

Birmingham City University



Project: I am Zero

Changing individual behaviours through digital technology to
reduce indoor emissions in UK homes from a behavioural
economics perspective

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Dedication

I dedicate this work to the cherished memory of my late grandparents

To my maternal and paternal grandparents, whose love, kindness, and gentle wisdom
continue to guide me even in their absence.

Your memories have been a source of comfort, motivation, and an inspiration throughout this
journey.

May this work honour your legacy.

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Abstract

The anthropogenic indoor air emissions, global warming, climate change, outdoor air pollution, and indoor air quality are interconnected as links in a continuous cycle, each reinforcing and worsening the others. Residential energy consumption highlights as one of the main contributors to anthropogenic indoor air emissions and poor indoor air quality in the UK. Existing research showed that reductions in household energy consumption is mainly rooted in the behaviours of the home occupants. This highlights the importance of behavioural economics in facilitating the sustainable behavioural change among the home occupants. Nudging, which is the practical application of behavioural economics, is highlighted as the solution for reducing household energy consumption and its related indoor air emissions and improving indoor air quality.

In the realm of digital technology, ‘smart nudging’, which is the extended version of digital nudging, has emerged as a main research focus that bridges the gap between nudging and digital technology. Focusing on smart nudging, this study aims to propose an actionable, practical, evidence-based, and validated smart nudge design for the household energy sector that facilitates the sustainable behavioural change. This study assesses the effectiveness of smart nudging interventions in improving different indoor air quality parameters, namely, carbon dioxide (CO₂), relative humidity, Total Volatile Organic Compounds (TVOC), and temperature. In addition, this study investigates the most effective smart nudging intervention in achieving the overall reduction of indoor air emissions related to household energy use and improvement of the indoor air quality holistically.

This research employed an action research methodology, using a within-subject design with repeated measures, multiple case studies design, and a mixed-method approach. The triangulated findings revealed that social comparison is the most effective smart nudging intervention in achieving the overall reduction of indoor air emissions and improving indoor air quality. Loss-aversion showed the highest effectiveness in reducing high CO₂ levels. Feedback showed the highest effectiveness in improving both relative humidity and TVOC levels. No smart nudging intervention was effective in improving temperature. In conclusion, this thesis contributes to the field of built environment by offering a smart nudge design for the household energy sector with new logic formulations for different smart nudging interventions to effectively nudge the home occupants towards achieving sustainable behavioural change, and thereby, reducing indoor air emissions and improving indoor air quality in the UK homes.

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Abbreviations

ANOVA - Analysis of Variance

ASHP – Air source heat pump

CH₄ – Methane

CO – Carbon monoxide

CO₂ – Carbon dioxide

CSV - Comma-Separated Values

FHS – Future Homes Standard

HCI – Human Computer Interaction

HER – Home energy report

HFC – Hydrofluorocarbons

IAQ – Indoor air quality

IHD – In-home display

MVHR - Mechanical Ventilation with Heat Recovery

N₂O – Nitrous oxide

NF₃ - Nitrogen trifluoride

NO - Nitric Oxide

NO₂ - Nitrogen dioxide

NO_x – Nitrogen oxides

O₃ – Ozone

PAH - Polycyclic aromatic hydrocarbons

PFC – Perfluorocarbons

PM – Particulate matter

PM₁₀ - Particles with diameters \leq 10 micrometres

PM_{2.5} - Particles with diameters ≤ 2.5 micrometres

ppb – Parts per billion

ppm – Parts per million

PRISMA - Preferred Reporting Items for Systematic Reviews and Meta-Analyses

PV – Photovoltaic

RH – Relative humidity

SF₆ - Sulphur hexafluoride

SO₂ - Sulphur dioxide

TVOC – Total volatile organic compounds

1 Chapter - Introduction

1.1 Background and context

Anthropogenic emission behaviours directly contribute to anthropogenic air emissions. Anthropogenic emission behaviours refer to the specific human behaviours and decisions that directly result in the release of anthropogenic air emissions including both greenhouse gases (e.g. CO₂, CH₄, N₂O) and air pollutants (e.g., NO₂, SO₂, PM_{2.5}) (Petrov, et al., 2023). The anthropogenic emission behaviours include activities such as fossil fuel combustion for heating, cooking, transportation choices, industrial operations, and material consumption (IPCC, 2021). USEPA (2014) states that anthropogenic air emissions, primarily driven by anthropogenic emission behaviours such as fossil fuel combustion and other human activities, are highlighted as a significant contributor to global warming and climate change by increasing atmospheric concentrations of long-lived greenhouse gases and air pollutants.

The anthropogenic air emissions increase the greenhouse effect. The greenhouse effect is a natural process where greenhouse gases trap part of the Earth's outgoing heat and keep the planet warm enough to sustain life. The increased concentration of greenhouse gases, more specifically, carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O), enhances the greenhouse effect by trapping more heat and disrupts the Earth's energy balance, leading to global warming and long-term climate impacts, including rising sea levels, extreme weather events, and eco-system degradation (IPCC,2021). The energy sector alone contributes around three-quarters of global greenhouse gas emissions, highlighting the scale of human influence on the global warming and climate change (IEA, 2025).

Global warming and climate change worsen outdoor air and increase outdoor air pollution, which in turn worsens indoor air quality through the infiltration of outdoor air into the indoor environments (Gherasim, et al., 2024). On the other hand, indoor air emissions derived from indoor activities (e.g. carbon emissions from heating) contribute to the increase of outdoor air pollution (USEPA, 2024). Therefore, anthropogenic emission behaviours, anthropogenic air emissions, global warming, climate change, outdoor air pollution, and poor indoor air quality are interconnected in a continuous cycle, creating a global crisis.

In response to this crisis, the Paris Agreement, adopted in 2015, set a legally binding international commitment to limit the global temperature rise to well below 2 °C and attempt to maintain it within 1.5 °C (UNFCCC, 2016). Aligned with this international commitment, the UK government has pledged to achieve net-zero air emissions by 2050 (GOV.UK, 2023).

The household energy sector plays a crucial role in the built environment and the reliance of UK households on fossil fuels triggers these anthropogenic air emissions. Roughly 74% of heating and hot water demand in UK homes is generated by natural gas, while around 10% generates from petroleum-based fuels (Committee on Climate Change, 2020). The UK government highlights that about 86% of households in England are connected to the gas grid and use natural gas boilers (GOV.UK, 2021). The UK households consumed approximately 26% of the UK's total final energy consumption in 2023, highlighting a considerable contribution to the national air emissions (Bolton, 2025). Moreover, these patterns show the scale of anthropogenic air emissions generated by UK households. As a result, the UK government is placing a strong emphasis on decarbonising the built environment.

The HECC report of GOV.UK (2023) states that people spend 66% of their time in their own homes and thereby, the residential sector serves as a primary context where people are regularly exposed to various indoor pollutants. The indoor air pollutants are generated from daily household energy consumption activities such as cooking, heating, combustion appliances, etc. Similarly, a recent study by the Grantham Research Institute found that average indoor concentrations of fine particulate matter (PM_{2.5}) in UK households were higher than outdoor PM_{2.5} levels during peak times, when home occupants are most likely to be indoors (16.00-23.00), and these high concentrations of particulate matter are largely driven by household activities such as cooking, heating, etc (Metcalf & Roth, 2025). The key parameters to assess indoor air quality are thermal conditions and air pollutant concentrations (Pipal & Taneja, 2023). The thermal conditions are temperature and relative humidity. The main indoor air pollutants generated by occupant daily activities are CO, CO₂, NO_x, PM_{2.5}, TVOC, etc (Tran, et al., 2020).

Achieving the UK's net-zero target by 2050 requires changes in home occupant behaviours, as they significantly influence both household energy consumption and indoor air quality outcomes (Taneja & Mandys, 2022). However, addressing occupant behaviours and their decision-making can be complex, as occupants' lifestyles are influenced by several social factors, cultural factors, past experiences, current environmental conditions, etc. Existing research shows that there can be significant variations in occupant behaviours in identical types of houses and those variations can lead to considerable differences in energy consumption outcomes (Andersen et al. 2009, as cited in Yang et al. 2020, p.2).

Behavioural economics is considered as a solution to nudge home occupants towards achieving sustainable behaviours and decision-making. Behavioural economics provides useful insights

from both psychology and economics to achieve sustainable energy consumption behaviours and reduce air emissions related to housed energy use by addressing cognitive biases of home occupants (Pollitt & Shaorshadze, 2011). Recently, the applied version of behavioural economics, namely, ‘nudging’ or ‘nudge theory’, has obtained the attention in the field of sustainable energy consumption. The nudge theory leverages behavioural interventions that influence decision-making of individuals without forbidding their freedom of choice and encouraging them to achieve sustainable goals and behaviours. Nudging is extended to digital nudging through digital technology by applying the same nudging interventions in digital environments, such as mobile applications, websites, smart devices, etc. to influence the decision-making of individuals (Weinmann, et al., 2016).

Digital nudging provides digital nudging elements or interventions in prompting environmentally sustainable behaviours in this domain (Berger, et al., 2022). Digital nudging interventions provide a promising approach to foster sustainable behaviours for reducing high energy consumption. However, the existing research showed that the designing of digital nudging interventions indicated challenges to promote sustainable energy consumption behaviours in an energy-saving context based on user autonomy, context sensitivity, and personalisation, while ensuring the nudging intervention is effective, user-friendly, and ethical. Smart nudging builds upon digital nudging by adding personalisation (knowledge about the user) and context-awareness (knowledge about the current situation of the user) to provide personalised, subtle, and more effective interventions to influence user behaviours and sustainable decision-making by avoiding some of the design challenges of digital nudging interventions (Karlsen & Andersen, 2019).

1.2 Problem statement/gap

Despite the growing interest in applying smart nudging to nudge home occupants towards achieving sustainable energy consumption in households through smart nudging interventions, there is no clear consensus in the existing literature regarding which type of smart nudging intervention is most effective. Previous research has largely relied on between-subject designs (application of a single smart nudging intervention to the same person) to find the effectiveness of the smart nudging interventions (e.g. Lynham et al., 2016; Aydin et al., 2018; Kim et al., 2020; Ghesla et al., 2020). One of the limitations of a between-subject design is that it may hinder the informed decision-making of home occupants, as occupants may end up adapting to the repeated exposure of a single smart nudging intervention over time, making the use of other types of study necessary to better understand the effectiveness of smart nudging interventions.

A within-subject repeated measures design, where different types of smart nudging interventions are applied to the same person at different timestamps over time, can provide a more robust comparison of the smart nudging interventions.

Existing empirical research has mainly assessed the effectiveness of smart nudging interventions on household energy consumption by focusing on metrics such as electricity, gas, room temperature, and hot water (e.g. Burchell et al., 2016; Cappa et al., 2020; Myres and Souza, 2020; Canale et al., 2021; Kim et al., 2022). No attention has been given to improving indoor air quality in households. As a result, occupant behaviour related to reducing indoor air emissions related to household energy consumption and improving indoor air quality remains unexplored in the context of smart nudging, leaving a knowledge gap. Furthermore, household energy sector lacks a smart nudge design to provide personalised, more accurate, and timely smart nudging interventions to avoid the design limitations of existing research such as overreliance of self-reported data, less accuracy of reported data, less user-friendliness, and limited frequency of the delivery of interventions that may hinder immediate behavioural change and influence of confounding variables on the impact. Therefore, it is important to overcome these design limitations through a better structured and a practical smart nudge design.

This thesis explores the effectiveness of smart nudging interventions in reducing indoor air emissions and improving indoor air quality related to household energy consumption in residential settings by applying a within-subject study approach. More specifically, this thesis assesses the most effective smart nudging intervention in reducing indoor air emissions related to household energy consumption and improving indoor air quality by nudging the home occupant towards achieving sustainable behaviours by deploying a smart nudge design designed for the household energy sector.

1.3 Research aim and objectives

1.3.1 Aim of the research

The primary aim of this research is to leverage the principles of behavioural economics and digital technology to change human behaviours with the goal of mitigating anthropogenic indoor air emissions and improving indoor air quality in the indoor home environments.

Specifically, this research aims to propose an efficient smart nudge design to influence human behaviours to empower individuals to make informed decisions regarding their behavioural

patterns and choices, ultimately contributing to the reduction of anthropogenic indoor air emissions related to household energy consumption and improvement of indoor air quality.

1.3.2 Research objectives

- 1) To define and examine the existing body of knowledge on anthropogenic air emissions and behavioural economics, including strategies to effectively nudge individuals towards reducing anthropogenic air emissions in home energy consumption and improving indoor air quality through the application of digital technology.
- 2) To develop a smart nudge design based on the literature review, complete with a process flow diagram and clearly articulate the steps involved in implementing the smart nudge design.
- 3) To compose smart nudging interventions within the newly designed smart nudge design, ensuring they are tailored to influence user behaviour, make informed decisions, reduce anthropogenic air emissions related to household energy use, and improve indoor air quality.
- 4) To conduct testing, analysis, and validation of the different smart nudging interventions by utilising the engagement analytics of the users and assessing user interviews through an action research methodology.
- 5) To propose an effective smart nudge design aimed at reducing anthropogenic air emissions related to household energy use and improving indoor air quality by changing human behaviours and consolidating findings from the literature review, design development, testing phases, and expert reviews to formulate an actionable design for behavioural change.

1.4 Research questions

- 1) Can smart nudging interventions induce behavioural changes that improve indoor air quality parameters to reach the recommended thresholds in houses?
- 2) What is the most effective smart nudging intervention in reducing indoor air emissions related to household energy consumption and improving indoor air quality holistically in the residential settings?
- 3) How do individuals perceive the effectiveness of smart nudging interventions across the different indoor air quality parameters in achieving the safe thresholds?

1.5 Significance of the study

This study contributes to the growing body of research by identifying the most effective smart nudging intervention on reducing anthropogenic indoor air emissions related to household energy consumption and improving indoor air quality in a within-subject repeated measures design. Moreover, by adopting a within-subject repeated measures design, this study enables a robust comparison of multiple smart nudging interventions within the same household, providing a more accurate assessment of their relative effectiveness to fill the research gap.

Unlike the previous studies that mainly focus on reducing household energy consumption including metrics such as electricity, gas, room temperature, and hot water, this research extends the scope by systematically assessing the impact of smart nudging interventions on improving specific indoor air quality parameters such as temperature, relative humidity, CO₂, and TVOC. Therefore, this study provides valuable insights into which smart nudging intervention is more impactful than other interventions, not only for each indoor air quality parameter separately but also for overall indoor air quality, including energy reduction and reduction of indoor air emissions, in a holistic way, including quantitative data from indoor quality sensors and qualitative data from interviews, to incorporate occupants' perceptions.

