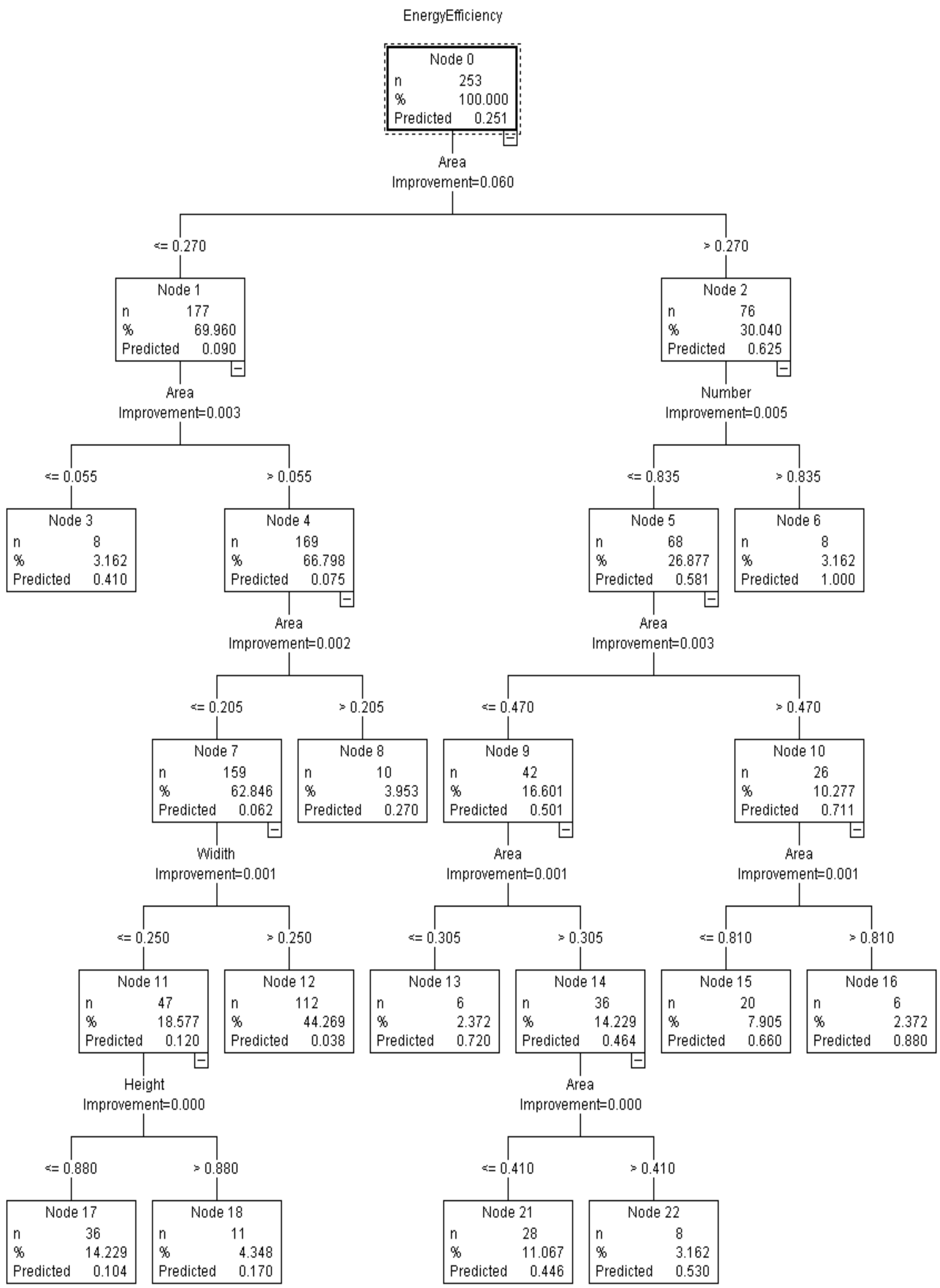


Figure 40: Housing energy efficiency prediction model (decision tree) via window parameters

6.2.4.3 Multidimensional measurement model

The multidimensional measurement model is a validated and ready-to-use version of ANN and decision tree-based predictive models developed to test the feasibility of the YYP. Overall, the developed aesthetic and marketability measurement model (i.e. ANN model and the decision tree in Figure 38) show very high performance to predict individuals' judgements based on the window configurations of housings. Accordingly, it can utilised in the future studies to compare the aesthetic and marketability of identical, low-rise, brick, terraced, and detached UK houses.

The developed aesthetic and marketability measurement model provided promising results for the applicability of the YYP, the validity of the objectivist doctrine in aesthetic judgment, and the feasibility of the computational aesthetic approach. The high performance of the proposed aesthetic and marketability measurement model clearly shows that there is a rationale behind the aesthetic judgements and buying decision of individuals, which can be predicted and modelled via computational approaches considering certain building parameters, particularly windows. This result is also in favour with the existence of common aesthetic appreciation (i.e. objectivist doctrine), because if there was no common aesthetic judgment, it would not be possible to predict the aesthetic judgment of the majority of participants via computational approaches. However, considering the limitations of this thesis (i.e. just considering windows), it should be underlined that the results obtained are insufficient to assert the existence of a common aesthetic judgment in a general context. This thesis only provides supportive arguments for the existence of common aesthetic judgment, but does not end the primordial debate about the subjectivity and objectivity of aesthetic judgment. Another point that should be emphasized is that this thesis does not claim that aesthetic judgment can be predicted at the individual level. The predictive models developed in this research and the more advanced models that can foreseeably be developed in the future can only model the common aesthetic judgements of the majority of housing customers but not each of the individuals.

It should be noted that the developed aesthetic and marketability measurement tools are limited to predicting the impact of identical windows on aesthetic judgement. Predicting the impact of the combination of different window configurations on the same façade with the proposed multidimensional measurement model may lead to misleading results. Considering the fact that most existing housings have combinations of different window configurations, the proposed measurement model is not yet ready to be applied for all housing scenarios. In order to develop multidimensional measurement tools that can be applied in real-life scenarios, further studies are necessary. For this purpose, first the mutual impacts of the combinations of different window configurations and other building parameters (e.g. building material, roof, colour, and architectural style etc.) on individuals' judgement must be investigated, and then much more sophisticated and advanced multidimensional measurement tools must be developed accordingly.

Surprisingly, compared to the performance achieved in aesthetic and marketability measurement tool, relatively poor performance was achieved in annual energy consumption measurement tool. This was because window area was the predominant parameter in terms of its impacts on annual energy consumption, which limited the sensitivity of the model to predict the impacts of other studied window parameters. Considering the performance of aesthetic and marketability measurement model to predict complex and abstract phenomena, such as individuals' aesthetic perceptions and decision making, it reasonable to claim the possibility to achieve better performance in scenarios utilising a greater number of effective parameters on annual energy consumption. Nevertheless, in general, developing multidimensional measurement tools for predicting housings' annual energy consumption is not efficient and practical due to three reasons: (1) BES programs that are very successful to simulate energy consumption of buildings are already available, (2) it is not rational to expect the multidimensional energy consumption measurement model to show same performance as current BES programs, because predictive models are trained with BES results, and it is not possible for the developed prediction models to have 100% prediction accuracy, (3) development of these multidimensional models is too time-consuming.

Therefore, coupling the aesthetic and marketability measurement model with one of the existing user-friendly BES programs via plug-in can be proposed as a more pragmatic strategy to ensure the applicability of YYP. Parametric data about the utilised housing model in the BES can be transferred to the pre-developed aesthetic and marketability measurement tool. In this way, the user can observe the energy efficiency, aesthetic and marketability of housings simultaneously, and take improvement decisions accordingly. However, it should be noted that coupling the aesthetic and marketability measurement model with BES program is out of the scope of this thesis, and this is proposed as a pragmatic solution that can developed in further studies. As a pioneering work, this Ph.D. thesis focuses on the validity of the theoretical concepts such as the phenomenon of IIBEE, widespread adoption approach, and YYP, and it opens an unexplored areas and new avenues for future studies focused on energy demand reduction in the building sector.

6.2.4.4 Summary

- Aesthetic and marketability measurement model show very high performance to predict individuals' judgements based on the window configurations of housings, yet relatively poor performance was achieved in annual energy consumption measurement model because window area was the only predominant parameter.

- The developed aesthetic and marketability measurement model provided promising results for the applicability of the YYP, the validity of the objectivist doctrine in aesthetic judgment, and the feasibility of the computational aesthetic approach.

- The proposed multidimensional measurement model is not yet ready to be applied for all housing scenarios due to its limitations. In order to develop multidimensional measurement tools that can be applied in real-life scenarios, further studies are necessary.

- Developing multidimensional measurement tools for predicting housings' annual energy consumption is not efficient and practical, thus coupling the aesthetic and marketability measurement model with user-friendly BES program can be a pragmatic solution for the applicability of YYP.

6.3 Limitations and future studies

- This thesis focuses on only the validity of the proposed theoretical concepts such as the phenomenon of IIBEE, widespread adoption approach, and YYP. Despite strong empirical evidences found for the validity of the proposed novel phenomenon and approach, further studies are required to claim the applicability of YYP in the building design. Coupling more advanced aesthetic and marketability measurement tools with a BES program is proposed as an expedient technique that can be developed in further studies.

- This thesis is limited to the UK housing. Therefore, it may be necessary to investigate the applicability of the proposed widespread adoption approach in countries with different climate, economy and development levels.

- This thesis is limited to low-rise detached and terraced UK residential housings, and thus the impact of building typologies (e.g. high-rise buildings, apartments, offices, and commercial buildings) should be investigated in future studies.

- The developed aesthetics and marketability measurement models are limited for prediction of the impact of identical windows on facades. Considering the fact that most existing housings have combinations of different window configurations and other physical aspects (e.g. materials, doors and other building components, and architectural typology etc.), these models needs further development to be yet practical to be applied for realistic housing scenarios.

- This thesis is limited to the impact of seven window parameters on housings' aesthetic, energy efficiency and marketability. The impact of other window features such as window typologies and shutters should be investigated in future studies.

- The optimal window area, for aesthetic, marketability and energy efficiency should be determined in future studies.

- Since in this thesis, two different studies about the relationship between aesthetics and symmetry have contradictory results, more studies should be done on this two parameters and window configurations.

CHAPTER VII

CONCLUSION

CHAPTER VII.

CONCLUSION

This chapter summarises the thesis and provide conclusion.

7.1 Overall summary of the thesis

In this Ph.D. thesis, the novel phenomenon of IIBEE was introduced. The lack of widespread adoption of EEBs due to their market failure was determined as the main reason behind the phenomenon of IIBEE. Increasing the number of EEBs with better marketability obtained with the enhancement of their aesthetic was introduced as a novel approach (widespread adoption approach) to tackle with the phenomenon of IIBEE. The aesthetic judgment differences between architects and clients and efficiency problems of the conventional paradigm and IDA were identified as the main obstacles to the applicability of the proposed widespread adoption approach in the practice. Therefore, the innovative YYP was introduced. The applicability of YYP in practice was tested with the performance of a multidimensional measurement model effective in evaluating different housing aspects.

In order to investigate the applicability of the proposed widespread adoption approach, two comprehensive surveys were conducted, and to develop these surveys eight pre-studies were conducted. Once valid evidences about the applicability of the proposed widespread adoption approach in UK were achieved in the conducted two main surveys, the study was extended to test the applicability of YYP. Ensuring the applicability of YYP in the context of building sector energy demand reduction targets necessitated a multidimensional measurement model or new generation simulation tools effective in measuring different aspects of housing, such as aesthetic marketing and energy efficiency. For this purpose, this thesis developed an ANN and decision tree-based computational predictive models, to predict the impact of the seven studied window parameters on housing aesthetics, marketability, and energy efficiency. In order to develop computational predictive models, a comprehensive survey, BES and novel symmetry index were utilized. Then developed predicative models' performance was tested according to the results of a comprehensive survey and BES.

7.2 Conclusion

- In the UK housing sector, it is unrealistic to expect to achieve considerable enhancement of EEBs' marketability and widespread adoption by highlighting or enhancing their energy performances and/or reducing their prices without new marketing motivations such as aesthetic enhancement.