This research makes a key theoretical contribution by developing and validating a proposed smart nudge design tailored specifically for the household energy sector, its related indoor air emissions, and indoor air quality. The smart nudge design extends the application of smart nudging beyond its current scope and is validated through a combination of empirical research findings, existing literature, and feedback from the industry partner. This validation strengthens the theoretical robustness and practical relevance of the smart nudge design. In addition, while a smart nudge design was introduced to the transportation sector, there has been no smart nudge design that focuses on household behaviours related to indoor air emissions, indoor air quality, and energy consumption in a holistic way. Therefore, the proposed smart nudge design bridges a significant theoretical gap by addressing the existing limitations shown in the development of smart nudging interventions such as less accuracy of self-reported data, limited frequency of delivery of smart nudging interventions, less user-friendliness, by providing a structured design that links with practical strategies. By bridging this theoretical and knowledge gap and existing research limitations, this research contributes to improve the understanding of the effectiveness of different smart nudging interventions to change behaviours of home occupants and offers a practical, structured, evidence-based, and a validated smart nudge design that can

inform future smart nudging interventions, policies, and sustainable strategies within the residential sector.

1.6 Overview of methodology

This study employs an action research methodology, which is underpinned by a pragmatic research philosophy, an abductive reasoning approach, and a mixed-method methodological approach to achieve the research aim and objectives. The pragmatic research philosophy, abductive approach, and mixed-method approach align with the research questions of this study and provide flexibility and adaptability to use multiple data collection methods and data analysis methods that match the scope of this study.

The research design of this study is a within-subject repeated measures design including a multiple case study approach to answer the research questions, align with the reasoning approach to obtain a holistic understanding of the observed phenomena in a real-world setting, and provide future recommendations. The research uses three plots in Project 80 as three individual case studies. The plots are selected using purposive and convenience sampling techniques to select plots with similar demographics and household characteristics.

The primary data collection methods are Passive sensor-based monitoring and semi-structured interviews. The passive sensor-based monitoring methods are monitoring indoor air quality parameters through the ‘Uhoo smart air monitors’ and monitoring the digital home user app. The smart nudging interventions are delivered through the mobile application as push notifications. The app automatically logged each instance of intervention delivery and timestamp throughout the intervention period, enabling accurate monitoring of user interaction. Furthermore, passive sensor-based monitoring method gathers objective data on indoor air quality parameters and user interactions with the interventions or the engagement analytics. Pre-intervention and post-intervention interviews are conducted to gather subjective information, or in-depth insights about the research participants’ behaviours, perceptions, and experiences related to smart nudging interventions. The secondary data is collected through a comprehensive literature review.

Quantitative data collected through monitoring indoor air quality parameters and engagement data from intervention delivery is analysed using SPSS software, including descriptive statistics and inferential statistics. The quantitative data analysis aims to identify the most effective smart nudging intervention in reducing indoor air emissions related to household energy use and improving indoor air quality holistically through behavioural change. The

qualitative data is thematically analysed using NVivo software. Interview data supports internal validation of the research findings through triangulation. The qualitative insights are used to cross-check and interpret the quantitative results to strengthen the credibility of the conclusions of this research. The external validation is conducted through comparing the research findings with the existing empirical studies and comparing across the three plots. Moreover, the internal and external validation helps to formulate a robust smart nudge design as one of the research contributions. The research methodology is summarised in Figure 1.

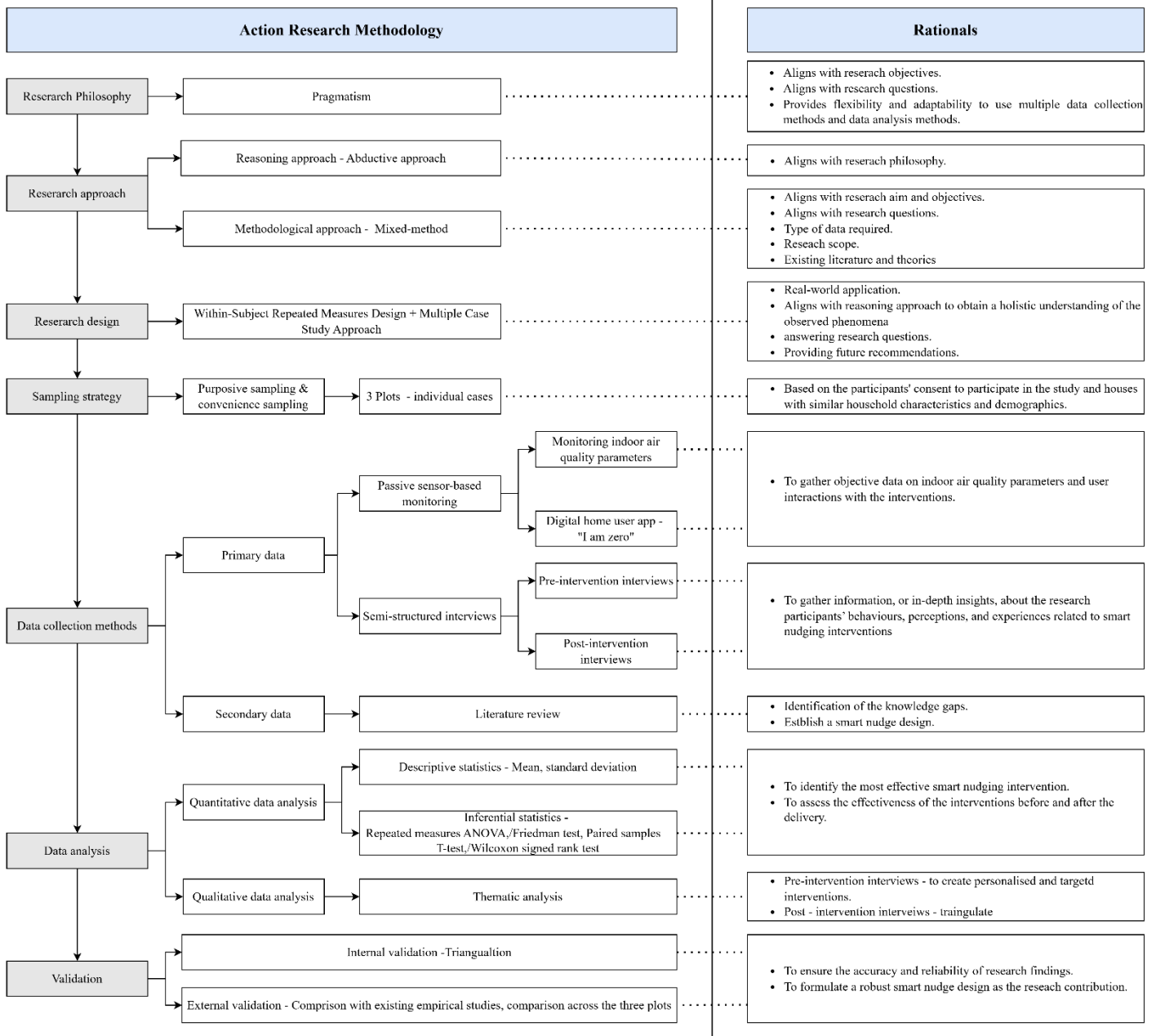


Figure 1: Overview of research methodology.

1.7 Thesis structure overview

The thesis structure is organised into 7 chapters. Each chapter contributes to achieving the research aim and objectives. The thesis structure and the contributions of each chapter is described below.

- Chapter 1: Introduction

The first chapter presents the background and context of the research, problem statement/gap, research aim and objectives, research questions, significance of the study, overview of methodology, thesis structure overview, and chapter summary. In general, this chapter provides an overview of the study.

- Chapter 2: Literature review

The second chapter systematically reviews existing literature on reducing anthropogenic indoor air emissions related to household energy consumption and improving indoor air quality by nudging home occupants towards achieving sustainable behaviours through smart nudging. This chapter identifies the knowledge gap and research gaps in the existing empirical research and provides the theoretical foundation of the study, ultimately leading to achieve the 1st research objective. Moreover, this chapter contributes to build the theoretical foundation for the smart nudge design.

- Chapter 3: Action research methodology

The third chapter presents the research philosophy, research approach, research strategy, data collection methods, data analysis methods, and ethical considerations of this study. Moreover, this chapter comprehensively explains the research methodology, including justifications and rationales for the selected philosophical approaches, reasoning approaches, methods and techniques. This chapter contributes to achieve the 4th objective.

- Chapter 4: Smart nudge design

The fourth chapter presents the formulation of the smart nudge design and the logics of the smart nudging interventions. The smart nudge design is build based on the theoretical foundation identified in the Chapter 2: Literature review. The smart nudge design addresses the research gaps identified in the Chapter 2: Literature review. Moreover, this chapter contributes to achieve objectives 2 and 3.

- Chapter 5: Results and Discussion

The fifth chapter presents and analyses the quantitative and qualitative data. More importantly, this chapter contributes to find the most effective smart nudging intervention in reducing household indoor air emissions related to energy usage and improve indoor air quality by changing occupant behaviours. Triangulation is used to internally validate the research findings. External validation is conducted by comparing the research findings of this study with the existing empirical studies and comparing the results across the three plots. This chapter contributes to achieve objective 4.

- Chapter 6: Proposed smart nudge design

The sixth chapter presents the proposed smart nudge design that builds on the empirical findings of this research and existing literature. The proposed smart nudge design is validated by obtaining the feedback from the industry partner. Moreover, the proposed smart nudge design intends to provide a contribution to the existing research by introducing a user friendly, practical, and evidence-based design that can inform future smart nudging interventions within the household sector. This chapter aims to achieve the 5th objective.

- Chapter 7 – Conclusion

The final chapter discusses the key findings of the research in relation to the research questions and existing literature. It describes the achievement of aims and objectives, theoretical and practical contributions of this research, limitations of the study, and provides recommendations for future research and practice.

The thesis structure is summarised in below Figure 2.

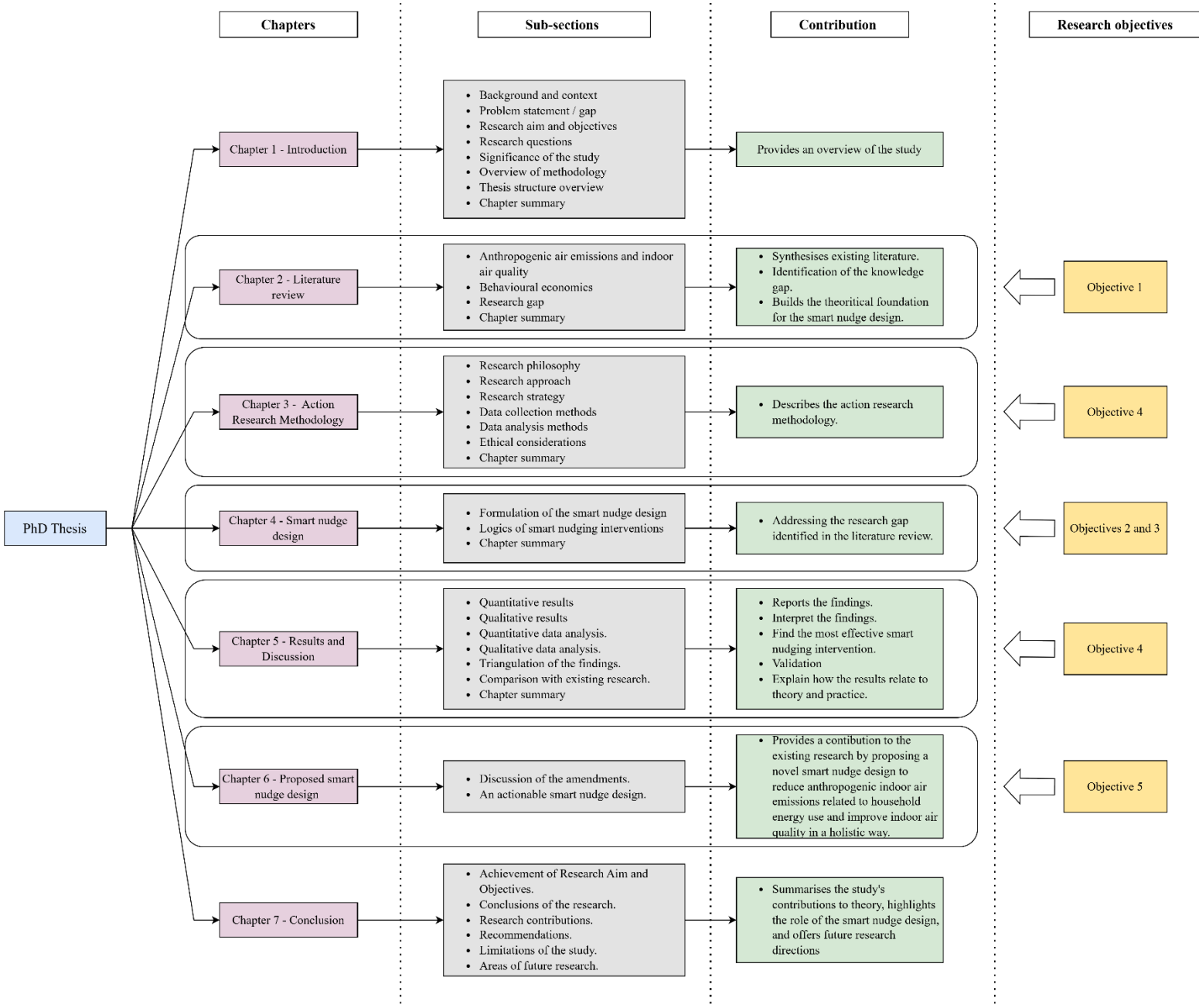


Figure 2: Thesis structure

1.8 Chapter summary

This chapter established the research background context, showing the importance of reducing indoor air emissions related to household energy consumption and improving indoor air quality through smart nudging. In addition, this chapter introduced the problem statement, research aim and objectives, research questions, significance of the study, overview of the methodology, and thesis structure, highlighting research contributions. The next chapter presents the comprehensive literature review, highlighting key theories, designs, and research gaps.

2 Chapter - Literature review

2.1 Introduction

Firstly, the literature review chapter will provide the body of knowledge on anthropogenic air emissions, specifically about the greenhouse gas emissions and air pollutants. More specifically, this will provide the body of knowledge on the relationship between anthropogenic air emissions related to household energy use, climate change, outdoor air pollution, and indoor air quality. Secondly, this chapter will focus on understanding behavioural economics. Moreover, this section will identify about how the behavioural economics theories have used in the field of household energy consumption through changing human behaviours. In addition, this chapter will highlight how behavioural economics theories have used on digital platforms to make informed decisions to individuals. Finally, this section will assess the research gap, knowledge gap, and the potential research contribution.

2.2 Anthropogenic air emissions and Indoor Air Quality

2.2.1 Air emissions

The term ‘air emissions’ defines the physical flow of gaseous or particulate materials from the economic system, such as production or consumption processes, into the atmosphere, which is a component of the environmental system. Air emissions include emissions of greenhouse gases and emissions of air pollutants (eurostat, 2015). Gases that trap heat in the atmosphere are known as greenhouses gases (USEPA, 2024). The greenhouse gases are carbon dioxide (CO₂), methane (CH₄), nitrous oxide (N₂O), hydrofluorocarbons (HFC), perfluorocarbons (PFC), sulphur hexafluoride (SF₆), and nitrogen trifluoride (NF₃) (GOV.UK, 2024). The air pollutants are nitrogen oxides (NO_x) comprising NO and NO₂, PM₁₀ and PM_{2.5} particles, Ozone (O₃), sulphur dioxide (SO₂), carbon monoxide (CO), volatile organic compounds (VOCs), Benzene, 1,3-Butadiene, metals (lead, cadmium, nickel, mercury, and the metalloid arsenic), and Polycyclic aromatic hydrocarbons (PAH) (GOV.UK, 2022). The air pollutants cause air pollution because the air pollution is identified as the contamination of indoor and outdoor air by air pollutants that change the natural composition of air (WHO, 2019).

2.2.2 Global warming, climate change, air pollution, and indoor air quality

Around 30% of sunlight that reaches the earth is reflected back into space by clouds, atmospheric particles, reflective surfaces, and ocean surfaces as thermal radiation and infrared rays, while the rest is absorbed by the land, air, and oceans (Shahzad & Riphah, 2015). However, some of the outgoing radiation is re-absorbed by the greenhouse gases in the

atmosphere due to their heat trapping capacity and radiated back into the earth's surface, warming the earth and making lives feasible on earth. This process is known as greenhouse effect. The problem begins when the concentration of greenhouse gases in the atmosphere is increased by human activities mainly by burning fossil fuels (Shahzad and Riphah 2015; Buha 2011). Anthropogenic greenhouse gas emissions are the primary cause of global warming since the mid-20th century (IPCC 2018; Williamson et al. 2018; USEPA 2024).

Climate change is the effect of global warming (Yahya & Marzuki, 2012). On the other hand, air pollution and climate change are deeply interconnected, as the air pollutants that lead to a deterioration in air quality are frequently co-emitted with greenhouse gas emissions (Orru, et al., 2017). For example, burning of fossil fuels emits nitrogen oxides, which are air pollutants, together with other greenhouse gases into the atmosphere (USEPA, 2024). Therefore, air emissions including both greenhouse gases and air pollutants escalate the climate change and air pollution.

The indoor air quality refers to the “*air quality within and around buildings and structures, especially as it relates to the health and comfort of building occupants*” (USEPA, 2024). Indoor air quality of a residential building is significantly affected by outdoor air quality or outdoor air pollution (Lin et al. 2017; Peng et al. 2017; Marc et al. 2018). In this line, the USEPA (2024) states that climate change can affect indoor air quality by worsening the quality of outdoor air or increasing outdoor air pollution, which infiltrates into the indoor environments. For example, the warmer temperatures and changing weather patterns can lead to severe wildfires. The smoke generated from wildfires can infiltrate into indoor spaces and reduce the indoor air quality by increasing indoor particulate matter (USEPA,2024). Moreover, Gherasim et al. (2024) state that climate change can affect the indoor air quality and make a negative impact on the health of the occupants by worsening the outdoor air. Similarly, the HECC report of GOV.UK (2023) reports that climate change is likely to affect indoor air quality, and thereby occupant's health and comfort, as people residing in the UK spend on average more than 95% of their time in indoor environments, and more specifically, 66% of their time in their own homes. In addition, Lewis et al. (2022) state that people spend most of their lives indoors (80-90%) and therefore, people are exposed to air pollutants, facing poor indoor air quality. Similarly, Kureshi et al. (2023) mention that indoor air quality influences human health 3-5 times worse than outdoor air quality, as people spend more time in an indoor environment. In conclusion, global warming, climate change, driven by anthropogenic air emissions, worsen outdoor air, which in turn affects indoor air quality like links in a chain.

2.2.3 Household energy consumption, climate change, and indoor air quality

The residential energy sector contributes to around 25% of global energy consumption, and 17% of global carbon dioxide (CO₂) emissions (IEA, 2016, as cited in Pablo-Romero et al., 2017, p.1). As per the Fifth Carbon Budget of the Committee on Climate Change (2016), 40% of UK air emissions are generated from households. The Energy Saving Trust (2020) showed that in 2017, the majority of household emissions were generated from household energy consumption, as an average household generated 2745kg and 755kg of carbon dioxide emissions from heating and electricity consumption per year, respectively. UK households emitted about 4-5 tonnes of CO₂ from home energy use in 2022, which is significantly high (GOV.UK, 2024). Similarly, in 2022, the air emissions from residential buildings reported for 20% of greenhouse gas emissions in the UK and these greenhouse gas emissions were generated mainly from fuel combustion (or burning of oil and gas for heating and hot water) and electricity consumption (Rowe & Rank, 2024). Therefore, household energy consumption is closely related to climate change through greenhouse gas emissions (Piao & Managi, 2023).

Air emissions related to household energy use and occupant activities can cause air pollution (Afifa, et al., 2024). Household energy consumption and related occupant activities, which includes cooking, heating, cleaning, etc. release indoor air pollutants such as particulate matter (PM), carbon monoxide (CO), and TVOC. These pollutants can be dangerous and affect occupants' health depending on the level and time of exposure. In turn, indoor air pollution can contribute significantly to outdoor air pollution (USEPA, 2024). Therefore, air emissions from household energy use, climate change, outdoor and indoor air pollution, and indoor air quality are interconnected, continuously rotating in a cycle where each factor influences and reinforces the other factors.

2.2.4 Importance of sustainable behavioural change related to household energy consumption

Households play a significant role in achieving the UK's net-zero emissions target in 2050 by reducing household energy consumption, as household energy consumption is one of the most significant contributors of anthropogenic air emissions. An in-house data analysis on the household energy consumption for space and water heating showed that occupant's characteristics and behaviours significantly affect energy consumption at 4.2% (Santin, et al., 2009, as cited in Zhao et al. 2017, p.224). In order to achieve the net-zero emissions target, it is important to understand and change household behaviours (Taneja & Mandys, 2022). Similarly, the Environment and Climate Change Committee (2022) reports that the net-zero

target of 2050 is not achievable without changing people's behaviours. Moreover, the Environment and Climate Change Committee (2022) states that “32 percent of emissions reductions up to 2035 relies on decisions by individuals and households”. However, occupant behaviours vary significantly between the individuals, causing significant variations in the energy consumption of the same type of buildings. For examples, 1) the electricity consumption of nine-identical low-energy social housing units varied by about 600% in some time periods of the year, 2) the heating consumption was varied significantly between English homes, and 3) energy consumption in 28 identical town houses showed that the most significant variation in energy consumption was two to one (Andersen et al. 2009, as cited in Yang et al. 2020, p.2). Therefore, these significant variations in the occupant behaviours in identical types of buildings make it more challenging to encourage the occupants towards achieving more sustainable behaviours.

Human behaviours related to household energy consumption play a significant role in improving indoor air quality (Kureshi, et al., 2023). Indoor air pollutants are generated from cooking, heating, combustion appliances, building occupants, cleaning, etc. (Royal Society of Chemistry, 2022). Daily activities such as cooking increase the concentrations of nitrogen dioxide, carbon monoxide, etc., lead to hazardous levels of these pollutants, and reduce indoor air quality (Lin, et al., 2017). Similarly, the study of Yu et al. (2024) showed that cooking using a gas stove led to significant changes in indoor air quality, as carbon monoxide, PM₁₀, and PM_{2.5} were increased by 24.4%, 9.8%, and 5.34%, respectively.

According to the study of Chenari et al. (2016), occupants' behaviour significantly affects the ventilation of a building and, consequently, its indoor air quality. As a result, proper ventilation is necessary to improve indoor air quality during cooking (Kureshi, et al., 2023). The main reason is that proper ventilation dilutes indoor air pollutants and creates a healthy indoor environment by mixing or transporting fresh outdoor air into the indoor environment (Tran, et al., 2020). A recent survey (March 2023) found that 65% and 61% of occupants opened a window when cooking and cleaning, respectively, to improve indoor air quality (Parliamentary Office of Science and Technology (POST), 2023). However, a study found that fewer than one in ten occupants ever adjusted their trickle vents and fewer than three in ten occupants kept their trickle vents constantly open to improve ventilation (Sharpe et al. 2015, as cited in Lewis et al. 2022, p.99). Moreover, people tend to dry clothes on radiators, consuming more energy, increasing indoor relative humidity levels, and reducing indoor air quality (NHBC, 2019). Therefore, human behaviours are a primary factor in improving indoor air quality. In

conclusion, changing household energy consumption behaviours and minimising indoor pollutants by adopting behaviours such as improving ventilation not only saves energy but also creates a healthier and more sustainable indoor environment in a holistic manner. On the other hand, it is important to educate the home occupants about the implications of their behaviours on indoor air quality related to household energy use through user guides, media, public awareness campaigns, and providing alternative solutions etc. to improve indoor air quality (Lewis et al. 2022; Parliamentary Office of Science and Technology (POST) 2023).

2.2.5 Indoor air quality measurements

The key parameters of evaluating indoor air quality are air pollutant concentrations and thermal conditions such as temperature and relative humidity (Pipal & Taneja, 2023). Table 1 shows the key parameters of evaluating indoor air quality and their descriptions. The key parameters shown in Table 1 are thermal conditions (temperature and relative humidity) and indoor air pollutants. The main indoor air pollutants generated by human activities are nitrogen oxides (NO_x), volatile organic compounds, sulphur dioxide, carbon dioxide, carbon monoxide, particulate matter (Tran, et al., 2020). The indoor air pollutants such as Total Volatile Organic Compounds (TVOC), carbon monoxide (CO), nitrogen oxides (NO_x), particulate matter (PM), and sulphur dioxide (SO₂) emit mainly from household energy use or cooking or combustion processes, while carbon dioxide (CO₂) is generated from human respiration. In addition, TVOCs are generated from cooking, fragrances, paints, flooring, etc. Moreover, the negative health impacts of each indoor air pollutant are described in Table 1.

Indoor air quality parameters		Description
Thermal comfort	Temperature	Temperature and relative humidity are the thermal comfort indicators in a house. Thermal conditions are important aspects of indoor air quality, as various problems related to poor indoor air quality can be solved by adjusting temperature or relative humidity (Tran, et al., 2020).
	Relative humidity	
Indoor air pollutants	TVOC	A common index of measuring all the VOCs is TVOC (Total Volatile Organic Compounds) (Halios, et al., 2022). Volatile Organic Compounds (VOC) tend to be more concentrated indoors than outdoors (basically up to 10 times higher than outdoors) (Parliamentary Office of Science and Technology (POST), 2023). Indoor VOCs emit from cooking in electrical hobs, paints, flooring, cleaning products, fragrances such as scented candles, perfumes, air fresheners, deodorants, etc, pesticides, usage of electronic devices such as printers, etc (Public Health England 2019; Heeley-Hill et al. 2021; Halios et al. 2022; USEPA 2024; Wojnowski et al. 2024). High VOC levels cause irritation of the eyes and respiratory track, allergies, asthma, damages to the organs, and cancers (Public Health England, 2019). In addition, high VOC levels can be reduced by opening windows and doors (Chin, et al. 2014; USEPA 2024).
	CO ₂	CO ₂ is an indicator of indoor air quality through evaluating building ventilation because CO ₂ itself is not an indoor air pollutant (Parhizkar, et al., 2023). CO ₂ emissions through breathing are considered as carbon neutral, as those emissions are not adding to the atmospheric CO ₂ concentrations and contributing to climate change. The reason for this is that the exhaled CO ₂ emissions are part of the natural closed-loop carbon cycle and are balanced by the carbon captured by plants. However, CO ₂ emissions from people reduces the indoor air quality. This deterioration of indoor air quality happens in the rooms or spaces that are poorly ventilated or occupied by many people. High CO ₂ levels reduce the cognitive ability or performance and attention of people (Lewis, et al. 2022; Parliamentary Office of Science and Technology (POST) 2023).
	CO	Carbon monoxide (CO) in indoor air is generated by combustion process such as cooking and heating (Tran, et al., 2020). Exposure to

		CO causes cognitive impairment at low concentrations and death at high concentrations (Parliamentary Office of Science and Technology (POST), 2023). Additional ventilation can be used as a temporary method when high CO levels are expected for a short period. Installing and using an exhaust fan vented to outdoors over gas stoves and property inspecting heating systems annually are considered as better solutions to reduce high CO levels (USEPA, 2024).
	Particulate Matter (PM)	Particulate Matter are the microscopic particles that primarily emit from combustion processes such as solid fuel burners, cookers, and gas boilers (Parliamentary Office of Science and Technology (POST), 2023). Exposure to Particulate Matter with diameter $\leq 2.5 \mu\text{m}$ or $\text{PM}_{2.5}$ is related with adverse health issues such as respiratory diseases and mortality (O'Leary, et al., 2019). Cooking is the primary source of $\text{PM}_{2.5}$ in a non-smoking household. Therefore, $\text{PM}_{2.5}$ concentrations are high at domestic kitchens. It is necessary to use appropriate ventilation mechanisms in the kitchen to reduce $\text{PM}_{2.5}$ (O'Leary, et al., 2019).
	Nitrogen oxides (NO_x)	Nitrogen oxides are formed indoors by combustion; especially, through gas cooking and gas heating (Lewis, et al., 2022). Nitrogen oxides are associated with causing asthma, wheezing, heart attacks, and cognitive decline. NO_2 is considered as the most dangerous component of Nitrogen oxides for human health (Parliamentary Office of Science and Technology (POST), 2023). Installation of an exhaust fan vented to outdoors over gas stoves, usage of an exhaust fan while cooking, and inspection of the heating systems annually can reduce high NO_2 levels (USEPA, 2024).
	Sulphur dioxide (SO_2)	SO_2 is primarily produced through combustion of solid fuels such as wood and coal and usage of gas appliances. However, outdoor SO_2 is considered as the primary cause of indoor SO_2 . Exposure to SO_2 can cause asthma and cardiovascular diseases (Parliamentary Office of Science and Technology (POST), 2023).