- EEBs are facing market resistance in the UK building market because energy efficiency features have very low market value in the eyes of housing buyers, and they have higher price compared to conventional buildings. All these shortcomings of EEBs support the existence of the proposed phenomenon of IIBEE in the UK.

- The phenomenon of IIBEE can be overcome via the aesthetic enhancement of EEBs. Even with minor aesthetic enhancement, significant marketability and monetary added value enhancement (in the eyes of buyers) can be achieved in housing. Accordingly, EEBs become more marketable when they have a more attractive appearance, and if EEBs would be more marketable, then their numbers in UK building stock would increase naturally in response. In other words, the proposed widespread adoption approach is premised on strong fundamentals and is highly applicable in the UK housing market.

- Amongst the studied window parameters, window area was determined to be the most influential parameter that simultaneously affects housings' aesthetic, marketability, and energy efficiency. Therefore, special importance should be attributed to window area during the design of EEBs.

- The proposed YYP has great potential to ensure the applicability of the proposed widespread adoption approach, and overcome the obstacles related to the applicability issues of IDA and aesthetic judgement differences between architects and clients.

- Developed aesthetic and marketability measurement model provides promising results for the applicability of the YYP. Yet, it is also too early to claim that the YYP is applicable in practice for housing design. Nevertheless, the generated aesthetic and marketability predictive model and its performance to measure individuals' cognitive perceptions provides enough empirical evidence to encourage further studies in this field, emphasising the potential achievements that can be obtained (e.g. widespread adoption of EEBs and development of computer aided design).

- As a pioneering work, this Ph.D. thesis focuses on only the validity of the proposed theoretical concepts such as the phenomenon of IIBEE, widespread adoption approach, and YYP, and it opens an unexplored areas and new avenues for future studies focused on energy demand reduction in the building sector.

REFERENCES

Aabrekk, S. E., & Haavik, T. (2007). *Business opportunities in sustainable housing. A Marketing guide based on experiences from 10 countries. SHC task 28/ECBCS Annex 38. International Energy Agency (IEA)*. Klagenfurt Austria.

Adnan, F., & Yunus, R. M. (2012). The Influence of Curvilinear Architectural Forms on Environment-Behaviour. *Procedia - Social and Behavioral Sciences*, *49*, 341–349.

Agatonovic-Kustrin, S., & Beresford, R. (2000). Basic concepts of artificial neural network (ANN) modeling and its application in pharmaceutical research. *Journal of Pharmaceutical and Biomedical Analysis*, *22*, 717–727.

Akalin, A., Yildirim, K., Wilson, C., & Kilicoglu, O. (2009). Architecture and engineering students' evaluations of house façades: Preference, complexity and impressiveness. *Journal of Environmental Psychology*, *29*(1), 124–132.

Akca, B. Ö. (2011). *Mimarlikta genel estetik değerlendirme ve çağrişimsal anlam: bir araç olarak analoji*. Gazi Universitesi.

Alcott, B. (2005). Jevons' paradox. *Ecological Economics*, *54*(1), 9–21.

Almási, A. D., Woźniak, S., Cristea, V., Leblebici, Y., & Engbersen, T. (2016). Review of advances in neural networks: Neural design technology stack. *Neurocomputing*, *174*, 31–41.

Alwin, D. F., & Krosnick, J. A. (1991). The reliability of survey attitude measurement the influence of question and respondent attributes. *Sociological Methods & Research*, *20*(1), 139–181.

Arriaza, M., Cañas-Ortega, J. F., Cañas-Madueño, J. A., & Ruiz-Aviles, P. (2004). Assessing the visual quality of rural landscapes. *Landscape and Urban Planning*, *69*(1), 115–125.

Asan, H. (2006). Numerical computation of time lags and decrement factors for different building materials. *Building and Environment*, *41*(5), 615–620.

ASHRAE. (2013). *ANSI/ASHRAE Standard 55-2010 - Thermal Environmental Conditions for Human Occupancy*. Retrieved from https://www.ashrae.org/File Library/Technical Resources/Standards and Guidelines/Standards Addenda/55_2010_g_Final.pdf

Audenaert, A., De Cleyn, S. H., & Vankerckhove, B. (2008). Economic analysis of passive houses and low-energy houses compared with standard houses. *Energy Policy*, *36*(1), 47–55.

Aydin, T. O., Smolic, A., & Gross, M. (2015). Automated aesthetic analysis of photographic images. *IEEE Transactions on Visualization and Computer Graphics*, *21*(1), 31–42.

Aydin, Y. C., & Mirzaei, P. A. (2017). Wind-driven ventilation improvement with plan typology alteration: A CFD case study of traditional Turkish architecture. *Building Simulation*, *10*(2), 239–254.

Baharvand, M., Hamdan, M., Ahmad, B., Safikhani, T., Binti, R., & Majid, A. (2013). DesignBuilder Verification and Validation for Indoor Natural Ventilation. *Journal of Basic and Applied Scientific Research*, *3*(4), 182–189.

Bansal, N. K., Garg, S. N., & Kothari, S. (1992). Effect of exterior surface colour on the thermal performance of buildings. *Building and Environment*, *27*(1), 31–37.

Basheer, I. A., & Hajmeer, M. (2000). Artificial neural networks : fundamentals , computing , design , and application. *Journal of Microbiological Methods*, *43*, 3–31.

Bashour, M. (2006). An objective system for measuring facial attractiveness. *Plastic and Reconstructive Surgery*, *118*(3), 757–774.

Beute, F., & de Kort, Y. A. W. (2013). Let the sun shine! Measuring explicit and implicit preference for environments differing in naturalness, weather type and brightness. *Journal of Environmental Psychology*, *36*, 162–178.

Bhattacharya, S., Sukthankar, R., & Shah, M. (2010). A framework for photo-quality assessment and enhancement based on visual aesthetics. In *Proceedings of the international conference on Multimedia - MM '10* (pp. 271–280). Firenze, Italy.

Birkhoff, G. D. (1933). *Aesthetic measure*. Cambridge: Harvard University Press.

Blackburn, S. (2016). *The Oxford Dictionary of Philosophy* (3th editio). Oxford: Oxford university Press.

Boccia, M., Barbetti, S., Piccardi, L., Guariglia, C., Ferlazzo, F., Giannini, A. M., & Zaidel, D. W. (2016). Where does brain neural activation in aesthetic responses to visual art occur? Meta-analytic evidence from neuroimaging studies. *Neuroscience and Biobehavioral Reviews*, *60*, 65–71.

Bourassa, S. C., Hoesli, M. E., & Sun, J. (2004). What's in a View ? *Environment and Planning A*, *36*(8), 1427–1450. Retrieved from file:///C:/Users/Y.C.A/Downloads/unige_5795_attachment01 (2).pdf

BRACE, I. (2013). *Questionnaire design: how to plan, structure, and write survey material for effective market research*. *Choice Reviews Online* (Vol. 51). Kogan Page Ltd. https://doi.org/10.5860/choice.51-0965

BREEAM. (2017). The number of BREEAM certificated buildings. Retrieved August 3, 2017, from http://www.breeam.com/

Buckley, B., & Logan, K. (2016). *World green building trends 2016: Developing markets accelerate global green growth. Dodge Data & Analytics*. Bedford. Retrieved from http://fidic.org/sites/default/files/World Green Building Trends 2016 SmartMarket Report FINAL.pdf

Cerosaletti, C. D., & Alexander, C. L. (2009). Measuring the perceived aesthetic quality of photographic images. In *Quality of Multimedia Experience, QoMEx 2009. International Workshop on. IEEE* (pp. 47–52).

Chan, A. L. S., & Chow, T. T. (2010). Investigation on energy performance and energy payback period of application of balcony for residential apartment in Hong Kong. *Energy and Buildings*, *42*(12), 2400–2405.

Chatterjee, A. (2011). Neuroaesthetics: A coming of age story. *Journal of Cognitive Neuroscience*, *23*(1), 53–62.

Chiang, Y. C., Nasar, J. L., & Ko, C. C. (2014). Influence of visibility and situational threats on forest trail evaluations. *Landscape and Urban Planning*, *125*, 166–173.

Chu, W.-T., Chen, Y.-K., & Chen, K.-T. (2013). Size Does Matter: How Image Size Affects Aesthetic Perception? *Proceedings of the 21st ACM International Conference on Multimedia*, *1*, 53–62.

Conti, J., Holtberg, P., Diefenderfer, J., LaRose, A., Turnure, J. T., & Westfall, L. (2016). *International Energy Outlook 2016 With Projections to 2040. No. DOE/EIA--0484 (2016). USDOE Energy Information Administration (EIA)*. Washington. Retrieved from https://www.eia.gov/outlooks/ieo/pdf/0484(2016).pdf

Costanzo, V., Evola, G., & Marletta, L. (2016). Energy savings in buildings or UHI mitigation? Comparison between green roofs and cool roofs. *Energy and Buildings*, *114*, 247–255.

Crawley, D. B., Hand, J. W., Kummert, M., & Griffit, B. T. (2008). Contrasting the capabilities of building energy performance simulation programs. *Building and Environment*, (43), 661–673.

Cubukcu, E., & Kahraman, I. (2008). Hue, saturation, lightness, and building exterior preference: An empirical study in Turkey comparing architects' and nonarchitects' evaluative and cognitive judgments. *Color Research and Application*, *33*(5), 395–405.

Datta, R., Joshi, D., Li, J., & Wang, J. Z. (2006). Studying aesthetics in photographic images using a computational approach. In *European Conference on Computer Vision* (Vol. Springer). Berlin Heidelberg.

Datta, R., & Wang, J. Z. (2010). ACQUINE : Aesthetic Quality Inference Engine – Real-time Automatic Rating of Photo Aesthetics. In *Proceedings of the international conference on Multimedia information retrieval* (pp. 1–4). Pennsylvania, USA. Retrieved from http://dl.acm.org/citation.cfm?id=1743457

DCLG. (2017). *A guide to energy performance certificates for the marketing, sale and let of dwelling*. London.

De Boeck, L., Verbeke, S., Audenaert, A., & De Mesmaeker, L. (2015). Improving the energy performance of residential buildings: A literature review. *Renewable and Sustainable Energy Reviews*, *52*, 960–975.

Department for Communities and Local Government. (2010). *English Housing Survey*

Housing stock report 2008. London.

Department for Communities and Local Government. (2015). *English Housing Survey: Profile of English Housing, Annual report on England's housing stock, 2013*. London.

Depecker, P., Menezo, C., Virgone, J., & Lepers, S. (2001). Design of buildings shape and energetic consumption. *Building and Environment*, *36*(5), 627–635.

Devlin, Ki., & Nasar, J. L. (1989). the Beauty a N D the Beast : Some Preliminary Comparisons of ' High ' Versus ' Popular '. *Journal of Environmental Psychology*, *9*(4), 333–344.

Dinc, P., & Yuksel, E. I. (2010). A Lens Model Approach for Analyzing the Judgment Differences of European and Turkish Architectural Students. *Arkitekt*, (April), 44–59.

Du, P., Zheng, L. Q., Xie, B. C., & Mahalingam, A. (2014). Barriers to the adoption of energy-saving technologies in the building sector: A survey study of Jing-jin-tang, China. *Energy Policy*, *75*, 206–216.

Dubey, A., Naik, N., Parikh, D., Raskar, R., & Hidalgo, C. A. (2016). Deep learning the city: Quantifying urban perception at a global scale. In *European Conference on Computer Vision* (pp. 196–212). Cham: Springer.

EHS. (2016). *The English Housing Survey (EHS) Headline Report 2015-2016. Department for Communities and Local Government (DCLG)*. *Department for Communities and Local government*. London.

Eisenman, R., & Gellens, H. K. (1968). Preferences for complexity-simplicity and symmetry-asymmetry. *Perceptual and Motor Skills*, *26*, 888–890.

Eisenthal, Y., Dror, G., & Ruppin, E. (2006). Facial attractiveness: Beauty and the machine. *Neural Computation*, *18*(1), 119–142.

Emch, A. (1900). Mathematical principles of esthetic forms. *The Monist*, *11*(1), 50–64.