Table 1: Indoor air quality parameters

2.3 Behavioural economics

2.3.1 Understanding behavioural economics

Human behaviours and decision making are complex, as they are influenced by various interacting factors such as social factors, past experiences, current environmental conditions, genetic, etc. (Skinner, 2014). The neo-classical economics postulates that human behaviours and human decision-making are purely based on rational choice theory (Frederiks, et al., 2015). The rational choice theory, which highlights that cost-benefit analyses are central, posits that *“behaviour results from individuals acting to maximize the expected benefit of their individual decisions”* (Williamson, et al., 2018). In other words, humans make their decisions after weighing expected benefits and costs and selecting the most appropriate behaviour that provides the highest expected net benefit or lowest expected net cost. In addition, the rational choice theory has three main assumptions. Firstly, the theory assumes that the decision-making of the individuals is purely rational. Secondly, it assumes that the individual behaviour is mainly driven by individuals’ decision-making, thereby making the individual the key focus of analysis. Thirdly, it assumes that individuals perform behaviours or select choices in a manner that maximises expected value and therefore is always based on the individual’s self-interest (Williamson, et al., 2018).

Darnton (2008) stated that rational choice theory fails in addressing the influence of social, emotional, and contextual factors on human behaviours and decision-making in the real-life context. Similarly, Williamson, et al. (2018) mentioned that the rational choice theory is identified as a limited theory for explaining human behaviours. The main reason is that it assumes that individuals always make purely rational decisions and thus, this theory ignores human emotions, morals, social and contextual dimensions of decisions, and unconscious behaviours. In addition, individuals will not always have perfect access to obtain all the information required to make the most suitable rational decision or to perform their cost-benefit analysis at every time. Therefore, this theory does not identify future uncertainties and the cost of gaining information (can be time consuming and expensive) in the present (Williamson, et al., 2018). As a result, behavioural economics emerged as a solution to avoid the limitations of the rational choice theory and improve decision-making behaviours of individuals. Behavioural economics highlighted as a unique field under the umbrella term of ‘behavioural science’ (Buheji, 2018).

Precisely, behavioural economics combines different fields such as psychology, economics, management, and sociology. Behavioural economics help develop communities and solve

complex problems by improving decision-making and thereby, leading to positive economic outcomes and community growth (Buheji, 2018). Furthermore, Avineri (2012) described that behavioural economics (being a discipline of economics and a branch of social sciences) targets to strengthen the economic theory by making it more accurate and realistic with psychological insights. Similarly, Alam (2022) stated that behavioural economics describes how the psychological, cognitive, emotional, cultural, and social factors make an effect on the individual's decisions. Therefore, the field of behavioural economics has the potential to examine the changes in human behaviour through the lenses of psychological, emotional, social, and cognitive areas and to improve the quality of lives (Buheji, 2018). However, behavioural economics does not completely abandon the rational choice theory. In contrast with rational choice theory, behavioural economics provides a descriptive and experimental approach to show systematic deviations from rationality in decision-making using cognitive biases, emotions, and social factors in decision-making, as behavioural economics does not make strong assumptions about purely rational decision-making (Pūce, 2019). Similarly, DellaValle (2019) stated that individuals exhibit systematic deviations from the assumptions of the rational choice theory and therefore, behavioural economics describes the irrational patterns in decision-making to provide more realistic insights on human behaviours.

2.3.2 Importance of behavioural economics in the household energy sector

Capturing the 'human dimension' in areas such as energy consumption behaviours, choices, practices, etc. is critical in consumer energy-related research. Motivating and engaging individuals in achieving sustainable energy consumption behaviours and decision-making can be challenging in real-life contexts due to their unique lifestyles (Good, 2019). In addition, Frederiks et al. (2015) stated that although individuals understand the importance of using renewable energy sources such as solar energy, adopting energy-saving behaviours, using low-carbon technologies, and the negative impacts of air emissions, individuals often fail to make sustainable decisions and show energy-saving behaviours in the real-life. This contrary is based on various gaps that exist between what they understand and how they act, as irrational tendencies or cognitive biases play an important role in decision-making. Therefore, behavioural economics provides insights from both psychology and economics to change household energy consumption behaviours and reduce air emissions related to household energy consumption by addressing cognitive biases (Pollitt & Shaorshadze, 2011). Behavioural economics has been shown to reduce air emissions related to household energy consumption by over 10% in one year by prompting sustainable behaviours using strategies such as

providing information about the similar households, indicating potential savings, and using incentives (GOV.UK, 2011). Similarly, Camara et al. (2017) concluded that “*behavioural economics seems likely to provide the magic bullet to reduce energy consumption and offers new suggestions for finding potential sustainable changes in energy consumption*”.

2.3.3 Theories of behavioural economics

Daniel Kahneman, a psychologist, won the Nobel prize in Economics for his work with Amos Tversky, as they introduced the ‘prospect theory’ in 1979. The prospect theory explains how individuals make decisions under uncertainty (risks) by showing how those decisions deviate from the most rational choice or expected rational behaviour (Williamson, et al., 2018). The prospect theory indicate that individuals suffer from cognitive biases that affect their decision making. For example, an individual tends to avoid risks when he has an opportunity to secure a definite gain (risk-averse). On the other hand, that individual is willing to take risks when faced with a potential loss to avoid that loss completely (Miller, et al., 2016).

In recent years, the ‘dual process theory’ emerged as a growing prominence in behavioural economics research (Kahneman, 2011, as cited in Miller, et al., 2016, p.2). The dual process theory of Kahneman indicates two distinctive types of reasoning, which are ‘system 1’ and ‘system 2’. The “System 1” involves an automatic way of processing information (quick, emotional, and less effort), while the “System 2,” includes a rational way of processing information (effortful, analytical, and involves significant cognitive resources) (Miller, et al., 2016). Therefore, the dual process theory explains how decisions do not often follow the assumptions of rational choice theory and highlights how those decisions are made by the impressionable and emotional system 1, while the more logical or rational system 2 attempts, often fails, to monitor and correct those decisions (Williamson, et al., 2018).

In 2017, Richard Thaler, who collaborated closely with Kahneman, won the Nobel Prize in Economics for his work that built on Kahneman and Tversky’s theories (prospect theory and dual-process theory) about how individuals make decisions (Williamson, et al., 2018). More specifically, in 2008, Richard Thaler and Cass Sunstein wrote the book ‘Nudge: Improving Decisions About Health, Wealth, And Happiness’ and introduced the ‘nudge theory’ (Alam, 2022). Thaler and Sunstein introduced nudge theory to understand and improve decision-making behaviours of individuals (Mele, et al., 2021). Nudge theory is primarily rooted in dual-process theory, and it draws insights from prospect theory, especially, how individuals perceive gains and losses irrationally (Williamson, et al., 2018). Nudge theory is identified as the

practical application of behavioural economics. The nudge theory defines a nudge as “*any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives*” (Thaler & Sunstein, 2008). Therefore, Thaler and Sunstein (2008) stated that nudges are not taxes, fines, subsidies, mandates, or bans. For example, arranging fruits at eye level in a cafeteria counts as a nudge, while banning junk food does not identify as a nudge. In addition, Berger et al. (2022) stated that a nudge helps to modify the decision-making context of an individual without restricting the number of available options by fiscal measures, rules, and regulations. Moreover, Mele et al., (2021) mentioned that a nudge can be any small intervention that helps individuals to overcome cognitive errors and select particular beneficial alternatives without restricting their freedom of choice in a complex decision-making environment.

2.3.3.1 Digital nudging

Research on nudging or nudge theory has been mainly conducted in offline contexts. Recently, the advancements in digital technologies have made individuals make their important decisions in the digital choice environments such as mobile applications, web sites, etc. (Weinmann, et al., 2016). Therefore, in the realm of digital technology and Information Systems, ‘digital nudging’ has highlighted as a main research focus (Meske & Amojó, 2020). Digital nudging bridges the gap between nudging and digital choice environments (Castmo & Persson, 2018). Therefore, the definition of nudging was extended by focusing on the digital choice environments and defined digital nudging as “*the use of user-interface design elements to guide people's behaviour in digital choice environments*” (Weinmann, et al., 2016). Digital nudging offers digital nudging elements or interventions, which are crucial design elements for positively influencing individuals’ decision-making in a digital choice environment. The digital nudging elements (interventions) can be implemented more quickly, more cheaply, and in a more customised way than in an offline context, as digital choice environments provide ways to track and analyse individual preferences (Berger, et al., 2022). Digital nudging delivers information, reminders, creative pop-up messages, alternative ideas etc. to make informed decisions among individuals (Mele, et al., 2021) In addition, Berger, et al., (2022) identified that the digital nudging elements or interventions are effective in an energy-saving context and reduce high energy consumption.

Berger, et al. (2022) introduced eight digital nudging elements (interventions) in promoting environmentally sustainable behaviours. The digital nudging interventions that were identified by Berger, et al. (2022) are described below.

- Priming – refers to a method of preparing individuals for their decision-making by stimulating feelings, thoughts, and behaviour by introducing particular topics, moods, and information related to the consequences of their decisions before they make decisions (Mirsch et al., 2017, as cited in Berger, et al., 2022, p.3). For example, displaying the store’s eco-friendly product collection before users are directed to the shopping page to subtly nudge users to purchase more sustainable products (Roozen et al., 2021, as cited in Berger, et al., 2022, p.3).
- Social norms – refers to individuals’ beliefs and standards about the typical and socially approved behaviour in a given context (Kormos et al., 2015, p. 480, as cited in Berger, et al., 2022, p.3). For example, showing the percentage of the participants who donated in the past before requesting the new participants to make donations towards a charity motivates participants to donate by highlighting how others have contributed (Fanghella et al., 2019, as cited in Berger, et al., 2022, p.3).
- Goal setting – refers to a pre-commitment strategy to nudge individuals towards achieving their own goals (specific and achievable goals) in a more focused way (Sunstein, 2014, as cited in Berger, et al., 2022, p.3). For example, committing towards achieving an energy-saving target, expressing that target as a percentage relative to their previous electricity consumption in kWh, and monitoring their electricity consumption over a period of 4.5 months to nudge them towards achieving that target (Loock et al., 2013, as cited in Berger, et al., 2022, p.3).
- Default rules – refers to a situation where the preferred choice has been pre-selected and will remain that choice if an individual does nothing to change it (Thaler and Sunstein, 2009, as cited in Berger, et al., 2022, p.3). For example, default CO₂ compensation in flight booking portals or servers has been selected to nudge individuals towards donating CO₂ offsets (Székely et al., 2016, as cited in Berger, et al., 2022, p.3).
- Simplification – refers to simplifying complex information or delivering product information in a more noticeable way (Sunstein, 2014, as cited in Berger, et al., 2022, p.3). For example, using logos or labels such as smiling world faces on environmentally sustainable products to nudge individuals towards buying those products (Berger et al, 2020, as cited in Berger, et al., 2022, p.3).
- (Real-time) Feedback – refers to providing information to support individuals to understand whether their behaviours are/were good or improvable and to highlight the

consequences of their decisions (Cappa et al, 2020, as cited in Berger, et al., 2022, p.3). For examples, 1) using a smart meter in hotel showers to provide real-time feedback on water consumption by showing a polar bear standing on a melting ice glacier to nudge individuals toward using less water consumption for showering (Tiefenbeck et al., 2019, as cited in Berger, et al., 2022, p.3), 2) providing a detailed and customised feedback on an individual's energy consumption in terms of cost and CO₂ emissions to nudge that individual towards achieving energy saving behaviours (Cappa et al., 2020, as cited in Berger, et al., 2022, p.3).

- Social comparison – refers to providing comparative information to individuals to understand how their peers are behaving in comparison to their behaviours (Zimmermann et al., 2021, as cited in Berger, et al., 2022, p.3). For example, providing comparative information to an individual on the consumption of similar or comparative households to understand whether an individual consumes more or less energy than his/her peers (Schultz et al., 2015, as cited in Berger, et al., 2022, p.3).
- Framing – refers to presenting the same information in different ways to help individuals decide in different ways (Thaler and Sunstein, 2009, as cited in Berger, et al., 2022, p.3). For example, renaming the vegetarian food on a menu as “environmentally friendly main courses for a happy planet” instead of “vegetarian main courses” to nudge individuals towards selecting more sustainable vegetarian dishes (Krpan and Houtsma, 2020, as cited in Berger, et al., 2022, p.3).

Berger, et al. (2022) classified the eight digital nudging elements or interventions based on the time of their application (before, during, after, and throughout the action). The time of application of each digital nudging intervention is described below.

- Before an action – priming, social norms, and goal setting.
- Action – defaults and simplification.
- After action – feedback and social comparison.
- Throughout the action – framing.

2.3.3.2 Smart nudging

Existing research shows that the designing of digital nudging elements or interventions is challenging even though the ongoing digitalisation provides multiple opportunities to implement digital nudging elements to promote environmentally sustainable behaviours and reduce anthropogenic air emissions in an energy-saving context (Berger, et al., 2022). This has

become challenging due to the complexity and variability of user behaviours, decision-making processes, and different contexts. As a result, Caraban et al. (2019) first introduced the term ‘smart nudging’, conceptualising it as adaptive, context-aware, and data-driven nudges in Human Computer Interaction (HCI). On the other hand, Karlsen and Andersen (2019) introduced the concept, ‘smart nudging’ as “*digital nudging, where the guidance of user behaviour is tailored to be relevant to the current situation of each individual user*”.

Smart nudging can address the challenge of designing digital nudging elements (interventions) that promote environmentally sustainable behaviours and reduce air emissions in an energy-saving context by tailoring digital nudging interventions through personalisation and context-awareness. More importantly, both digital nudging and smart nudging use digital technology to nudge individuals, however, they differ in the design of the interventions. Precisely, digital nudging involves generically designing the interventions without using personalisation and context-awareness. In contrast, smart nudging involves designing the interventions using personalisation and context-awareness to increase the effectiveness of the interventions and nudge the users to make informed decisions.