EnergyPlus. (2019). *EnergyPlus^{TM} Version 9.1.0 Documentation Engineering Reference*. Retrieved from https://energyplus.net/sites/all/modules/custom/nrel_custom/pdfs/pdfs_v9.1.0/EngineeringReference.pdf

ENERGYSTAR. (2017). The number of ENERGYSTAR certificated buildings. Retrieved August 3, 2017, from https://www.energystar.gov/buildings/about-us/facts-and-stats

Erdogan, E., Akalin, A., Yildirim, K., & Erdogan, H. A. (2010a). Aesthetic differences between freshmen and Pre-architects. *Gazi University Journal of Science*, *23*(4), 501–509.

Erdogan, E., Akalin, A., Yildirim, K., & Erdogan, H. A. (2010b). Students' evaluations of different architectural styles. *Procedia - Social and Behavioral Sciences*, *5*, 875–881.

EU_FS. (2017). Fact Sheets on the European Union. Retrieved August 4, 2017, from http://www.europarl.europa.eu/atyourservice/en/displayFtu.html?ftuId=FTU_5.7.3.html

EU. (2017). EU Buildings Database. Retrieved August 4, 2017, from http://ec.europa.eu/energy/en/eu-buildings-database

Eysenck, H. J. (1941). The empirical determination of an aesthetic formula. *Psychological Review*, *48*(1), 83–92.

Ferdous, F. (2013). Examining the Relationship Between Key Visual Characteristics of Urban Plazas and Aesthetic Response. *SAGE Open*, *3*(2), 1–10.

Field, A. (2013). *Discovering statistics using IBM SPSS statistics* (4th ed.). London: SAGE.

Fuerst, F., McAllister, P., & Murray, C. B. (2011). Designer buildings: Estimating the economic value of “signature” architecture. *Environment and Planning A*, *43*(1), 166–184.

Gallaher, M. P., O’Connor, A. C., Dettbarn, J. L., & Gilday, L. T. (2004). *Cost Analysis of Inadequate Interoperability in the U.S. Capital Facilities Industry. National Institute of Standards and Technology (NIST)*. Maryland. Retrieved from http://www.bentleyuser.dk/sites/default/files/nist_report.pdf

Gardner, J. S., Fowlkes, C., Nothelfer, C., & Palmer, S. E. (2008). Exploring aesthetic principles of spatial composition through stock photography. *Journal of Vision*, *8*(6), 337-337a.

Garip, E., & Garip, B. (2012). Aesthetic Evaluation Differences between two Interrelated Disciplines: A Comparative Study on Architecture and Civil Engineering Students. *Procedia - Social and Behavioral Sciences*, *51*, 533–540.

George, D., & Mallery, M. (2010). *SPSS for Windows Step by Step: A Simple Guide and Reference 17.0 Update* (10th ed.). Boston: Pearson.

Gifford, R., Hine, D. W., Muller-Clemm, W., & Shaw, K. T. (2002). Why architects and laypersons judge buildings differently: Cognitive properties and physical bases. *Journal of Architectural and Planning Research*, *19*(2), 131–148.

GOV.UK. (2013). *The UK Building Regulations Approved Document: A*. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/429060/BR_PDF_AD_A_2013.pdf

GOV.UK. (2019). *Updated energy and emissions projections 2018*. London.

GREENSTAR. (2017). The number of GREEN STAR certificated buildings. Retrieved

August 3, 2017, from http://new.gbca.org.au/green-star/

Groat, L. (1982). Meaning in post-modern architecture: an examination using the multiple sorting task. *Journal of Environmental Psychology*, *2,* 3–22.

Gynther, L., Lapillonne, B., & Pollier, K. (2015). *Energy Efficiency Trends and Policies in the Household and Tertiary Sectors. An Analysis Based on the ODYSSEE and MURE Databases*. EU. Retrieved from http://www.odyssee-mure.eu/publications/br/energy-efficiency-trends-policies-buildings.pdf

Halicioglu, F. H., Arditi, D., & Gunhan, S. (2013). Towards Advanced Solutions for Achieving Sustainability Goals in Buildings: Lessons Learned from Case Studies. In *ICSDEC 2012: Developing the Frontier of Sustainable Design, Engineering, and Construction* (pp. 835–843).

Hanyu, K. (1997). Visual properties and affective appraisals in residential areas after dark. *Journal of Environmental Psychology*, *17*, 301–315.

Hassab, W. (2011). An Approach to Arrange Aesthetic Values in Architectural Design. *Journal of Engineering and Applied Science*, *58*(3), 197–217.

Hasse, C., & Weber, R. (2012). Eye Movements on Facades: The Subjective Perception of Balance in Architecture and Its Link to Aesthetic Judgment. *Empirical Studies of the Arts*, *30*(1), 7–22.

Hassoun, M. H. (2018). Wayne State University Computation and Neural Networks Laboratory online sorurces.

Hauge, Å. L., Thomsen, J., & Berker, T. (2011). User evaluations of energy efficient buildings: Literature review and further research. *Advances in Building Energy Research*, *5*(1), 109–127.

Hernández-Pérez, I., Xamán, J., Macías-Melo, E. V., Aguilar-Castro, K. M., Zavala-Guillén, I., Hernández-López, I., & Simá, E. (2018). Experimental thermal evaluation of building roofs with conventional and reflective coatings. *Energy and Buildings*, *158*, 569–579.

Higgins, N. (2017). *Dwelling Stock Estimates: 2016, England. Department for Communities and Local Government (DCLG) Housing Statistical Release*. London.

Hoffman, A. J., & Henn, R. (2008). Overcoming the Social and Psychological Barriers to Green Building. *Organization & Environment*, *21*(4), 390–419.

Humphrey, G. K., & Humphrey, D. E. (1989). The role of structure in infant visual-pattern perception. *Canadian Journal of Psychology*, *43*(2), 165–182.

Huovila, P., Ala-Juusela, M., Melchert, L., & Pouffary, S. (2007). *Buildings and climate change: status, challenges, and opportunities. United Nations Environment Programme (UNEP)*. Paris.

Ibrahim, A. F., Abu-Obeid, N., & Al-Simadi, F. (2002). The Effect Of Personality Traits On Architectural Aesthetics' Evaluation: Familiar And Non-Familiar Environments As Evaluated By Architectural And Non-Architectural Students. *Architectural Science Review*, *45*(3), 197–210.

Ikemi, M. (2005). The effects of mystery on preference for residential fa??ades. *Journal of Environmental Psychology*, *25*(2), 167–173.

Ilieva, J., Baron, S., & Healey, N. M. (2001). On-line Surveys in International Marketing Research: Pros and Cons. *Manchester Metropolitan University Business School Working Paper Series*.

Imamoglu, C. (2000). Complexity, Liking and Familiarity: Architecture and Non-

Architecture Turkish Students' Assessments of Traditional and Modern House Facades. *Journal of Environmental Psychology*, *20*(1), 5–16.

Inanici, M. N., & Demirbilek, F. N. (2000). Thermal performance optimization of building aspect ratio and south window size in five cities having different climatic characteristics of Turkey. *Building and Environment*, *35*(1), 41–52.

IPCC. (2007). *Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4) Climate Change 2007: Mitigation of Climate Change Chapter 6: Residential and commercial buildings*. Cambridge. Retrieved from https://www.ipcc.ch/pdf/assessment-report/ar4/wg3/ar4-wg3-chapter6.pdf

IPPC-CC. (2014). *Cliamte Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment report of the Intergovernmental Panel on Climate Change. Summery for Policymakers*. Retrieved from https://www.ipcc.ch/pdf/assessment-report/ar5/wg3/ipcc_wg3_ar5_summary-for-policymakers.pdf

Isaksson, C., & Karlsson, F. (2006). Indoor climate in low-energy houses-an interdisciplinary investigation. *Building and Environment*, *41*(12), 1678–1690.

Ishizu, T., & Zeki, S. (2011). Toward a brain-based theory of beauty. *PLoS ONE, 6*(7), e21852.

Ishizu, Tomohiro, & Zeki, S. (2017). The experience of beauty derived from sorrow. *Human Brain Mapping*, *38*(8), 4185–4200.

Jacobsen, T., & Höfel, L. (2003). Descriptive and evaluative judgment processes: Behavioral and electrophysiological indices of processing symmetry and aesthetics. *Cognitive, Affective and Behavioral Neuroscience*, *3*(4), 289–299.

Jacobsen, T., Schubotz, R. I., Höfel, L., & Cramon, D. Y. V. (2006). Brain correlates of aesthetic judgment of beauty. *NeuroImage*, *29*(1), 276–285.

Jin, Y., Wu, Q., & Liu, L. (2012). Aesthetic photo composition by optimal crop-and-warp. *Computers and Graphics (Pergamon)*, *36*(8), 955–965.

Johansson, T. B., Patwardhan, A., Nakicenovic, N., & Gomez-Echeverri, L. (2012). *Global energy assessment: Toward a sustainable future, Chapter 10. International Institute for Applied Systems Analysis (IIASA)*. Cambridge University Press.

Karava, P., Stathopoulos, T., & Athienitis, A. K. (2011). Airflow assessment in cross-ventilated buildings with operable facade elements. *Building and Environment*, *46*(1), 266–279.

Karlik, B., & Olgac, V. (2011). Performance Analysis of Various Activation Functions in Generalized MLP Architectures of Neural Networks. *International Journal of Artificial Intelligence And Expert Systems (IJAE)*, *1*(4), 111–122.

Kim, G., Lim, H. S., Lim, T. S., Schaefer, L., & Kim, J. T. (2012). Comparative advantage of an exterior shading device in thermal performance for residential buildings. *Energy and Buildings*, *46*, 105–111.

Kindangen, J., Krauss, G., & Depecker, P. (1997). Effects of roof shapes on wind-induced air motion inside buildings. *Building and Environment*, *32*(1), 1–11.

Krosnick, J. A., & Fabrigar, L. R. (1997). Designing Rating Sclaes for Effective Measurement in Surveys. In *Survey measurement and process quality* (pp. 141–164).

Kwak, S. Y., Yoo, S. H., & Kwak, S. J. (2010). Valuing energy-saving measures in residential buildings: A choice experiment study. *Energy Policy*, *38*(1), 673–677.

Lai, H. K., Kendall, M., Ferrier, H., Lindup, I., Alm, S., Hanninen, O., … Nieuwenhuijsen,

M. J. (2004). Personal exposures and microenvironment concentrations of PM 2.5, VOC, NO2 and CO in Oxford, UK. *Atmospheric Environment*, *38*(37), 6399–6410.

Langlois, J. H., Ritter, J. M., Roggman, L. A., & Vaughn, L. S. (1991). Facial diversity and infant preferences for attractive faces. *Developmental Psychology*, *27*(1), 79–84.

Langlois, J. H., Roggman, L. A., & Rieser-Danner, L. A. (1990). Infants' Differential Social Responses to Attractive and Unattractive Faces. *Developmental Psychology*, *26*(1), 153–159.

Laustsen, J. (2008). *Energy efficiency requirements in building codes, energy efficiency policies for new buildings. International Energy Agency (IEA)*. Paris. Retrieved from https://www.iea.org/publications/freepublications/publication/Building_Codes.pdf

Lee, W. L., & Yik, F. W. H. (2004). Regulatory and voluntary approaches for enhancing building energy efficiency. *Progress in Energy and Combustion Science*, *30*(5), 477–499.

LEED. (2017). The number of LEED certificated buildings. Retrieved August 3, 2017, from http://www.usgbc.org/articles/leed-numbers-16-years-steady-growth

Liang, Y., Su, Z., Wang, C., Wang, D., & Luo, X. (2013). Optimised image retargeting using aesthetic-based cropping and scaling. *IET Image Processing*, *7*(1), 61–69.

Limsombunc, V. (2004). House Price Prediction: Hedonic Price Model vs. Artificial Neural Network. In *New Zealand Agricultural and Resource Economics Society Conference*.

Lindal, P. J., & Hartig, T. (2013). Architectural variation, building height, and the restorative quality of urban residential streetscapes. *Journal of Environmental Psychology*, *33*, 26–36.

Lindal, P. J., & Hartig, T. (2015). Effects of urban street vegetation on judgments of restoration likelihood. *Urban Forestry & Urban Greening*, *14*(2), 200–209.

Liu, J., Lughofer, E., & Zeng, X. (2015). Aesthetic perception of visual textures: a holistic exploration using texture analysis, psychological experiment, and perception modeling. *Frontiers in Computational Neuroscience*, *9*(134), 1–14.

Lu, P., Peng, X., Li, R., & Wang, X. (2015). Towards aesthetics of image: A Bayesian framework for color harmony modeling. *Signal Processing: Image Communication*, *39*, 487–498.

Marquardt, S. R. (1997). Method and apparatus for analyzing facial configurations and components", "U.S. Patent No. 5,659,625.

Meijer, F., Itard, L., & Sunikka-Blank, M. (2009). Comparing European residential building stocks: performance, renovation and policy opportunities. *Building Research & Information*, *37*(5–6), 533–551.

Mirzaei, P. A., Haghighat, F., Nakhaie, A. A., Yagouti, A., Giguère, M., Keusseyan, R., & Coman, A. (2012). Indoor thermal condition in urban heat Island e Development of a predictive tool. *Building and Environment*, *57*, 7–17.

Mitchell, T. M. (1997). *Machine Learning*. McGraw-Hill.

Naceur, K. Ben. (2015). *Energy Efficiency Market Report 2015: Market Trends and Medium-Term Prospects. International Energy Agency (IEA)*. Paris. Retrieved from https://www.iea.org/publications/freepublications/publication/MediumTermEnergyefficiencyMarketReport2015.pdf

Nair, G., Gustavsson, L., & Mahapatra, K. (2010). Owners perception on the adoption of building envelope energy efficiency measures in Swedish detached houses. *Applied*

Energy, *87*(7), 2411–2419.

NASA-GCC. (2019). NASA Global Climate Change Cital Signs of the Planet. NASA/GCC. Retrieved June 1, 2017, from http://climate.nasa.gov/vital-signs/global-temperature/

Nikunen, H. J., & Korpela, K. M. (2009). Restorative Lighting Environments-Does the Focus of Light Have an Effect on Restorative Experiences? *Journal of Light & Visual Environment*, *33*(1), 37–45.

NOMIS. (2017). Official labour market statistics. Retrieved June 11, 2017, from www.nomisweb.co.uk

OED. (2018). Oxford English Dictionary. Retrieved April 29, 2017, from https://en.oxforddictionaries.com

Office for national statistics. (2013). *2011 Census: Population and household estimates for the United Kingdom, March 2011*.

Ozbudak Akca, Y. B., Erdogan, E., & Akalin, A. (2015). Mimarların Halkın Dilini Anlamasına Yönelik Bir Çalışma; Mimar Ve Mimar Olmayan Benzerliği. *Metu Journal of the Faculty of Architecture*, *32*(2), 171–189.

Palmer, J., & Cooper, I. (2013). *United Kingdom housing energy fact file. Department of Energy & Cliamte Change (DECC)*. *Department of Energy & Climate Change*. Cambridge. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/345141/uk_housing_fact_file_2013.pdf

Parkinson, A., De Jong, R., Cooke, A., & Guthrie, P. (2013). Energy performance certification as a signal of workplace quality. *Energy Policy*, *62*, 1493–1505.

Perén, J. I., van Hooff, T., Leite, B. C. C., & Blocken, B. (2015). Impact of eaves on cross-ventilation of a generic isolated leeward sawtooth roof building: Windward eaves, leeward eaves and eaves inclination. *Building and Environment*, *92*(0), 578–590.

Pérez-Lombard, L., Ortiz, J., & Pout, C. (2008). A review on buildings energy consumption information. *Energy and Buildings*, *40*(3), 394–398.

Pires, L., Silva, P. D., & Gonçalves, L. C. (2005). Surface configuration relevance in the overall thermal resistance of a wall. *Energy and Buildings*, *37*(10), 1068–1074.

Preston, C. C., & Colman, A. M. (2000). Optimal number of response categories in rating scales: reliability, validity, discriminating power, and respondent preferences. *Acta Psychologica*, *104*(1), 1–15.

Rashevsky, N. (1938). Contribution to the mathematical biophysics of visual perception with special reference to the theory of aesthetic values of geometrical patterns. *Psychometrika*, *3*(4), 253–271.

Reimann, M., Zaichkowsky, J., Neuhaus, C., Bender, T., & Weber, B. (2010). Aesthetic package design: A behavioral, neural, and psychological investigation. *Journal of Consumer Psychology*, *20*(4), 431–441.

Reis, A. T. da L., & Lay, M. C. D. (2010). Internal and External Aesthetics of Housing Estates. *Environment and Behavior*, *42*(2), 271–294.

Reuben, J., & Price, C. (2017). *Personal incomes statistics: tables 3.12 to 3.15a for the tax year 2014 to 2015. UK National Statistics*. London. Retrieved from https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/610763/National_Statistics_T3_12_to_T3_15a_Publication_2014_15.pdf

Rhodes, G., Yoshikawa, S., Clark, A., Kieran, L., McKay, R., & Akamatsu, S. (2001).

Attractiveness of facial averageness and symmetry in non-western cultures: In search of biologically based standards of beauty. *Perception*, *30*(5), 611–625.

Robichaud, L. B., & Anantatmula, V. S. (2011). Greening Project Management Practices for Sustainable Construction. *Journal of Management in Engineering*, *27*(1), 48–57.

Ryghaug, M., & Sørensen, K. H. (2009). How energy efficiency fails in the building industry. *Energy Policy*, *37*(3), 984–991.

Sadamori, K. (2016). *Energy Efficiency Market Report 2016. International Energy Agency (IEA)*. Paris. Retrieved from https://www.iea.org/eemr16/files/medium-term-energy-efficiency-2016_WEB.PDF

SAP. (2014). *SAP 2012 The Government ' s Standard Assessment Procedure for Energy Rating of Dwellings*. *BRE*. Retrieved from http://www.bre.co.uk/filelibrary/SAP/2009/SAP-2009_9-90.pdf

Saris, W. E., & Gallhofer, I. N. (2007). *Design, evaluation, and analysis of questionnaires for survey research*. John Wiley & Sons, Inc.

Schaeffer, N. C., & Presser, S. (2003). The Science of Asking Questions. *Annual Review of Sociology*, *29*(2003), 65–88.

Schnieders, J., & Hermelink, A. (2006). CEPHEUS results: Measurements and occupants' satisfaction provide evidence for Passive Houses being an option for sustainable building. *Energy Policy*, *34*(2 SPEC. ISS.), 151–171.

Serpell, A., Kort, J., & Vera, S. (2013). Awareness, actions, drivers and barriers of sustainable construction in Chile. *Technological and Economic Development of Economy*, *19*(2), 272–288.

Shafii, F., Arman Ali, Z., & Othman, M. Z. (2006). Achieving Sustainable Construction in

The Developing Countries Southeast Asia. In *Proceedings of the 6th Asia-Pacific Structural Engineering and Construction Conference (APSEC 2006), 5 – 6 September 2006, Kuala Lumpur, Malaysia* (Vol. 1, pp. C29–C44). Kuala Lumpur.

Stamps, A., & Miller, S. (1993). Advocacy Membership, Design Guidelines, and Predicting Preferences for Residential Infill Designs. *Environment and Behavior*, *25*(5), 367–409.

Stamps III, A. E. (1997). Some streets of San Francisco: Preference effects of trees, cars, wires, and buildings. *Environment and Planning B: Planning and Design*, *24*(1), 81–93.

Stamps III, A. E. (1999). Demographic effects in environmental aesthetics: A meta-analysis. *J. Plan. Literature*, *14*(2), 155–175.

Susorova, I., Tabibzadeh, M., Rahman, A., Clack, H. L., & Elnimeiri, M. (2013). The effect of geometry factors on fenestration energy performance and energy savings in office buildings. *Energy and Buildings*, *57*, 6–13.

Svobodova, K., Sklenicka, P., Molnarova, K., & Vojar, J. (2014). Does the composition of landscape photographs affect visual preferences? The rule of the Golden Section and the position of the horizon. *Journal of Environmental Psychology*, *38*, 143–152.

Thayer-Hart, N. (2010). *Survey fundamentals: A guide to designing and implementing surveys*. Office of Quality Improvement University of Wisconsin Survey Center. Retrieved from https://oqi.wisc.edu/resourcelibrary/uploads/resources/Survey_Guide.pdf

Tso, G. K. F., & Yau, K. K. W. (2007). Predicting electricity energy consumption: A comparison of regression analysis, decision tree and neural networks. *Energy*, *32*(9), 1761–1768.

UCLA. (2017). Institute for Digital Research and Education- CHOOSING THE CORRECT STATISTICAL TEST GUIDANCE. Retrieved June 8, 2017, from https://stats.idre.ucla.edu/other/mult-pkg/whatstat/

UK_Gov. (2018). UK House Price Index. Retrieved May 1, 2016, from http://landregistry.data.gov.uk/app/ukhpi

UK_Power. (2018). The energy price comparison service. Retrieved October 15, 2017, from https://www.ukpower.co.uk/home_energy/average-energy-bill

UN-FCCC. (2015). *United Nations (UN) Framework Convention on Climate Change (FCCC) FCCC/CP/2015/L.9/Rev.1 Conference of the Parties Twenty-first session Paris, 30 November to 11 December 2015 Agenda item 4(b) Durban Platform for Enhanced Action (decision 1/CP.17)*. Retrieved from https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf

UN-WPP. (2015). *United Nations (UN), Department of Economic and Social Affairs, Population Division (2015). World Population Prospects: The 2015 Revision, Key Findings and Advance Tables. Working Paper No.* (Vol. 1). New York. Retrieved from https://esa.un.org/unpd/wpp/publications/files/key_findings_wpp_2015.pdf

UNEP. (2011). *United Nations Environment Programme (UNEP) Towards a Green Economy: Pathways to Sustainable Development and Poverty Eradication*. Retrieved from http://www.unep.org/pdf/green_economy_2011/GreenEconomyReport.pdf

UNISDR. (2012). *Number of Climate-related Disasters Around the World (1980-2011)- The United Nations Office for Disaster Risk Reduction*. Retrieved from http://www.preventionweb.net/files/20120613_ClimateDisaster1980-2011.pdf

Vardoulakis, S., Dimitroulopoulou, C., Thornes, J., Lai, K.-M., Taylor, J., Myers, I., … Wilkinson, P. (2015). Impact of climate change on the domestic indoor environment and associated health risks in the UK. *Environment International, 85*, 299–313.

Vessel, E. A., Stahl, J., Maurer, N., Denker, A., & Starr, G. G. (2014). Personalized visual aesthetics. *SPIE Human Vision and Electronic Imaging*, *9014*(212), 1–8.

Voland, E., & Grammer, K. (2003). *Evolutionary aesthetics*. Springer Science & Business Media.

WEC-WES/2050. (2013). *World Energy Council World Energy Scenarios: Composing energy futures to 2050*. London. Retrieved from https://www.worldenergy.org/wp-content/uploads/2013/09/World-Energy-Scenarios_Composing-energy-futures-to-2050_Full-report.pdf

Weijters, B., Cabooter, E., & Schillewaert, N. (2010). The effect of rating scale format on response styles: The number of response categories and response category labels. *International Journal of Research in Marketing*, *27*(3), 236–247.

Yue, X., Vessel, E. A., & Biederman, I. (2006). The neural basis of preference for natural scenes. *Journal of Vision*, *6*(6), 474.

Zai, J. (2015). *Taoism and Science: Cosmology, Evolution, Morality, Health and more*. Ultravisum.

Zhang, T., Nefs, H. T., Redi, J., & Heynderickx, I. (2014). The aesthetic appeal of depth of field in photographs. In *2014 6th International Workshop on Quality of Multimedia Experience, QoMEX 2014* (pp. 81–86).