As the pioneers of smart nudging, Caraban et al. (2019) and Karlsen and Andersen (2019) set the foundation for this field, however, their work took two different directions. The contribution of Caraban et al. (2019) lies in focusing on adaptive, context-aware, and data-driven nudges and providing a conceptual review and taxonomy of nudging in HCI that classifies nudging mechanisms, transparency, cognitive biases, and design considerations to inform digital intervention design. Caraban et al. (2019) did not propose any specific smart nudge design. Moreover, the work of Caraban et al. (2019) is mostly theoretical and digital-focused, not particularly focused in the real-world contexts. In contrast, Karlsen and Andersen (2019) focused on ethical, human-centred, and real-world applications of smart nudging, particularly in public sector and sustainability contexts. Karlsen and Andersen (2019) proposed a smart nudge design for the transportation sector by extending the digital nudge design of Schneider et al. Therefore, the design of Karlsen and Andersen (2019) can be argued to be more robust for this research context, particularly for smart nudging interventions aiming at sustainable behaviour change to reduce anthropogenic indoor air emissions related to household energy consumption and improve indoor air quality, as it offers a practical, user-centric, ethical, and real-world applicable design.

Although the smart nudge design of Karlsen and Andersen (2019) was originally framed for the transportation sector, the steps for designing a smart nudging intervention are not restricted to the transportation sector and can be used in any domain, even in the residential energy sector. The steps are explained below. The smart nudge design is shown in below Figure 3.

- 1) Define the goal – the first step determines the nudging goal. This step includes the overall goal that needs to be achieved through nudging.
- 2) Understand the users – this step determines understanding the user profile (understanding users in general and understanding the specific user). For example, demographic information of the user.
- 3) Understand the situation – this step determines understanding the situation or the specific decision-making context of the user such as time of the day, location, weather, etc.
- 4) Select the targeted activity – this step involves suggesting a set of relevant activities that help achieve the nudging goal to the user.
- 5) Select relevant information – this step involves collecting relevant information that requires to design the nudge. This information is used for informing the user about the selected targeted activities and subtly nudge the user towards positively reacting to the nudge and achieving the nudging goal.
- 6) Design the nudge – this step involves designing the nudge or the intervention by combining the selected targeted activity with relevant information and thereby, presenting a practical and convenient recommendation to achieve the nudging goal using non-coercive means.
- 7) Present the nudge – this step involves presenting the nudge (intervention) to the user promptly and using an appropriate method to help the user make informed decisions.
- 8) Evaluate the nudge - this step involves assessing the effectiveness of the nudge (intervention) in making a behavioural change. The outcome (successful or not) of the presented nudge may show an impact on every other step of the smart nudge design.

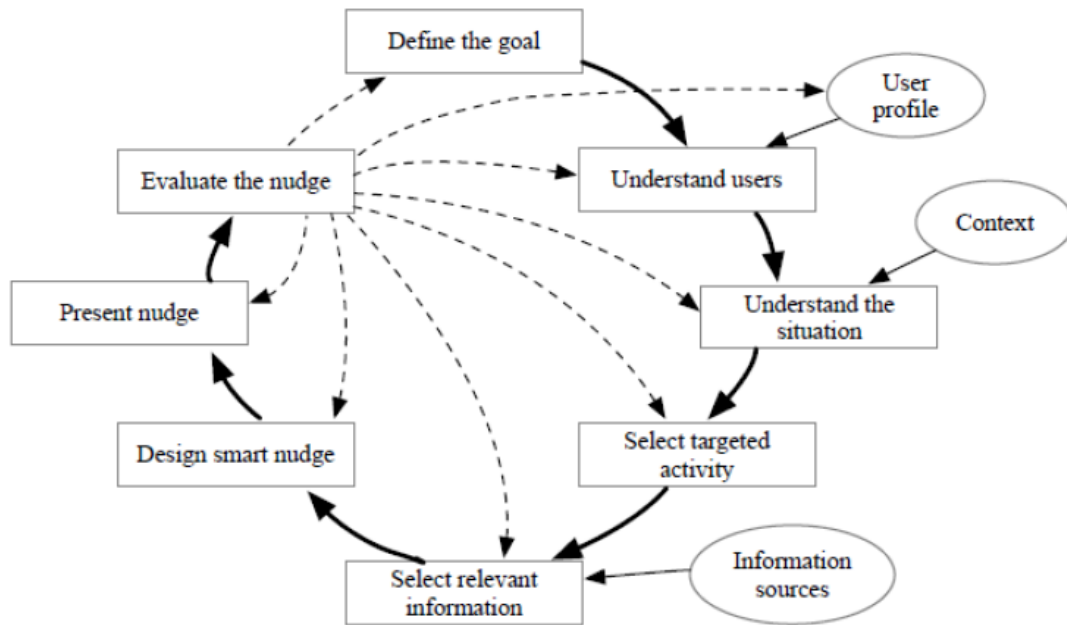


Figure 3: Smart nudge design introduced by Karlsen and Andersen (2019)

Karlsen and Andersen (2022) described the smart nudge components. A smart nudge or smart nudging intervention can be described as “*Smart nudge = {A, I, C, T, P}*”. The components of the smart nudging intervention are described below.

- A – Activity – targeted activity selected to nudge an individual towards achieving a nudging goal.
- I – Influence – motivational factors or information provided for an individual to achieve the nudging goal.
- C – Contents – practical information related to the targeted activity provided for an individual to achieve the nudging goal.
- T – Time frame – the most suitable time for presenting the smart nudging intervention.
- P – Presentation – the way in which the smart nudging intervention is presented to the user.

Karlsen and Andersen (2022) presented the design principles of a smart nudge design. The design principles are explained below.

- Challenge the user – selecting activities that are more challenging than the user’s normal behaviour and thereby, subtly nudge the user to achieve the nudging goal.
- Variation – presenting different types of smart nudging interventions for the user to avoid making the smart nudging interventions tedious and ineffective.

- Consolidate – detecting an improved behaviour of a user and thereby, maintaining the new activity level for a certain period of time to keep the user consistent.
- Progress – challenging the user again with the next step to achieve the nudging goal after stabilising the user on a certain activity level for some time.
- Timeliness – presenting or delivering the smart nudging intervention at a suitable time to provide the possibility to react to the intervention by the user.
- Avoid impossible nudges – avoiding the smart nudging interventions that are impossible to react.
- Avoid annoying the user – irritating smart nudging interventions should be avoided.

2.3.4 Impact of smart nudging interventions in the context of household energy consumption and air emissions

A PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) was conducted to assess existing empirical research on smart nudging in the built environment. More specifically, this review was conducted to evaluate how smart nudging interventions have made an impact on reducing energy consumption and thereby, reducing air emissions in the residential energy sector. The studies included in the PRISMA review were organised based on the type of smart nudging intervention used to gain a better understanding of the effectiveness of the interventions and identify research gaps in this domain. The parameters used in this review for comparison are the research design (country/context, research strategy, sample size, and intervention period) of a study, metrics, research limitations, research findings, and the information delivery methods or the digital platforms. The research limitations section includes the research limitations identified by the authors of the studies and the limitations that were not addressed in the studies but that could have influenced the overall effectiveness of the interventions and generalisability of the research findings. The findings of the review are presented in the below Tables 2 to 7.

In addition, the studies analysed using PRISMA method were assessed and grouped based on the type of nudging intervention each study included. This categorisation enabled a structured comparison of the nudging interventions and identification of their effectiveness broadly. Some studies included only a single nudging intervention and were grouped accordingly based on the type of intervention used such as feedback, social comparison, social norms and framing. Some studies used a combined intervention, namely, combination of feedback and goal setting. On the other hand, some studies compared the effectiveness of the different types of interventions within a single study.

2.3.4.1 Feedback

In analysing the six studies that examined the impact of feedback on reducing household energy consumption, these studies have used different digital platforms to deliver feedback and, therefore, show a multifaceted landscape, as shown in Table 2. The studies vary significantly in terms of their research designs (sample size, context, intervention periods) and information delivery methods. In comparing the studies that used feedback, the study of Lynham et al. (2016), which used IHDs to deliver the feedback, with one month of intervention period and a sample size of 58 households, showed an average electricity consumption reduction up to 11% based on the time of the day. The ‘learning effect’ (learning about energy consumption of various activities) primarily contributed to the reduction in household electricity consumption. In addition, Lynham et al. (2016) found that this reduction in household electricity consumption became less noticeable overtime. This might have occurred due to the repeated exposure of the same intervention over time, leading to reduced sensitivity or attention. In addition, the research findings of Lynham et al. (2016) showed a limited generalisability, as this research was conducted in a specific location, which is a faculty condominium complex with a homogeneous sample.

The study of Cappa et al. (2020), which delivered feedback using a web-based platform, with a sample size of 123 householders and an intervention period of one year, showed that feedback nudged the householders to shift the appliance use towards better energy-demand management with lower costs and comparatively lower air emissions. However, this study did not show the percentage of energy consumption reduction. In addition, the study of Cappa et al. (2020) showed research limitations, as this research obtained direct inputs (information about each appliance) from the users to generate the personalised feedback. Therefore, this process reduced the user-friendliness of the intervention and raised concerns about the accuracy of the feedback.

The study of Mogles, et al. (2017), with a sample size of 43 households and an intervention period of three months, showed that personalised feedback, which was tailored using action prompts and personal values, reduced the mean household temperature from 22.4 °C to 21.7 °C. This internal (mean) temperature reduction was statistically significant. In addition, this study showed that the gas consumption was reduced overall by 22% and 27.2% in high consumers after the delivery of the feedback that included only action prompts, which is a significant reduction. Moreover, this study by Mogles, et al. (2017) showed that feedback increased the energy literacy of the householders from 0.52 to 1.28 (on a 0-4 scale) and

suggested that the best practice is to deliver feedback only to the high consumers instead of delivering to everyone. Mogles, et al. (2017) delivered feedback using a software application (iBert). However, this study showed limited generalisability of the research findings to other demographic groups, as the research participants were residents of a social housing unit in the UK. In addition, this research could not prompt immediate behavioural changes among research participants based on the limited frequency of the delivery of the feedback (weekly feedback). However, this research could have obtained significant reduction in indoor temperature if they delivered feedback daily.

The study of Glerup et al (2010) delivered feedback using mobile phone (text messages) and emails, while the study of Shafqat et al. (2019) delivered feedback using a mobile phone application. The study of Glerup et al. (2010), with a sample size of 1452 participants and an intervention period of one year, showed that total annual electricity consumption was reduced by 3%, which is a noteworthy reduction. However, the research findings of Glerup et al. (2010) showed limited generalisability, as this study involved householders with specific house types (detached, terraced or town houses) and excluded householders that use electricity as their main heating source. In addition, this study showed choice complexity, as the householders were required to choose different types and frequencies of feedback, and therefore, that complicated the ability to isolate the impact of feedback on their energy consumption. The study of Shafqat et al. (2019) showed that feedback is not practical to use unless householders have a personal curiosity, and the householders lose interest over time. Shafqat et al. (2019) used a case study with 15 householders and an intervention period of six months for apartment residents and one year for townhouse residents. The study of Shafqat et al. (2019) showed that the intervention is not user-friendly, as it needed direct inputs (labelling appliances in the Smappee device) from the householders to provide the feedback.

The study of Kim et al. (2022) used feedback to nudge individuals towards achieving energy-saving behaviours. The experiment involved 41 households and an intervention period of seven months. The intervention was delivered using mobile phones. Results of this study revealed that the intervention made a positive impact on occupant behaviours but did not specifically present the reduction percentage. This research showed limited generalisability, as the experiment was conducted in a particular affordable housing community that includes different characteristics from the other demographics.

In reviewing the metrics, it can be seen that 4 studies evaluated only electricity consumption as the metrics, while one study evaluated electricity consumption with other metrics such as gas consumption, room temperature, and ventilation rate. One study evaluated only thermostat temperature as the metrics. In summary, it can be seen that the impact of feedback differs based on many factors, such as the type of digital platform and the research design of the studies. However, despite all these differences, empirical research showed that feedback can reduce high energy consumption, ultimately reducing high indoor air emissions.

Table 2: Impact of smart nudging interventions - feedback overview

Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country / Context	Research strategy	Sample size	Research duration			
(Lynham, et al., 2016)	<i>“Why does real-time information reduce energy consumption?”</i>	Disentangle two different and competing mechanisms, namely, 1) the learning effect (learning about energy consumption of different activities) and the saliency effect (constant reminders of energy consumption), through which real-time feedback influences energy consumption behaviours of residential households.	Electricity	Faculty of condominium complex in Honolulu, Hawaii	Experiment	58 households	Intervention period - 1 month	Electricity consumption of the residential households showed an average reduction up to 11% based on the time of the day (especially in the morning and in the evening). However, this effect or the reduction of electricity consumption became less noticeable overtime. Moreover, this reduction is driven mainly by “learning” effect and not by saliency effect.	<ul style="list-style-type: none"> Limited generalisability, as this research has conducted in a specific context (faculty condominium complex) with a homogeneous sample. 	IHD
(Cappa, et al., 2020)	<i>“Nudging and citizen science: The effectiveness of feedback in energy-demand management”</i>	Assessment of the impact of a detailed and customised feedback within an energy-demand management project.	Electricity	B.E. Smart project	Experiment	123 participants	Intervention period - Academic year 2016–2017	Two types of feedback namely, personal cost savings and emissions reduction, persuaded to shift the appliance use towards better energy-demand management and showed lower costs and comparatively lower emissions.	<ul style="list-style-type: none"> Direct inputs from the user – the users need to input the details for each appliance separately (hours of appliance usage, location, type of appliance, energy class of the appliance or the power that appliance requires) to get personalised feedback. This process can reduce the user friendliness of the intervention and the accuracy of the feedback. 	Web-based platform

(Mogles, et al., 2017)	<i>“How smart do smart meters need to be?”</i>	Evaluate the impact of a combination of two personalised digital feedback namely, personal values and tailored action prompts.	Electricity consumption, thermostat temperature (room temperature), gas consumption, and ventilation rate.	Residents of social housing recruited in, Exeter, UK	Experiment	43 households	Intervention period – 3 months (January 2016 to March 2016)	<ul style="list-style-type: none"> • Mean household temperature was reduced from 22.4 °C to 21.7 °C (using both action prompts and personal values). The internal temperature reduction was statistically significant. • Gas consumption was reduced overall by 22% and 27.2% in high consumers (using action prompts only). • Energy literacy was increased from 0.52 to 1.28 (on a 0-4 scale). • The best practice is to message only high consumers instead of messaging everyone. 	<ul style="list-style-type: none"> • The participants were residents of a social housing unit in the UK. Therefore, this may limit the generalisability of the findings to other demographic groups. • The limited frequency of personalised feedback, as the feedback was generated once per week based on the aggregated data from the previous week and show it in the subsequent week. Therefore, this may not deliver timely feedback to prompt immediate behaviour changes in the householders. 	Application called iBert via a tablet computer
(Gleerup, et al., 2010)	<i>“The Effect of Feedback by Text Message (SMS) and Email on Household Electricity Consumption: Experimental Evidence”</i>	Analyse the impact of feedback delivered through text messages and emails on residential electricity consumption.	Electricity	Denmark	Experiment	1452 participants	Intervention period - mid-November 2006 - December 31, 2007	Total annual electricity consumption was reduced by 3%.	<ul style="list-style-type: none"> • Choice complexity – householders choose the type of feedback and the frequency of the feedback. • Limited generalisability – this study involves householders living in a detached or terrace/town house and excluded householders that use electricity as their main energy source for heating the house and thereby, limiting the generalisability of the research findings. 	Mobile phone, emails