APPENDIX

APPENDIX

A

A guide for statistical model preference *(Adapted from (Field, 2013) and (UCLA, 2017))*

Number of Outcome variables[39]	Type of outcome	Predictor variables number[40]	Type of predictor	Categories number	Entities in each category	Assumption of linear model met	Assumption of linear model not met
One	Continuous variables41	One	Continuous			Pearson correlation or regression	Bootstrap correlation/regression, Spearman correlation, Kendall's tau
			Categorical	Two	Same	Paired-samples t-test (Dependent t-test)	Bootstrapped t-test or Wilcoxon signed-rank test
					Different	Independent t-test or Point-biserial correlation	Bootstrapped t-test or Mann-Whitney test
				More than two	Same	One-way repeated measures ANOVA	Bootstrapped ANOVA or Friedman's ANOVA
					Different	One-way independent ANOVA	Rebust ANOVA or Kruskal-Wallis test
		Two or more	Continuous			Multiple regression	Bootstrapped multible regression
			Categorical		Same	Factorial repeated measures ANOVA	Rebust factorial repeated measures ANOVA
					Different	Independent factorial ANOVA/multiple regression	Rebust independents factorial repeated measures ANOVA/ multible regression
					Both	Factorial mixed ANOVA	Rebust factorial mixed ANOVA
			Both			Multiple regression/ANCOVA	Rebust ANCOVA/ bootstrapped regression
	Categorical (Metric-Scale) variables42	One	Continuous			Logistic regression or biserial/point biserial correlation	
			Categorical		Different	Pearson chi-square or likehood ratio	
		Two or more	Continuous			Logistic regression	
			Categorical		Different	Loglinear analysis	
			Both		Different	Logistic regression	
Two or more	Continuous	One	Categorical			MANOVA	
		Two or more	Categorical			Factorial MANOVA	
			Both			MANCOVA	

[39] *Dependent variables "A variable whose values we are trying to predict from one or more predictor variables* (Field, 2013) (Page:880)"

[40] *Independent variables "A variable that is used to try to predict values of outcome variable* (Field, 2013) (Page:882)"

[41] Binary, nominal (or categorical) and ordinal variables.

[42] Interval and ratio variables.

B

A survey (S1) conducted with real estate agencies to test the applicability of widespread adoption approach

ATTENTION! Please answer the following 7 questions *according to your market experience*, not your personal opinion!

1. In your opinion, how influential is each of the following factors in consumer decision-making when buying a house?

	I am undecided	Not at all influential	Slightly influential	Influential	Significantly influential
House price	○	○	○	○	○
Similarity with conventional house types	○	○	○	○	○
Energy efficiency	○	○	○	○	○
Existence of balcony	○	○	○	○	○
Attractive appearance of the house	○	○	○	○	○
Window properties (e.g. size, material, insulation etc.)	○	○	○	○	○

You can write here if you want to specify any other comments (optional)

2. Imagine a house worth £200,000. How much extra money do you expect that an intermediate-income buyer (£31,800 per year) would spend for the following housing features <u>if they find those features to be very impressive</u> when buying this house?

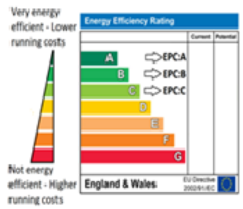
Window properties (e.g. size, material, insulation etc.)	£0	£15.000	£30.000
Balcony	£0	£15.000	£30.000
Energy efficiency	£0	£15.000	£30.000
Appearance of the house	£0	£15.000	£30.000

You can write here if you want to specify any other comments (optional)

3 Over the last 1 year, approximately how many of the houses sold by you were of the category of EPC: A to C?

Please tick the button below if you do not know what EPC is.

○ I do not know what Energy Performance Certificate (EPC) is.

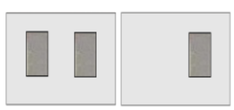
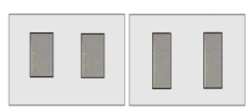
	EPC: A	0 5 15
	EPC: B	0 5 15
	EPC: C	0 5 15

You can write here if you want to specify any other comments (optional)

4. How important are the following features for a house to be more marketable?

ATTENTION!

Pictures are for illustrative purposes only, please do not be influenced by them when you are answering.

Symmetry	 Symmetry Asymmetry	Total window area		Window position	
Number of windows	 Area = Area	Window depth		Window width	
Reflectivity of window	 Transparent Reflective	Window height			

	I am undecided	Not at all important	Slightly important	Important	Very important
Symmetry	○	○	○	○	○
Number of windows	○	○	○	○	○
Reflectivity of window (transparent or mirror glass)	○	○	○	○	○
Total window area	○	○	○	○	○
Window depth (related to wall thickness and window position)	○	○	○	○	○
Window height	○	○	○	○	○
Window position	○	○	○	○	○
Window width	○	○	○	○	○

You can write here if you want to specify any other comments (optional)

5. Comparing high energy-efficient houses with ordinary houses, how strongly do you agree with the following statements?

	I am undecided	Disagree	Slightly agree	Agree	Strongly agree
More expensive	○	○	○	○	○
Have marketability challenges due to higher price	○	○	○	○	○
Have marketability challenges because the value of energy savings in the eyes of the buyers is less than other house properties	○	○	○	○	○
If they are visually more attractive, they will be more marketable	○	○	○	○	○
If they are more marketable, numbers will increase faster in the UK	○	○	○	○	○

You can write here if you want to specify any other comments (optional)

6. How many years of experience do you have in the field of housing real estate?

	I have no experience	1 to 3 years	4 to 6 years	7 to 9 years	More than 10 years
The year of your housing real estate experience	○	○	○	○	○

You can write here if you want to specify any other comments (optional)

7. Where did you participate in this survey?

C

A pre-study (PS5) to determine the impact of housing typology on aesthetic judgment

INTRODUCTION

A questionnaire comparing the impact of housing typology on the visual aesthetic appreciation

Visual aesthetic appreciation: Describing a house as beautiful or ugly

* We are only interested in your first impressions about the overall appearance of the illustrated house pictures, so please do not spend time to think about your answers.

* There are no right or wrong answers to these questions.

Please mark on the appropriate box on the given scales for each questions.

This is expected to take approximately 2 minutes. Thank you.

1- How would you describe the overall appearance of the house pictured above?

	Unattractive	○	○	○	○	○	○	○	Attractive

-How much would you be enthusiastic (keen) to live in the house pictured above?

	Unenthusiastic	○	○	○	○	○	○	○	Enthusiastic

You can write here if you want to specify any other comments (optional)

2- How would you describe the overall appearance of the house pictured above?

	Unattractive	○	○	○	○	○	○	○	Attractive

-How much would you be enthusiastic (keen) to live in the house pictured above?

	Unenthusiastic	○	○	○	○	○	○	○	Enthusiastic

You can write here if you want to specify any other comments (optional)

What is your gender?
Male ☐ Female ☐ Other ☐

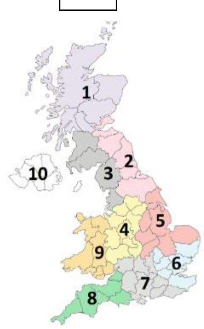
Which age group do you belong to?
Under 18 ☐ 18-24 ☐ 25-34 ☐ 35-44 ☐ 45-54 ☐ 55-64 ☐ 65+ ☐

What is the highest degree of school you have completed or currently enrolled?
If currently enrolled, highest degree received.

Bachelor's degree ☐ Ph.D. degree ☐
Master's degree ☐ Other ☐

What is your approximate average annual income before tax?
Under £2,500 ☐ Between £20,001 and £30,000 ☐
Between £2,501 and £10,000 ☐ Over £30,001 ☐
Between £10,001 and £20,000 ☐

43- Which part of the UK are you from? ☐



D

A pre-study (PS6) to determine the illustrations utilized in the main survey (S2)

INTRODUCTION

A questionnaire comparing the impact of different window parameters on the visual aesthetic appreciation

Visual aesthetic appreciation: Describing a house as beautiful or ugly

* We are only interested in your <u>first impressions about the overall appearance of the illustrated house pictures</u>, so please do not spend time to think about your answers.

* There are no right or wrong answers to these questions.

Please mark on the appropriate box on the given scales for each questions.

This is expected to take approximately 15 minutes. Thank you.

1- How would you describe the overall appearance of the house pictured above?

	Unattractive	○	○	○	○	○	○	○	Attractive

You can write here if you want to specify any other comments (optional)

Similar questions were applied to illustrations in Figure 22

E

A pre-study (PS8) to identify the most attractive and unattractive housing illustrations

INTRODUCTION

A questionnaire comparing the impact of different window parameters on the <u>visual aesthetic appreciation</u> of the houses' façades

Visual aesthetic appreciation: Describing a house as beautiful or ugly

* We are only interested in your **<u>first impressions about the overall appearance</u>** of the illustrated house pictures, so please do not spend time to think about your answers.

*There are no right or wrong answers to these questions.

*Please mark on the appropriate box on the given scales for each questions.

This is expected to take approximately **7 minutes**. Thank you.

Section 1

- How would you describe the overall appearance of the house pictured above?

	Unattractive	○	○	○	○	○	○	○	Attractive

- How much money would you spend for buying the above house?

£

*The average typical house price in the UK is £200,000.
**Imagine you have savings of £300,000 to buy a house.

You can write here if you want to specify any other comments (optional)

Similar questions were applied to illustrations in Figure 10 and the ones below.

Section 2

ATTENTION: Each number can be used only one time.

- Please rank the following pictures from 1 (least attractive) to 19 (most attractive), depending on your first impression about their overall appearance.


















You can write here if you want to specify any other comments (optional)

Section 3

- Imagine you have savings of £300,000 to buy a house and you have 4 different house options to buy. Which house would you prefer to buy?

*The average typical house price in the UK is £200,000.

	Houses	Price	Energy bill
A		£160,000	Monthly: £97 Annual: £1,164
B		£160,000	Monthly: £97 Annual: £1,164
C		£160,000	Monthly: £97 Annual: £1,164
D		£160,000	Monthly: £14 Annual: £168

You can write here if you want to specify any other comments (optional)

Similar format were applied to below scenarios

Houses	Price	Energy bill
A	£160,000	Monthly: £166 Annual: £2,000
B	£160,000	Monthly: £166 Annual: £2,000
C	£160,000	Monthly: £97 Annual: £1,164
D	£160,000	Monthly: £14 Annual: £168

Houses	Price	Energy bill
A	£200,000	Monthly: £97 Annual: £1,164
B	£200,000	Monthly: £97 Annual: £1,164
C	£160,000	Monthly: £97 Annual: £1,164
D	£240,000	Monthly: £14 Annual: £168

Houses	Price	Energy bill
A	£200,000	Monthly: £166 Annual: £2,000
B	£200,000	Monthly: £166 Annual: £2,000
C	£160,000	Monthly: £97 Annual: £1,164
D	£240,000	Monthly: £14 Annual: £168

Houses	Price	Energy bill
A	£240,000	Monthly: £97 Annual: £1,164
B	£240,000	Monthly: £97 Annual: £1,164
C	£160,000	Monthly: £97 Annual: £1,164
D	£240,000	Monthly: £14 Annual: £168

Houses	Price	Energy bill
A	£240,000	Monthly: £166 Annual: £2,000
B	£240,000	Monthly: £166 Annual: £2,000
C	£160,000	Monthly: £97 Annual: £1,164
D	£240,000	Monthly: £14 Annual: £168

F

A survey (S2) conducted with potential UK housing buyers to test the applicability of the proposed widespread adoption approach

INTRODUCTION

*There are no right or wrong answers to these questions.
* You can switch between questions by clicking the "Next" and "Previous" buttons below each page.

Section 1

1- Please rate the above housing photos from 1 (least attractive) to 4 (most attractive), depending on your initial impression of their overall appearance.

A B C D

	A
	B
	C
	D

You can write here if you want to specify any other comments (optional)

Section 2

When you are answering the following questions, imagine that;

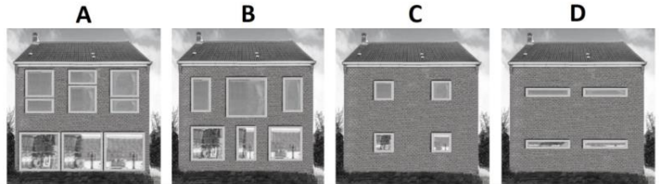
* You have savings of £300,000 for buying a house

Note: The average typical house price in the UK is £200,000.

* You have only 4 different house options to buy.

Please select the house you prefer to buy amongst those 4 options.

A B C D



Price:	£200,000	£200,000	£200,000	£200,000
Monthly:	£97	£97	£97	£14
Annual: Energy bill	£1,164	£1,164	£1,164	£168

Which house you prefer to buy?

○ A ○ B ○ C ○ D

You can write here if you want to specify any other comments (optional)

Similar format were applied to scenarios in Table 14.

Section 3

What is your gender?

Male ☐ Female ☐ Other ☐

Which age group do you belong to?

Under 18 ☐ 18-24 ☐ 25-34 ☐ 35-44 ☐ 45-54 ☐ 55-64 ☐ 65+ ☐

What is the highest degree of school you have completed or currently enrolled? *If currently enrolled, highest degree received.*

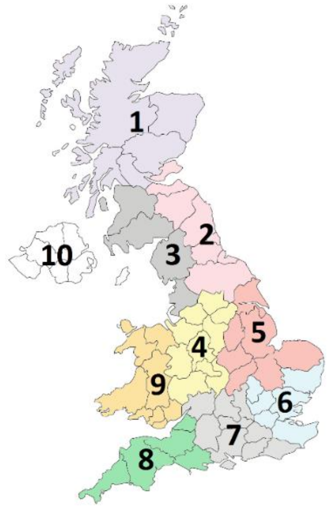
No schooling completed ☐ Bachelor's degree ☐ Ph.D. degree

High school graduate or the equivalent ☐ Master's degree ☐ Other

What is your approximate average annual income before tax?

Under £5,000	☐	Between £25, 001 and £35,000	☐	Between £55,001 and £65,000	☐
Between £5,001 and £15,000	☐	Between £35, 001 and £45,000	☐	Between £65,001 and £75,000	☐
Between £15,001 and £25,000	☐	Between £45,001 and £55,000	☐	Over £75,001	☐

43- Which part of the UK are you from? ☐



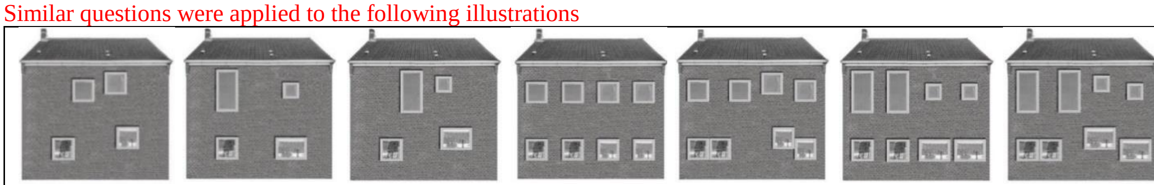
G

A survey (S3) to validate the developed symmetry measurement model (SI)

How would you describe the houses pictured below?

	Symmetric Beautiful	○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○ ○	Asymmetric Ugly

Similar questions were applied to the following illustrations



- What is your gender?
Male ☐ Female ☐ Other ☐

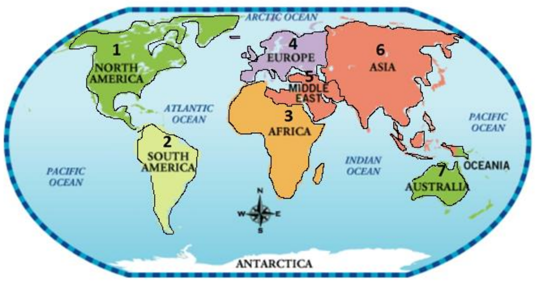
- Which age group do you belong to?
Under 18 ☐ 18-24 ☐ 25-34 ☐ 35-44 ☐ 45-54 ☐ 55-64 ☐ 65+ ☐

- What is the highest degree of school you have completed or currently enrolled?
Bachelor's degree ☐ Ph.D. degree ☐
Master's degree ☐ Other ☐

- Please select the department you are belong to:
Architecture ☐
Other ☐

- Where are you from? ☐

1- North America 2- South America 3- Africa 4- Europe 5- Middle East 6- Asia 7- Australia



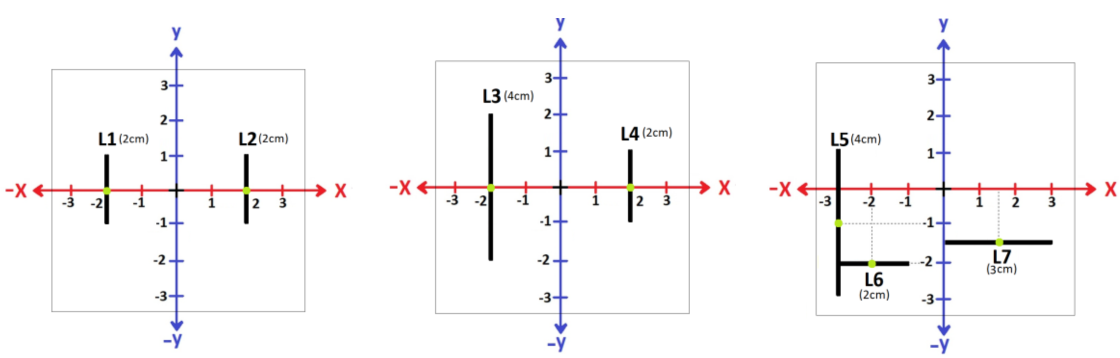
H

Step by Step application of developed mathematical symmetry models

Step-by-step demonstration of the developed mathematical expressions is presented via three simple examples. The calculation of the symmetry indices of Figures a, b, and c is as described below.

Step 1: XY coordinates are established to the centre of visual stimuli.
Step 2: The linear components are labelled (e.g. L1, L2).

a) b) c)



Step 3: *DSm* values are calculated using Eq. (27):

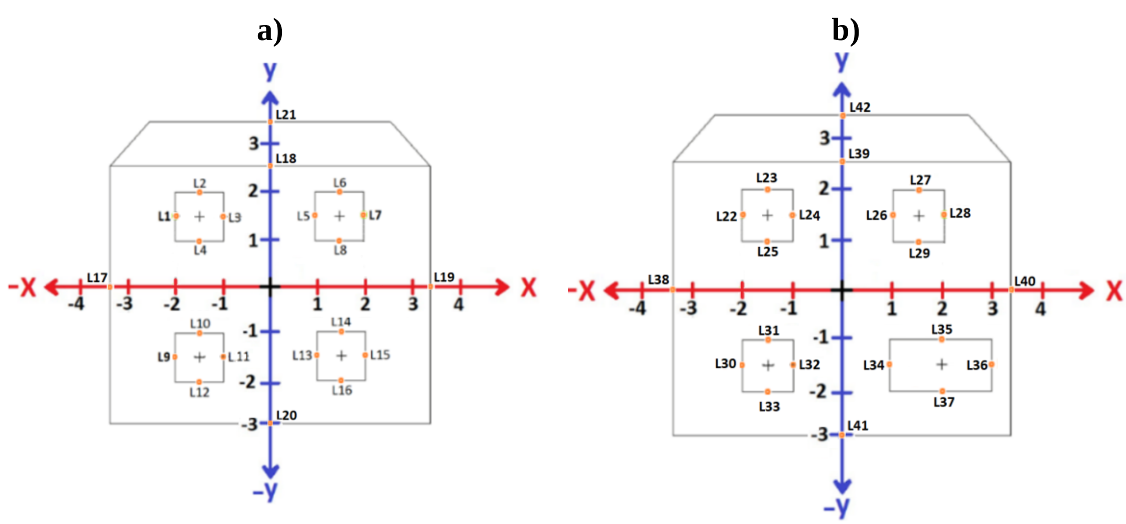
	Figure a		Figure b		Figure c		
Linear components	L1	L2	L3	L4	L5	L6	L7
PLCX	-2	2	-2	2	-3	-2	1.5
$\sum PLCX$	Fig a: 0		Fig b: 0		Fig c: -3.5		
$\lvert \sum PLCX \rvert$	Fig a: 0		Fig b: 0		Fig c: 3.5		
PLCY	0	0	0	0	-1	-2	-1.5
$\sum PLCY$	Fig a: 0		Fig b: 0		Fig c: -4.5		
$\lvert \sum PLCY \rvert$	Fig a: 0		Fig b: 0		Fig c: 4.5		
$(\lvert \sum PLCX \rvert + \lvert \sum PLCY \rvert) * 2$	Fig a: 0		Fig b: 0		Fig c: 16		
LLC	2	2	4	2	4	2	3
$PLCX / \lvert PLCX \rvert$	-1	1	-1	1	-1	-1	1
Note: *If* $PLCX / \lvert PLCX \rvert = 0$ *then* $PLCX / \lvert PLCX \rvert$ *is accepted as 1*							
$(PLCX / \lvert PLCX \rvert) * LLC\dot{I}$	-2	2	-4	2	-4	-2	3
$\lvert \sum ((PLCX / \lvert PLCX \rvert) * LLC\dot{I}) \rvert$	Fig a: 0		Fig b: 2		Fig c: 3		
$PLCY / \lvert PLCY \rvert$	(0) 1	(0) 1	(0) 1	(0) 1	-1	-1	-1
Note: *If* $PLCY / \lvert PLCY \rvert = 0$ *then* $PLCY / \lvert PLCY \rvert$ *is accepted as 1*							
$(PLCY / \lvert PLCY \rvert) * LLC\dot{I}$	2	2	4	2	-4	-2	-3
$\lvert \sum ((PLCY / \lvert PLCY \rvert) * LLC\dot{I}) \rvert$	Fig a: 4		Fig b: 6		Fig c: 9		
$(\lvert \sum ((PLCX / \lvert PLCX \rvert) * LLC\dot{I}) \rvert + \lvert \sum ((PLCY / \lvert PLCY \rvert) * LLC\dot{I}) \rvert) / 7$	Fig a: 0.6		Fig b: 1.1		Fig c: 1.7		
$((\lvert \sum PLCX \rvert + \lvert \sum PLCY \rvert) * 2) + ((\lvert \sum ((PLCX / \lvert PLCX \rvert) * LLC\dot{I}) \rvert + \lvert \sum ((PLCY / \lvert PLCY \rvert) * LLC\dot{I}) \rvert) / 7)$					Fig a: 0.6		
					Fig b: 1.1		Fig c:17.7
DSm	Fig a:0.3		Fig b: 0.6		Fig c: 8.9		
DSm_{min}	0.3						
DSm_{max}	8.9						

Step 4: *SI* indices are calculated using Eq. (26):

SI	Fig a:1.00	Fig b: 0.97	Fig c: 0.00

Step 5: Hierarchical order of the figures symmetry and complexity level are found as below:

Symmetry (SI)	Fig a (1.00) > Fig b (0.97) > Fig c (0.00)



L: linear components of visual stimuli, ● *Centre of the linear components*

L	*PLCX*	*PLCY*	*LLC*	L	*PLCX*	*PLCY*	*LLC*
Calculation for Figure a				Calculation for Figure b			
1	-2	1.5	1	**22**	-2	1.5	1
2	-1.5	2	1	**23**	-1.5	2	1
3	-1	1.5	1	**24**	-1	1.5	1
4	-1.5	1	1	**25**	-1.5	1	1
5	1	1.5	1	**26**	1	1.5	1
6	1.5	2	1	**27**	1.5	2	1
7	2	1.5	1	**28**	2	1.5	1
8	1.5	1	1	**29**	1.5	1	1
9	-2	-1.5	1	**30**	-2	-1.5	1
10	-1.5	-1	1	**31**	-1.5	-1	1
11	-1	-1.5	1	**32**	-1	-1.5	1
12	-1.5	-2	1	**33**	-1.5	-2	1
13	1	-1.5	1	**34**	1	-1.5	1
14	1.5	-1	1	**35**	2	-1	2
15	2	-1.5	1	**36**	3	1.5	1
16	1.5	-2	1	**37**	2	-2	2
17	-3.3	0	5.5	**38**	-3.3	0	5.5
18	0	2.5	7	**39**	0	2.5	7
19	3.3	0	5.5	**40**	3.3	0	5.5
20	0	-3	7	**41**	0	-3	7
21	0	3.5	5	**42**	0	3.5	5

Figure a:

$$\sum_{i=1}^{n} \boldsymbol{PLCXi} = \mathbf{0.0} \qquad \sum_{i=1}^{n} \boldsymbol{PLCYi} = \mathbf{3.0}$$

$$\left|\sum_{i=1}^{n}\left(\left(\frac{PLCXi}{|\,PLCXi\,|}\right) LLCi\right)\right| = 0.0 \qquad \left|\sum_{i=1}^{n}\left(\left(\frac{PLCYi}{|\,PLCYi\,|}\right) LLCi\right)\right| = 5.0$$

DSm =3,4

SI=1.0

Figure b:

$$\sum_{i=1}^{n} \boldsymbol{PLCXi} = \mathbf{2.0} \qquad \sum_{i=1}^{n} \boldsymbol{PLCYi} = \mathbf{6.0}$$

$$\left|\sum_{i=1}^{n}\left(\left(\frac{PLCXi}{|\,PLCXi\,|}\right) LLCi\right)\right| = 2.0 \qquad \left|\sum_{i=1}^{n}\left(\left(\frac{PLCYi}{|\,PLCYi\,|}\right) LLCi\right)\right| = 5.0$$

DSm =8.5

SI=0.0

Symmetry comparison — Figure a (1.0) > Figure b (0.0)

I

A survey (S4) to investigate the impact of different window parameters on aesthetic and marketability of housings

Based on your first impression for the housing pictured above

- How would you describe the overall appearance of the house pictured above?