(Shafqat, et al., 2019)	<i>“Per-appliance energy feedback as a moving target”</i>	Investigate how users or householders understand and respond to different levels of feedback received from the device (Smappee) and how that affects their behaviours. Smappee provides the energy consumption feedback of each appliance.	Electricity	Scandinavian city	Case study	15 householders (9 apartments and 6 town houses)	Intervention period - 6 months for apartment residents, 1 year for townhouse residents.	De-aggregated feedback is difficult to use practically unless householder has a personal curiosity, and householders lost their interest over time.	<ul style="list-style-type: none"> Direct inputs from the user – labelling appliances in the Smappee device was not user-friendly to the householders. 	Mobile phone application
(Kim, et al., 2022)	<i>“MySmartE – An eco-feedback and gaming platform to promote energy conserving thermostat-adjustment behaviours in multi-unit residential buildings”.</i>	Present a cloud-based eco-feedback and gaming platform (MySmartE app) to encourage energy-saving thermostat-adjustment behaviours in multi-unit householders.	Thermostat temperature	Multi-unit residential community in Fort Wayne, Indiana	Experiment	41 households	Intervention period - January 1st, 2021 - August 1st, 2021	Results indicated a positive impact on occupant behaviours.	<ul style="list-style-type: none"> This research was conducted in a specific affordable housing community (building with electric heat pumps, and specific smart thermostats). Therefore, the findings may not be generalised to other demographics. 	Mobile phone

Table 2: Impact of smart nudging interventions - feedback overview

2.3.4.2 Social comparison

Table 3 presents the studies that used social comparison. The study of Liu et al. (2022), which investigated the impact of social comparison, with a sample size of 32 university dormitory rooms and three weeks of intervention period, showed that the overall energy consumption was decreased by 5.97% over the last two weeks (weeks 2 and 3) compared to week 1 (baseline week). However, Liu et al. (2022) found that there is no statistically significant reduction in energy consumption before and after the delivery of the interventions. The lack of statistical significance might be caused due to the limited sample size and high variability of data, as the number of rooms and participants in each subgroup was relatively small (8 rooms) and the absence of uniformity of students per subgroup. The intervention was delivered using a mobile phone. Furthermore, this study of Liu et al. (2022) indicated limited generalisability of the research findings, as all the research participants were university students, and thus, the outcomes of this study might vary significantly compared to the other real-life contexts.

Similarly, the study of Makivierikko et al. (2023) delivered interventions using a mobile phone. The study of Makivierikko et al. (2023) conducted an experiment in Sweden involving 550 student apartments and an intervention period of 16 months and found that the average electricity consumption was significantly reduced by 46%. In addition, the research participants showed prolonged engagement with the mobile application, which is a significant observation. However, this research was conducted in student apartments. As a result, the research findings show a limited generalisability. In comparing the studies that delivered social comparisons using mobile phones, it is clear that the study of Makivierikko et al. (2023) showed the highest effectiveness and long-term effectiveness in this domain, compared to the study of Liu et al. (2022). The 46% reduction might have been achieved because the interventions delivered through the mobile application effectively engaged users by combining social comparison with timely notifications about peak hours and including a community-focused social network design (connecting residents with each other like a local social network), motivating users to actively participate and change their behaviours in the long-term.

The study of Myers and Souza (2020), with a sample size of 400 students and an intervention period of three months, indicated that the intervention delivered through electronic Home Energy Reports (HERs) made no impact (null results) on residents who do not pay their energy bills. The null results might be caused by the limited frequency (once a week) of delivering the intervention to the residents. Therefore, weekly interventions might not encourage immediate behaviour changes in the residents. Similarly, the study of Henry et al. (2019) delivered the

interventions using electronic HERs. The study of Henry et al. (2019), with a sample size of 9383 households and an intervention period of one-year, showed that the electricity consumption was decreased by 2.9%, which is a positive reduction. However, the interventions were delivered monthly. Hence, this limited frequency of the intervention delivery might hinder the positive impact, as delivering the social comparison daily could potentially increase the overall impact even further. In addition, the study of Henry et al. (2019) showed a positive and a sustained impact of the intervention throughout a year, compared to the study of Myers and Souza (2020). The main difference between the results of these two studies may be attributed to the characteristics of the research participants, as motivating residents who do not pay their energy bills is more challenging due to the absence of a direct financial incentive. As a result, the study of Myers and Souza (2020) showed null results.

The studies (Aydin et al. (2018), Burchell et al. (2016), and Canale et al. (2021)) have used In-Home Displays (IHDs) to deliver the interventions. More specifically, two studies (Aydin et al. (2018) and Canale et al. (2021)) showed a significant positive impact in reducing household energy consumption. The study of Aydin et al. (2018), with a sample size of 158 households and an intervention period of eight months, showed that the electricity consumption was reduced by around 23%, which is a significant reduction. The interventions were delivered in every 15 minutes (real-time). However, the research findings of Aydin et al. (2018) showed a limited generalisability, as the experiment was conducted in a different location (Texel, a small island in the Netherlands) with unique geographic and demographic features, and thereby, results might differ across other contexts in the same country.

The study of Canale et al. (2021) revealed that the average consumption of hot water, electricity, and heating was reduced by 23%, 12%, and 17% respectively. The study of Canale et al. (2021) included 244 apartments and a longer intervention period of 30 months. The interventions were delivered hourly. In addition, the study of Canale et al. (2021) showed a limited generalisability based on the particularity of the case-study building. More importantly, in analysing these two studies that delivered social comparisons using IHDs, it can be concluded that social comparison showed both short-term and long-term effectiveness in reducing energy consumption. However, it is clear that the study of Aydin et.al (2018) showed the highest reduction in overall energy consumption by delivering interventions through IHDs.

On the other hand, the study of Burchell et al. (2016), indicated that the IHDs can maintain long-term engagement with the users, as 40% of users monitored their energy consumptions

daily. The research strategy of Burchell et al. (2016) was action research with 400 households and an intervention period of two years. However, this study did not explicitly mention the energy reduction percentage. This might have been caused by some limitations of the study, as this study showed a limited frequency of delivery of the interventions through the website, as the interventions were delivered weekly, and hence, it might not prompt immediate behavioural changes in householders. Moreover, this study showed reporting bias, as this study was based on self-reported data from the users. Therefore, in comparing the three studies of Aydin et al. (2018), Burchell et al. (2016), and Canale et al. (2021), the frequency of the intervention delivery is important, as the intervention delivery every 15-minutes (Aydin et al. (2018)) or hourly (Canale et al. (2021)) through IHDs prompted behavioural change and showed significant reductions in energy consumption, except the study of Burchell et al. (2016), which delivered interventions weekly through a website.

The study of Brülisauer et al. (2020) showed that the interventions reduced electricity consumption by 17% compared to the baseline period, which is a significant reduction. Brülisauer et al. (2020) conducted the intervention period for seven weeks with 389 students in Singapore (Graduate residence). However, this research showed limited generalisability, as the research was conducted in a university context with graduate students, which may be different from other real-world contexts. Brülisauer et al. (2020) delivered the interventions using emails weekly. Similarly, Asensio and Delmas (2016) delivered the interventions using emails once a week. Asensio and Delmas (2016), with 118 householders and 100 days of intervention period, showed that the interventions combined with a health-based framing approach encouraged energy-saving behaviours between 8-10% over 100 days, while interventions combined with a cost framing approach did not encourage any significant energy savings. However, this research indicated that there may be misunderstandings and inaccuracies in converting consumed energy (kWhs) to costs of air emissions.

In analysing the overall studies that used social comparisons, the study of Makivierikko et al. (2023) showed the highest effectiveness in achieving energy-saving behaviours in this context despite the information delivery methods and research designs of the studies. In reviewing the metrics, it is clear that 6 studies assessed only electricity consumption as the metrics, while 2 studies evaluated electricity consumption with other metrics such as gas consumption (or heating) and hot water. A single study assessed thermostat temperature as the metrics.

Table 3: Impact of smart nudging interventions –social comparison overview

Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country/context	Research strategy	Sample size	Research duration			
(Liu, et al., 2022)	<i>“The effect of normative-based feedback messaging on room air conditioner usage in university dormitory rooms in winter season”</i>	Investigate the impact of the intervention on room air-conditioner use.	Electricity	Chongqing, China	Experiment	32 university dormitory rooms	Intervention period – 3 weeks in December, 2021	The overall energy consumption was reduced by 5.97% over two weeks (weeks 2 and 3) compared to the baseline week 1. However, no statistically significant reduction was observed before and after the delivery of the interventions.	<ul style="list-style-type: none"> Limited generalisability – all the study participants are university students. 	Mobile phone
(Myers & Souza, 2020)	<i>“Social comparison nudges without monetary incentives: Evidence from home energy reports”</i>	Investigate the impact of intervention that delivered through HERs.	Thermostat temperature	Residence hall, University of Illinois at Urbana-Champaign	Experiment	400 students	Intervention period - September 13th to December 15th	No effect (null results) on residents who do not pay their energy bills.	<ul style="list-style-type: none"> Limited frequency of delivering the personalised interventions – social comparisons were delivered weekly. Therefore, that may not prompt immediate behaviour changes in the householders. 	Electronic HER
(Brülisauer, et al., 2020)	<i>“Appliance-specific feedback and social comparisons: Evidence from a field experiment on energy conservation”</i> .	Understand the impact of the intervention on household electricity consumption (air-conditioning use).	Electricity	Graduate residence, Singapore	Experiment	389 students	Intervention period - seven weeks	Interventions reduced electricity consumption by about 17% compared to the baseline period.	<ul style="list-style-type: none"> Limited generalisability – this research was conducted in a university residence with graduate students. 	Emails

(Asensio & Delmas, 2016)	<i>“The dynamics of behaviour change: Evidence from energy conservation”.</i>	Examine the impact of the intervention on household energy consumption over time.	Electricity	Los Angeles	Experiment	118 households	Intervention period – 100 days	Interventions combined with health-based framing messages persuaded energy saving behaviours between 8-10% over 100 days and cost-saving framing approach did not prompt any significant savings.	<ul style="list-style-type: none"> • Converting consumed kWhs to costs of air pollutant emissions may indicate misinterpretations and misunderstandings. 	Emails
(Aydin, et al., 2018)	<i>“Information provision and energy consumption: Evidence from a field experiment”</i>	Examine the impact of the intervention on energy consumption.	Electricity	Texel, Netherlands	Experiment	158 households	Intervention period 2 – May15, 2014 to January 2015.	The electricity consumption of the householders was reduced by around 23% (on average), compared to the control group.	<ul style="list-style-type: none"> • Generalisability – this research was conducted in a specific location. As a result, some factors like weather, energy infrastructure may differ across other locations in the same country. 	IHD
(Burchell, et al., 2016)	<i>“Householder engagement with energy consumption feedback: the role of community action and communications”</i>	Assess the impact of the intervention on electricity and gas consumption.	Electricity and gas consumption	Kingston upon Thames, UK	Action research	400 households	Intervention period - May 2011 to May 2013	Results indicated that long-term engagement with the intervention is possible, as 40% of participants used the IHDs daily to monitor their energy consumptions. Additionally, women engagement with intervention is high.	<ul style="list-style-type: none"> • This study is based on self-reported electricity meter readings from the occupants. The self-reported data may lead to reporting biases. • Feedback is delivered weekly and that limited frequency of delivery may not prompt immediate behaviour changes in the householders. 	IHD, website
(Canale, et al., 2021)	<i>“Do in-home displays affect end-user consumptions? A mixed method analysis of electricity, heating and water use in Danish apartments”</i>	Explore the impact of the intervention on the consumption of electricity, heating, and water.	Hot water, electricity, and heating.	Denmark	Case study	244 apartments	Quantitative study - December 2016 to June 2019	The average consumption of cold water, hot water, electricity, and heating reduced by 17%, 23%, 12% and 17% respectively compared to the control group.	<ul style="list-style-type: none"> • The results may not be generalisable based on the particularity of the case-study building. 	IHD

(Henry, et al., 2019)	<i>“The behavioural effect of electronic home energy reports: Evidence from a randomised field trial in the United States”</i>	Report the impact of social comparisons and personalised feedback on energy consumption.	Electricity	One American state with consumers from seven utilities.	Experiment	9383 households	Intervention period - January 2016 to December 2016	Electricity consumption was reduced by 2.9%.	<ul style="list-style-type: none"> The interventions are delivered monthly. Thus, this limited frequency of delivery may not encourage immediate behaviour changes in the householders. 	Electronic HER
(Makivierikko, et al., 2023)	<i>“Reducing electricity peak loads through ‘pause hours’ - a community-based behavioural demand response approach”</i>	Investigate a novel needs-based approach to demand response management as a solution for prolonged engagement and peak load electricity consumption reduction over long-term.	Electricity	Sweden	Experiment	550 student apartments	Intervention period - February 2020 and June 2021	Results showed an average reduction of 46% (peak-load consumption) among occupants in pause hours. In addition, many app users (occupants) showed prolonged engagement with the app.	<ul style="list-style-type: none"> This research was conducted in student apartments. Thus, this may limit the generalisability of the research findings. 	Mobile phone

Table 3: Impact of smart nudging interventions - social comparison overview

2.3.4.3 Social norms

According to the Table 4, it can be seen that only two studies have deployed social norms. The study of Kim et al. (2020), with a sample size of 1700 households (approximately) and an intervention period of five months in Japan, revealed that social norms reduced the electricity consumption by 1.3%. Moreover, the results of this study showed that the opening ratios of the push notifications were increased from 1.2 to 1.3 times, indicating considerable engagement with the interventions. The interventions were delivered using mobile phones. However, this research highlighted that the householder's demographics such as household size, house type, and heating energy source significantly exceeded the national average of Japan. Therefore, this affects the generalisability of the research findings and the external validity of the results.