Attractive ○ ○ ○ ○ ○ ○ ○ Unattractive

- How much would you be enthusiastic to live in the house pictured above?

Enthusiastic ○ ○ ○ ○ ○ ○ ○ Unenthusiastic

You can write here if you want to specify any other comments (optional)

Note: Same question structure was applied in all of the illustrations in Figure 13

- What is your gender?

Male ☐ Female ☐ Other ☐

- Which age group do you belong to?

Under 18 ☐ 18-24 ☐ 25-34 ☐ 35-44 ☐ 45-54 ☐ 55-64 ☐ 65+ ☐

- What is the highest degree of school you have completed or currently enrolled?

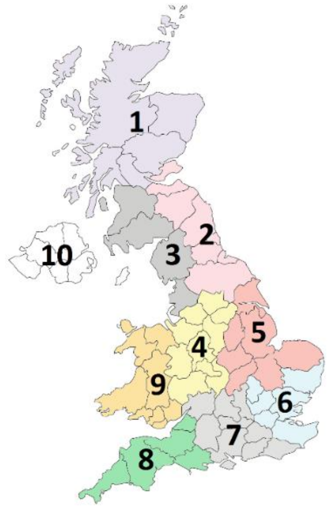
If currently enrolled, highest degree received.

Bachelor's degree ☐ Ph.D. degree ☐
Master's degree ☐ Other ☐

- Please select the department you are belong to:

Architecture ☐
Art ☐
Other ☐

43- Which part of the UK are you from?



J

Energy performance certificate (EPC) is an instrument utilizing to make the energy efficiency of buildings transparent in the European Union. The building is given a rating from A (Very efficient) to G (Inefficient) and these EPC certificates are valid 10 years. EPC has been utilizing since 2007 and is developed based on the EU Directive on the energy performance of buildings. EPC ratings are based on the buildings' fabric and services such as heating, insulation, ventilation, and fuels used. EPC certifications can be carried out only by an accredited domestic energy assessor. EPC calculation of a building is based on a combination of several factors such as:

- The type of building (i.e. flat, house or bungalow) and whether it is detached or not
- The age of the building
- The number of habitable rooms (excluding kitchens, bathroom hallways, stairs and landings)
- Extensions and their construction and rooms in the roof

- The dimensions of the building and the number of floors
- The amount and type of glazing (i.e. single or double glazing)
- The material used to build the property (e.g. brick, stone, timber frame, etc.)
- Wall insulation
- Roof construction (e.g. flat, pitched) and insulation
- The number of chimneys and open flues
- The heating systems and the type of fuel used
- Floor area of a building (Note: the energy rating is adjusted for the floor area)

In order to ensure the results are consistent for similar building types, the EPC rating is calculated based on several reference parameters. EPC calculation is independent of the number of occupants, the number of domestic appliances (e.g. washing machines and refrigerators) and their efficiencies, occupants preferred hating set point to heat their homes (i.e. individual temperature settings and how long it is heated during the day or night). This allows comparing the energy rating of buildings on a like basis.

Once the assessment is completed by the assessors the data is entered into a government-approved software program Standard Assessment Procedure or Reduced Standard Assessment Procedure software. EPC and recommendations for improving the energy performance are provided by this software. Further details can be found in the guide to energy performance certificates for the marketing, sale and let of dwellings, published by DCLG (Department for Communities and Local Government) (DCLG, 2017).

K

Data that utilized for the development of ANN and decision tree based predictive models

Visual stimuli of utilised buildings

V2: second version of window configurations, Exp: photos that belong to experimental categories

Input and output data for ANN and decision tree

Samples	Input variables								Output variables	
Building Name	**Area**	**Height**	**Number**	**Position X**	**Position Y**	**Symmetry**	**Width**	**Proportion**	**Aesthetic**	**Energy efficiency**
Benchmark	0,11	0,13	0,25	0,62	0,79	1,00	0,12	0,16	0,26	0,26
Area_L1	0,29	0,22	0,25	0,62	0,79	1,00	0,20	0,16	1,00	1,00
Area_L2	0,47	0,29	0,25	0,62	0,79	1,00	0,27	0,16	0,91	0,91
Area_L3	0,75	0,38	0,25	0,62	0,79	1,00	0,35	0,16	0,68	0,68
Height_L1	0,11	0,22	0,25	0,62	0,79	1,00	0,06	0,06	0,56	0,56
Height_L2	0,08	0,29	0,25	0,62	0,79	1,00	0,02	0,02	0,39	0,39
Height_L3	0,09	0,38	0,25	0,62	0,79	1,00	0,00	0,00	0,25	0,25
Height_V2_L1	0,19	0,22	0,25	0,62	0,79	1,00	0,12	0,11	0,82	0,82
Height_V2_L2	0,24	0,29	0,25	0,62	0,79	1,00	0,12	0,08	0,83	0,83
Height_V2_L3	0,32	0,38	0,25	0,62	0,79	1,00	0,12	0,06	0,75	0,75
Number_L1	0,09	0,22	0,00	0,00	0,79	1,00	0,20	0,16	0,32	0,32
Number_L2	0,11	0,09	0,50	1,00	0,79	1,00	0,08	0,16	0,39	0,39
Number_L3	0,12	0,07	0,75	NaN	0,79	1,00	0,06	0,16	0,31	0,31
Number_L4	0,11	0,04	1,00	NaN	0,79	1,00	0,04	0,16	0,18	0,18
Number_V2_L1	0,00	0,13	0,00	0,00	0,79	1,00	0,12	0,16	0,14	0,14
Number_V2_L2	0,22	0,13	0,50	1,00	0,79	1,00	0,12	0,16	0,64	0,64
Number_V2_L3	0,32	0,13	0,75	NaN	0,79	1,00	0,12	0,16	0,54	0,54
Number_V2_L4	0,43	0,13	1,00	NaN	0,79	1,00	0,12	0,16	0,31	0,31
Poziton_Hor_L1	0,11	0,13	0,25	0,27	0,79	1,00	0,12	0,16	0,11	0,11
Poziton_Hor_L2	0,11	0,13	0,25	0,42	0,79	1,00	0,12	0,16	0,32	0,32
Poziton_Hor_L3	0,11	0,13	0,25	0,96	0,79	1,00	0,12	0,16	0,20	0,20
Poziton_Ver_L1	0,11	0,13	0,25	0,62	0,37	1,00	0,12	0,16	0,14	0,14
Poziton_Ver_L2	0,11	0,13	0,25	0,62	0,58	1,00	0,12	0,16	0,45	0,45
Poziton_Ver_L3	0,11	0,13	0,25	0,62	1,00	1,00	0,12	0,16	0,27	0,27
Symmetry_L1	0,11	0,13	0,25	NaN	NaN	0,72	0,12	0,16	0,08	0,08
Symmetry_L2	0,11	0,13	0,25	NaN	NaN	0,41	0,12	0,16	0,02	0,02
Symmetry_L3	0,11	0,13	0,25	NaN	NaN	0,10	0,12	0,16	0,00	0,00
Widith_L1	0,11	0,07	0,25	0,62	0,79	1,00	0,20	0,35	0,39	0,39
Widith_L2	0,11	0,02	0,25	0,62	0,79	1,00	0,31	0,65	0,17	0,17
Widith_L3	0,12	0,00	0,25	0,62	0,79	1,00	0,41	1,00	0,07	0,07
Widith_V2_L1	0,19	0,13	0,25	0,62	0,79	1,00	0,20	0,24	0,78	0,78
Widith_V2_L2	0,28	0,13	0,25	0,62	0,79	1,00	0,31	0,33	0,78	0,78
Widith_V2_L3	0,38	0,13	0,25	0,62	0,79	1,00	0,41	0,43	0,64	0,64
Exp. 1	1,00	1,00	0,00	0,62	0,00	1,00	0,41	0,06	0,45	NaN
Exp. 2	0,06	0,00	0,13	NaN	NaN	0,00	0,41	1,00	0,00	NaN
Exp. 3	0,95	0,38	0,00	0,00	0,79	1,00	1,00	0,47	0,41	NaN
Exp. 4	0,04	0,22	0,00	0,00	0,79	1,00	0,12	0,11	0,14	NaN
Exp. 5	0,00	0,07	0,00	0,00	0,79	1,00	0,20	0,35	0,07	NaN

Technical details of ANN (MATLAB ANN toolbox (nntool))

Network properties	
Network type:	feed-forward backpropagation
Transfer function:	TANSIG (Tangent sigmoid)
Training function:	TRAINLM (Levenberg-Marquardt backpropagation)
Adaption learning function:	LARNGDM (Gradient descent with momentum weight and bias adaptation)
Performance function	MSE (mean squared error)
Number of hidden layers:	2
Number of neurons:	13
Training parameters	
Show Window:	true
Show Command Line:	false
Show:	25
Epochs	1000
Time	Inf
Goal:	0
Min_grad:	1e-07
Max-fail	1000
mu	0.001
Mu_dec	0.1
Mu_inc	10
Mu_max	10000000000
Validation and test data	
	Percentages to randomly dividing the samples
Training:	70%
Validation:	15%
Testing:	15%

Explanation:
Training: These are presented to the network during training, and the network is adjusted according to its error.
Validation: These are used to measure network generalization, and to halt training when generalization stop improving
Testing: These have no effect on training and so provide an independent measure of network performance during and after training.
Note: The mentioned stages above are automatically applied in the ANN tool during the development process.

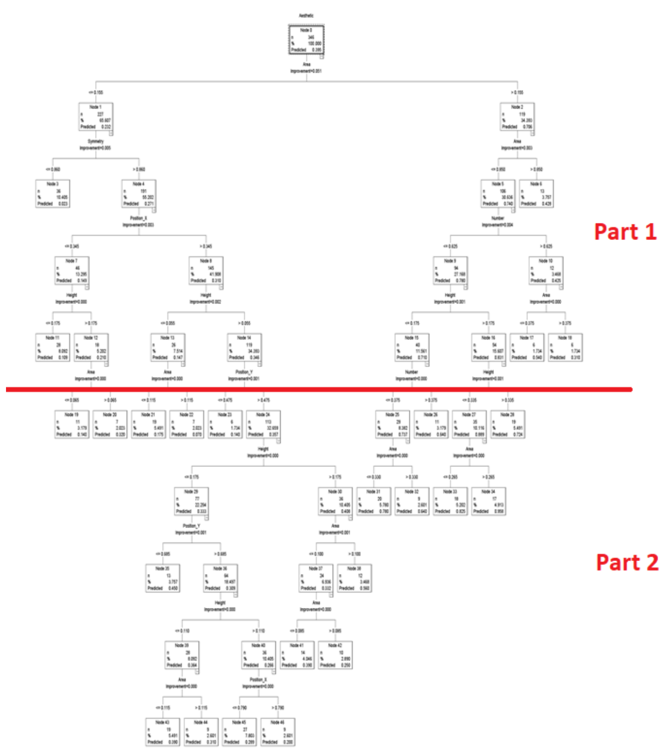
Decision tree technical details

Partition settings	
Partitions:	Train and test
Training partition size:	60
Testing partition size:	40
Values:	Append labels to system-defined values
Repeatable partition assignment:	True
Speed:	1234567
CRT model	
Building options	
Objective	
Build new model:	True
Build a single tree:	True
Mode:	Generate model
Basics	
Maximum tree depth:	11
Prune tree to avoid overfitting:	True
Maximum surrogates:	5
Stooping Rules	