On the other hand, the study of Stieglitz et al. (2023), with 391 research participants and with no specified intervention period, showed a positive impact on reducing high energy consumption. However, this study did not mention the reduction percentage. The social norms were delivered using mobile phones. However, this study showed limited generalisability and sample bias, as the research participants were selected based on their English-speaking ability, and thus, it reduced the diversity of the sample. Therefore, in analysing the two studies, the study of Kim et al. (2020) showed the highest effectiveness in achieving the energy-saving behaviours. In reviewing the metrics, it can be seen that only one study (Stieglitz, et al., 2023) evaluated electricity consumption and heating as the metrics, while the other study (Kim, et al., 2020) only evaluated electricity consumption.

Table 4: Impact of smart nudging interventions - Social norms overview										
Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country/context	Research strategy	Sample size	Research duration			
(Kim, et al., 2020)	<i>“Field experiment of smartphone-based energy efficiency services for households: Impact of advice through push notifications”</i>	Indicate the impact of energy efficiency advice (social norms) in the residential sector.	Electricity	Kanto region, Japan	Experiment	Approximately 1700 households	Intervention period - July 2, 2018, to December 2, 2018	1.3% reduction in electricity use. In addition, the opening ratios of the push notifications were increased from 1.2 and 1.3 times using personalised sentences and adjusting the timing of the delivery of the push notifications.	<ul style="list-style-type: none"> Limited generalisability, as this study highlights that the resident’s demographic, such as household size, housing type, and energy source significantly exceeded the national average of the country. Thus, this affects the external validity of the findings and limits the generalisability. 	Mobile phone
(Stieglitz, et al., 2023)	<i>“The potential of digital nudging to bridge the gap between environmental attitude and behaviour in the usage of smart home applications”</i>	Test the impact of digital nudging interventions (social norms) in reducing attitude-behaviour gap between environmental attitudes and occupant behaviours.	Electricity and heating.	European countries	Experiment	391 participants	-	No significant impact on occupants in reducing behavioural gap between pro-environmental attitudes and energy-saving behaviours. However, social norms showed an impact on reducing energy consumption and promoting energy-saving behaviours of the occupants.	<ul style="list-style-type: none"> Limited generalisability, as the research participants were chosen using ‘Prolific’ (English-speakers from European countries, etc.), which may reduce the diversity of the sample and conduct to a sample bias. 	Mobile phone

Table 4: Impact of smart nudging interventions – social norms overview

2.3.4.4 Framing

Two studies have examined the effectiveness of framing in this domain, as shown in Table 5. The study of Bager and Mundaca (2017) assessed the impact of loss-aversion on reducing high energy consumption, with 16 participants and an intervention period of one month, showed that loss-aversion (loss-framed information) reduced electricity consumption by 7-11%, which is a significant reduction. The loss-aversion was delivered using mobile phones. However, this study showed that the margin of error is 24.5%, indicating uncertainty based on variability in the data.

The study of Ghesla et al. (2020), with a sample size of 1636 householders and an intervention period of one month, showed that loss-aversion (loss-framed information) was more effective than gain-framed information in achieving electricity-saving behaviours and reduced electricity consumption by 5% compared to the control group. Ghesla et al. (2020) proposed a 5% electricity reduction goal to all the research participants. Therefore, research participants received that specific reduction goal of 5%, which was calculated relative to their baseline electricity consumption. The loss-aversion or loss-framed information was delivered through emails. However, this study was based on self-reported electricity meter readings, which may lead to reporting biases and inaccuracies of research findings. In summary, it can be concluded that loss-aversion has shown significant reductions in high energy consumption. In studying the metrics, it can be seen that both of the studies evaluated electricity consumption as the metrics.

Table 5: Impact of smart nudging interventions – framing overview

Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country/context	Research strategy	Sample size	Research duration			
(Bager & Mundaca, 2017)	<i>“Making ‘Smart Meters’ smarter? Insights from a behavioural economics pilot field experiment in Copenhagen, Denmark”</i>	Examine the impact of loss-aversion on residential electricity consumption.	Electricity	Denmark	Experiment	16 participants	Intervention period - Four weeks	Loss-framed and salient information reduced electricity consumption by 7-11% compared to unframed information.	<ul style="list-style-type: none"> Limited generalisability, as the sample size is small (16), and the margin of error is 24.5%. 	Mobile phone
(Ghesla, et al., 2020)	<i>“Pro-environmental incentives and loss aversion: A field experiment on electricity saving behaviour”</i>	Examine the impact of gain-framed incentives and loss-framed incentives on pro-environmental behaviours.	Electricity	Southern Germany	Experiment	1636 households	Intervention period - mid-November to mid-December 2016	Householders showed an average monthly electricity saving of 5% compared to the control group. In addition, the effectiveness lasted beyond the intervention period.	<ul style="list-style-type: none"> This study relies on self-reported electricity meter readings. Thus, data may be subjected to reporting biases. 	Emails

Table 5: Impact of smart nudging interventions – framing overview

2.3.4.5 Combination of feedback and goal setting

Table 6 showed that only one study has evaluated the impact of the combined intervention, which is a ‘combination of feedback and goal setting’. The metrics used was electricity consumption. The study of Aydin et al. (2018) showed that electricity consumption was reduced by around 20%, which is a noteworthy reduction. The intervention was delivered using In-Home Displays (IHDs). The study of Aydin et al. (2018) involved a sample size of 158 households and an intervention period of two months. However, the research findings of this study presented a limited generalisability, as the experiment was conducted in a context with unique demographic features that show differences to other contexts in the same country.

Table 6: Impact of smart nudging interventions - combination of feedback and goal setting overview

Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country/context	Research strategy	Sample size	Research duration			
(Aydin, et al., 2018)	<i>“Information provision and energy consumption: Evidence from a field experiment”</i>	Examine the impact of high-frequency feedback (feedback combined with goal setting) on energy consumption.	Electricity	Texel, Netherlands	Experiment	158 households	Intervention period 1 - March 15, 2014, to May 15, 2014 (information provided and advised to set their own goals)	Electricity use was reduced by around 20% (on average), compared to the control group.	<ul style="list-style-type: none"> This research was conducted in a specific location. Therefore, some factors like weather, energy infrastructure may differ across other locations in the same country. 	IHD

Table 6: Impact of smart nudging interventions - combination of feedback and goal setting overview

2.3.4.6 Intervention comparisons in the same research

Three studies have compared and evaluated the impact of different interventions in the same research project, as shown in Table 7. All the studies have used electricity consumption as the metrics. The study of Ruokamo et al. (2022) investigated the impact of two main nudging interventions namely, feedback and social comparison. The results suggested that only feedback including versatile energy saving tips promoted daily electricity savings of around 10% on average. Therefore, it can be seen that social comparison was not effective in this research. Ruokamo et al. (2022) conducted this study in Finland selecting 657 participants and an intervention period of three years. The interventions were delivered using online newsletters and online service platforms. However, the study participants were not fully representative of Finnish citizens. As a results, this research showed a limited generalisability of the research findings.

The study of Kazukauskas et al. (2021), which investigated the impact of social comparison on household energy consumption, found a notable reduction of daily household electricity consumption by 6.7% compared to the control group which received only real-time feedback. Kazukauskas et al. (2021) conducted a one-year experiment with a sample size of 525 newly built apartments in Sweden. However, this research conducted randomization at the building-level which might possibly limit the generalisability of the research findings to other demographic groups or contexts where individual-level variability is more evident.

The study of Dominicis et al. (2019) compared and evaluated the long-term impact of two main interventions namely, real-time feedback and social comparison. The interventions were delivered using In-home Displays (IHDs). This study found that only social comparison reduced residential electricity consumption by 4.57%. Therefore, in comparison, the most effective intervention is social comparison. Dominicis et al. (2019) conducted this research by involving 390 single-family households, and hence, this might limit the generalisability of the results. The intervention period is 27 months. In summary, the studies of Kazukauskas et al. (2021) and Dominicis et al. (2019) showed that social comparisons delivered through IHDs were more effective than the feedback. However, all these three studies (Ruokamo et al. (2022), Kazukauskas et al. (2021), and Dominicis et al. (2019)) did not expose all the research participants to all types of nudging interventions. Therefore, each research participant was exposed to only one intervention.

Table 7: Impact of smart nudging interventions - comparison of different interventions in the same research project

Reference	Title	Aim of the study	Metrics	Research design				Results	Research limitations	Information delivery medium/digital platform
				Country/context	Research strategy	Sample size	Research duration			
(Ruokamo, et al., 2022)	<i>“The effect of information nudges on energy saving: Observations from a randomized field experiment in Finland”</i>	Investigate the impact of 1) energy-saving tips together with and without feedback, 2) social comparison on household’s electricity consumption.	Electricity	The Porvoo region, Finland	Experiment	657 participants	Intervention period - September 2017 to September 2020.	Feedback including versatile energy-saving tips (without social comparison) can promote electricity savings around 10% in average daily electricity use.	<ul style="list-style-type: none"> The study participants or householders were not fully representative of Finnish citizens. Therefore, results may not be generalisable. 	Online newsletters, Online Service Platform
(Kazukauskas , et al., 2021)	<i>“Social Comparisons in Real Time: A Field Experiment of Residential Electricity and Water Use”</i>	Investigate the impact of the social comparison on household energy and water consumption.	Electricity	Sweden	Experiment	525 newly built apartments	Intervention period – 12 months (March 1, 2016, to February 28, 2017)	Social comparison showed a reduction of daily electricity consumption by 6.7%, compared to the control group which received only real-time feedback.	<ul style="list-style-type: none"> Randomization at building level may possibly limit the generalisability of the findings to other contexts where individual-level variability is more evident. 	IHD
(Dominicis, et al., 2019)	<i>“Making the smart meter social promotes long-term energy conservation”</i>	Investigate the long-term impact of social comparison and feedback.	Electricity	A region of 6500 single-family homes in North County, San Diego, California	Experiment	390 single-family households	Intervention period - July 2013 to September 2015	Social comparison reduced electricity use by 4.57%.	<ul style="list-style-type: none"> This study was conducted only with single-family households. As a result, this may limit the generalisability of the results. 	IHD

Table 7: Impact of smart nudging interventions – comparison of different interventions in the same research project

In analysing the existing empirical research, it is interesting to point out that the studies analysed using PRISMA and presented in above Tables 2-7 have not acknowledged the term ‘smart nudging’ even though all those studies have used smart nudging by tailoring digital nudging interventions using personalisation and context-awareness to nudge individuals towards achieving sustainable energy consumption behaviours. While 19 studies have used only a single intervention (as shown in Tables 2, 3, 4, and 5), one study has used a combined intervention, which is a ‘combination of feedback and goal setting’ (as shown in Table 6) to assess the impact of smart nudging intervention in reducing high energy consumption. In addition, three studies have used different types of smart nudging interventions (as shown in Table 7) to assess the most effective smart nudging intervention that nudge individuals towards achieving sustainable energy saving behaviours. The frequency of smart nudging interventions used within the existing empirical research is shown in Figure 4.

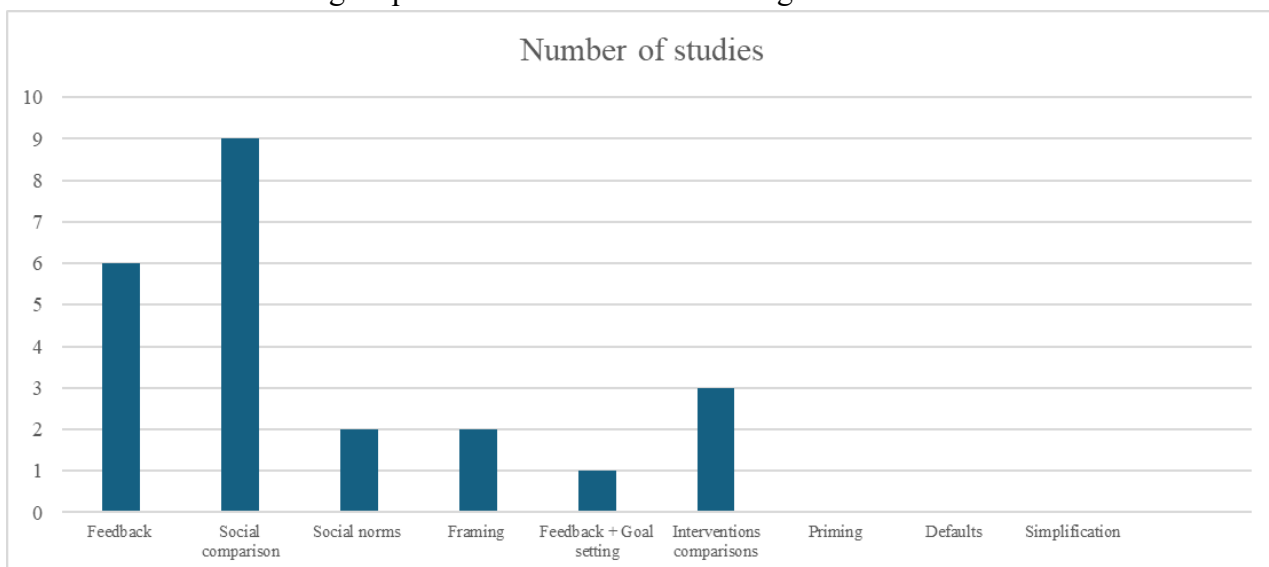


Figure 4: The frequency of smart nudging interventions used within the empirical research

In analysing the frequency of smart nudging interventions used within the existing empirical research, social comparison, emerges as the most used intervention in this domain. The reason is that this social comparison was used in nine studies. Feedback ranks as the second most used intervention, as feedback was used in six studies. Social norms and framing were used in two studies each. The combined intervention, which is a ‘combination of feedback and goal setting’ was used only in one study. In addition, three studies have compared the effectiveness of the different interventions (particularly feedback and social comparison) to find the most effective intervention in this domain. Other nudging interventions namely, priming, defaults, and simplification have not been used in those studies.

Generally, the empirical evidence from exiting studies (shown in Tables 2-7) reveals that smart nudging interventions are effective in reducing high energy consumption by achieving energy-saving behaviours. However, the research findings related to a single intervention or combined intervention differ significantly among existing empirical studies based on 1) the information delivery method or digital platform used to deliver the nudging interventions and 2) the research design of the studies, such as sample size, intervention period, context, and different research methods and approaches used to assess the impact of the deployed nudging interventions.

The below Figure 5 shows the frequency of different information delivery methods or digital platforms used within the empirical studies to assess the impact of different smart nudging interventions in this domain. Mobile phones including mobile applications have been used in eight studies and thereby, mobile phones emerge as the most used, popular and versatile digital platform. In-Home displays (IHDs) have been used in seven studies. Emails have been used to deliver nudging interventions in four studies. Electronic Home Energy Reports (HERs), and web-based platforms have been used in two studies each. Software applications and newsletters have been used less frequently in one study each.