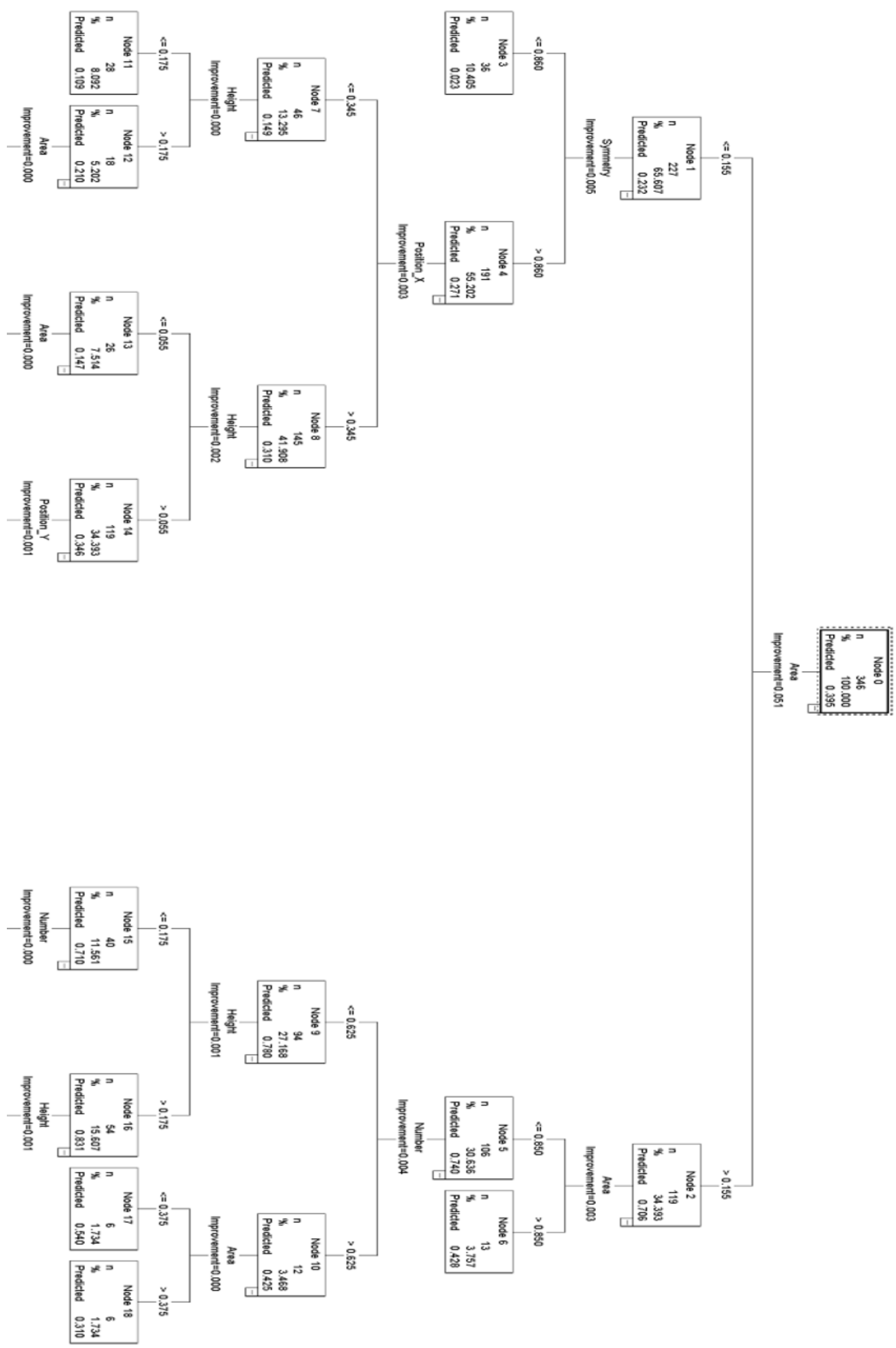
Use percentage:	True
Minimum records in parent branch (%):	2
Minimum records in child branch (%):	1
Ensembles	
Default combining rule for categorical targets:	Voting
Default combining rule for continuous targets:	Mean
Number of component models for boosting or bagging:	10
Advanced	
Minimum change in impurity:	0.0001
Impurity measure for categorical targets:	Gini
Overfit prevention set (%):	30
Replicate results:	True
Random seed:	681644031
Model Options	
Model name:	Auto
Calculate predictor importance:	True

L

Larger illustration for Figure 41: Housing aesthetic and marketability prediction model (decision tree) for window parameters

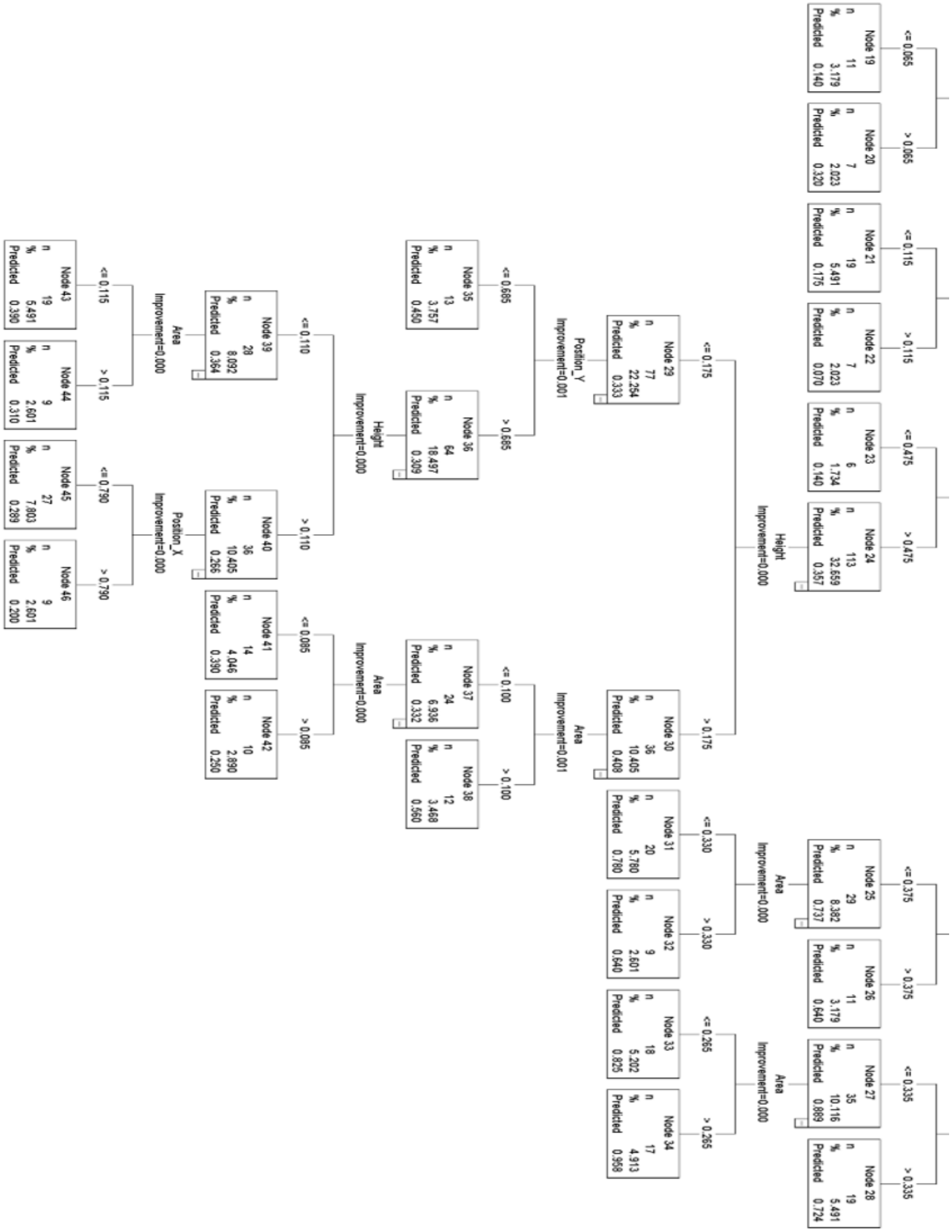


Part1



Aesthetic
Node 0
n 346
% 100.000
Predicted 0.395
Area
Improvement=0.051
<= 0.155
> 0.155
Node 1
n 227
% 65.607
Predicted 0.232
Symmetry
Improvement=0.005
Node 2
n 119
% 34.393
Predicted 0.706
Area
Improvement=0.003
<= 0.860
> 0.860
Node 3
n 36
% 10.405
Predicted 0.023
Node 4
n 191
% 55.202
Predicted 0.271
Position_X
Improvement=0.003
<= 0.850
> 0.850
Node 5
n 106
% 30.636
Predicted 0.740
Number
Improvement=0.004
Node 6
n 13
% 3.757
Predicted 0.428
<= 0.345
> 0.345
Node 7
n 46
% 13.295
Predicted 0.149
Height
Improvement=0.000
Node 8
n 145
% 41.908
Predicted 0.310
Height
Improvement=0.002
<= 0.625
> 0.625
Node 9
n 94
% 27.168
Predicted 0.780
Height
Improvement=0.001
Node 10
n 12
% 3.468
Predicted 0.425
Area
Improvement=0.000
<= 0.175
> 0.175
Node 11
n 28
% 8.092
Predicted 0.109
Node 12
n 18
% 5.202
Predicted 0.210
Area
Improvement=0.000
<= 0.055
> 0.055
Node 13
n 26
% 7.514
Predicted 0.147
Area
Improvement=0.000
Node 14
n 119
% 34.393
Predicted 0.346
Position_Y
Improvement=0.001
<= 0.175
> 0.175
Node 15
n 40
% 11.561
Predicted 0.710
Number
Improvement=0.000
Node 16
n 54
% 15.607
Predicted 0.831
Height
Improvement=0.001
<= 0.375
> 0.375
Node 17
n 6
% 1.734
Predicted 0.540
Node 18
n 6
% 1.734
Predicted 0.310

Part2



<= 0.065
> 0.065
Node 19
n 11
% 3.179
Predicted 0.140
Node 20
n 7
% 2.023
Predicted 0.320
<= 0.115
> 0.115
Node 21
n 19
% 5.491
Predicted 0.176
Node 22
n 7
% 2.023
Predicted 0.070
<= 0.475
> 0.475
Node 23
n 6
% 1.734
Predicted 0.140
Node 24
n 113
% 32.659
Predicted 0.357
Height
Improvement=0.000
<= 0.375
> 0.375
Node 25
n 29
% 8.382
Predicted 0.737
Node 26
n 11
% 3.179
Predicted 0.640
<= 0.335
> 0.335
Node 27
n 35
% 10.116
Predicted 0.889
Node 28
n 19
% 5.491
Predicted 0.724
Area
Improvement=0.000
<= 0.175
> 0.175
Node 29
n 77
% 22.254
Predicted 0.333
Node 30
n 36
% 10.405
Predicted 0.408
<= 0.330
> 0.330
Node 31
n 20
% 5.780
Predicted 0.780
Node 32
n 9
% 2.601
Predicted 0.640
<= 0.265
> 0.265
Node 33
n 18
% 5.202
Predicted 0.825
Node 34
n 17
% 4.913
Predicted 0.968
Position_Y
Improvement=0.001
<= 0.685
> 0.685
Node 35
n 13
% 3.757
Predicted 0.450
Node 36
n 64
% 18.497
Predicted 0.309
Area
Improvement=0.001
<= 0.100
> 0.100
Node 37
n 24
% 6.936
Predicted 0.332
Node 38
n 12
% 3.468
Predicted 0.560
Height
Improvement=0.000
<= 0.110
> 0.110
Node 39
n 28
% 8.092
Predicted 0.364
Node 40
n 36
% 10.405
Predicted 0.266
Area
Improvement=0.000
<= 0.085
> 0.085
Node 41
n 14
% 4.046
Predicted 0.390
Node 42
n 10
% 2.890
Predicted 0.250
Area
Improvement=0.000
<= 0.115
> 0.115
Node 43
n 19
% 5.491
Predicted 0.390
Node 44
n 9
% 2.601
Predicted 0.310
Position_X
Improvement=0.000
<= 0.790
> 0.790
Node 45
n 27
% 7.803
Predicted 0.289
Node 46
n 9
% 2.601
Predicted 0.200