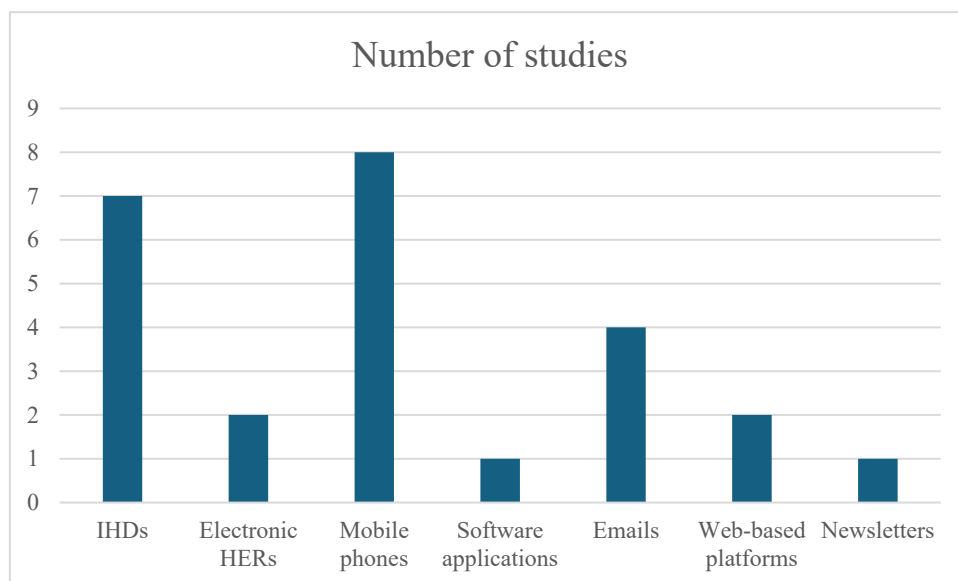


Figure 5: The frequency of information delivery methods used within the empirical research

2.3.5 Identification of the most effective smart nudging intervention across the empirical studies

In analysing the studies, it is important to identify which smart nudging intervention (either as a single intervention or combined intervention) has indicated the best effectiveness. Table 8 presents the smart nudging interventions along with the study that showed the highest effectiveness and highest energy reduction percentage. However, Table 8 shows the empirical studies that primarily used single interventions or combined interventions but not studies that compared different types of interventions in the same research to avoid confusion and clearly understand how a single intervention or a combined intervention performed within a specific context.

Smart nudging intervention	Study that showed the highest effectiveness	Energy reduction percentage
Feedback	(Mogles, et al., 2017)	22%
Social comparison	(Makivierikko, et al., 2023)	46%
Social norms	(Kim, et al., 2020)	1.3%
Framing	(Bager & Mundaca, 2017)	7-11%
Combination of feedback and goal setting	(Aydin, et al., 2018)	20%

Table 8: Most effective smart nudging intervention across the empirical studies

In analysing the results in Table 8, the highest effectiveness of feedback was shown as 22% in the study of Mogles et al. (2017), compared to the other studies that used feedback to nudge the individuals towards achieving energy-saving behaviours. Social comparison showed the highest effectiveness as 46% in the study of Makivierikko et al. (2023). The social norms indicated the highest effectiveness as 1.3% in the study of Kim et al. (2020). However, social norms indicated comparatively low effectiveness than the other nudging interventions. Framing, more specifically, loss-aversion (loss-framing) showed the highest effectiveness as 7-11% in the study of Bager & Mundaca (2017). The combined intervention, which is a combination of feedback and goal setting, showed the highest effectiveness as 20% in the study of Aydin et al. (2018). Therefore, despite the research designs and information delivery methods, it can be concluded that the highest effectiveness was shown by social comparison, and the second highest effectiveness was demonstrated by feedback.

2.4 Research gap

Table 8 showed that the most effective intervention is social comparison, despite the research designs and information delivery methods. However, in examining the three studies that compared different types of interventions in the same experimental setting, the study of Ruokamo et al. (2022) revealed that feedback was more effective than social comparison, while

the other two studies (Dominicis et al. (2019) and Kazukauskas et al. (2021)) showed that social comparison was more effective than feedback. These contradictory findings might be related to the research designs of those studies, as the existing studies have not compared and assessed the different types of interventions in the same research for the same individual to identify the most effective nudging intervention in this domain. Existing empirical research (shown in Table 2-7) showed that each research participant received only one type of intervention. Although interventions were effective, exposing participants to just one intervention can lead to limitations, as participants can get familiarised and show adaptation to the repeated exposure of the single intervention over time, potentially hindering their informed decision-making. In addition, effective comparison between interventions might be limited as they are not applied to the same individual, and different individuals might react differently to interventions due to their behaviours, attitudes and beliefs. Thus, this leaves a research gap in this domain. The deployment of different interventions to the same individual over time can help to better assess the most effective smart nudging intervention. This new focus, although potentially more complex to deploy, can bring a new perspective into how the same participant reacts to different types of smart nudging interventions.

Moreover, existing empirical research has assessed smart nudging in relation to household energy consumption and its related metrics such as electricity, gas, thermostat temperature, and hot water. However, there has been limited assessment of smart nudging in the context of indoor air emissions related to household energy use and indoor air quality. Existing empirical studies have not assessed the most effective smart nudging intervention for improving the indoor air quality parameters. This remains a gap in the existing knowledge, making this analysis necessary to bring new knowledge and understanding into how smart nudging interventions can influence home occupants towards achieving sustainable behaviours that impact indoor air quality and emissions related to energy use.

The existing empirical research (shown in Tables 2-7) showed some research limitations. Firstly, empirical research showed limited generalisability of the research findings (for example, Lynham et al. (2016), Canale et al. (2021), etc.). Secondly, research showed overreliance on self-reported data and direct inputs from the user (for example, Burchell et al. (2016), Ghesla et al. (2020), etc.) that lead to reporting biases, less user friendliness of the interventions, and less accuracy of the data. Thirdly, research showed limited frequency of the delivery of the interventions (weekly or monthly), which may not prompt and hinder the immediate behavioural changes of the individuals. In addition, that may cause challenges to

isolate the impact of the intervention on making a sustainable behavioural change among individuals, as other random or confounding variables might influence the impact of the nudging intervention (for example, Henry et al. (2019), Mogles et al. (2017), etc.). Some of these limitations might be linked to the lack of consistency and structure in the designing of the smart nudging interventions. For effective and structured smart nudge composition, Karlsen and Andersen (2019) proposed a smart nudge design for the transportation sector, as described in section 2.3.3.2. However, there is not currently a smart nudge design specific to the household energy sector, which could in turn address some of the research limitations identified in the literature and help to design more accurate and timely smart nudging interventions. The absence of a specific smart nudge design for built environment sector highlights a knowledge gap in this domain, making it necessary to address this gap in order to help reduce indoor air emissions and improve indoor air quality through effective behavioural change.

2.5 Chapter summary

In conclusion, this chapter identified that the factors, namely, anthropogenic air emissions, global warming, climate change, outdoor air pollution, and indoor air quality are interconnected and rotate in a cycle where each factor influences and reinforces the other factors. The existing research showed that household energy consumption is one of the primary contributors of anthropogenic air emissions and poor indoor air quality. More specifically, existing studies showed that human behaviours related to household energy consumption play an important role in reducing anthropogenic air emissions and increasing indoor air quality. However, nudging home occupants towards achieving sustainable energy consumption behaviours is challenging, as cognitive biases influence human behaviours and decision-making. Therefore, behavioural economics was deemed as a positive solution that provides insights from both psychology and economics to change human energy consumption behaviours and decision-making by addressing cognitive biases.

The nudge theory in behavioural economics play a significant role in changing behaviours and making informed decisions. More importantly, in the realm of digital technology, smart nudging, which combines personalisation and context-awareness with digital nudging, has been highlighted as a solution to achieve sustainable behavioural change and make informed decisions. In assessing the existing empirical research, it was noticed that the existing studies have not acknowledged the term ‘smart nudging’ even though the studies have tailored digital nudging interventions using personalisation and context-awareness to nudge individuals

towards achieving sustainable energy consumption behaviours. The existing empirical studies showed that smart nudging was effective in reducing high household energy consumption.

In analysing the existing empirical studies, social comparison was identified as the most effective smart nudging intervention in reducing high household energy consumption in the studies that used only social comparison. However, in analysing the studies that used more than one intervention, revealed contradictory results, as some studies showed that social comparison is more effective, while some studies showed that feedback is more effective in reducing energy consumption, leaving a research gap based on the research designs, as one research participant was exposed to only one type of intervention. Therefore, it is necessary to fill this research gap by using a within-subject repeated measures design. This research design can deploy different types of smart nudging interventions for the same individual over time to understand the most effective smart nudging intervention. In addition, the existing empirical research showed that there are limitations in designing the smart nudging interventions such as the frequency of the delivery, obtaining self-reported data, etc. This research gap can be filled using a proper smart nudge design, which is absent in the household energy sector. Finally, it is important to assess how smart nudging interventions nudge householders towards achieving sustainable behaviours that impact indoor air quality and emissions related to energy use in a holistic way using different metrics such as room temperature, CO₂, TVOC, etc.

Figure 6 shows a theoretical framework that indicates the transition from literature to methodology. This theoretical framework shows key findings and limitations identified in the literature into methodological decisions by linking smart nudging to study design. Insights such as the need for using multiple smart nudging interventions, a within subject repeated measures design, avoiding order bias, reducing reliance on self-reported data, improving measurement accuracy, etc, provides a clear bridge between literature and methodology.

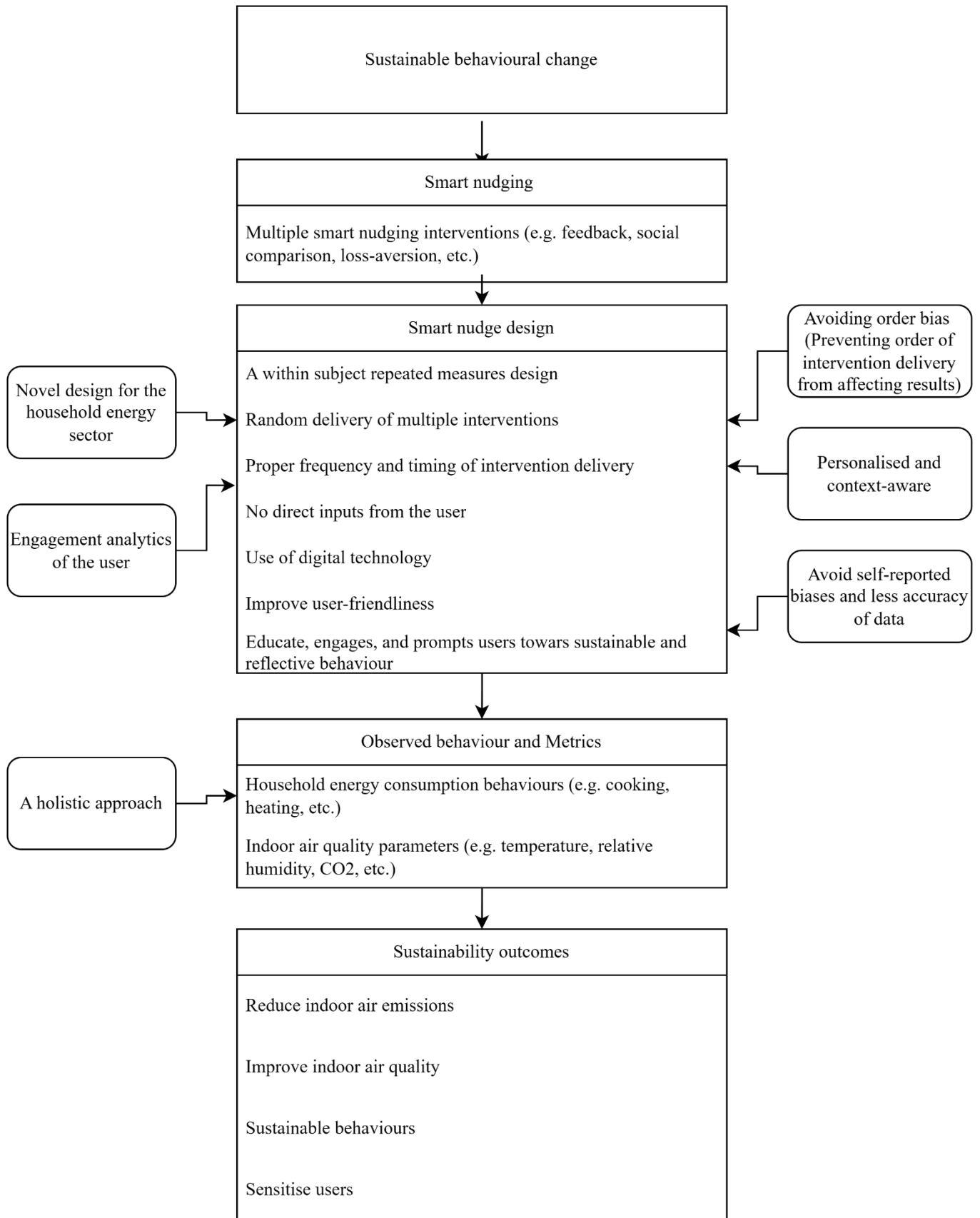


Figure 6: Theoretical framework

3 Chapter – Action Research Methodology

3.1 Introduction

Research methodology helps achieve research objectives (Kumar, 2011). Rajasekar et al. (2013) stated that research methodology is a systematic way to solve a particular problem. However, Igwenagu (2016) mentioned that “*methodology does not set out to provide solutions - it is, therefore, not the same thing as a method*”. Instead, a research methodology provides the theoretical underpinning for identifying, understanding and justifying which method, set of methods, and best practices can be used in research to obtain a specific result (Igwenagu, 2016). Research methodology begins with identifying the main research philosophy, selecting the research approach, selecting appropriate research strategies, and outlining time horizons, which collectively guide the development of research design that includes the main techniques and methods of data collection and analysis (Dissanayake, 2023).

The methodology selected for this research is action research. Action research is an interactive process of inquiry that combines problem-solving actions with data-driven collaborative analysis or research. This helps to understand the real-world problems, the underlying causes, issues, and make predictions about future changes (Sundarakani, et al., 2021). In other words, action research is a practical way of conducting research where the researcher identifies a real-world problem, take personalised and context-specific actions to improve it, observe and assess the results of the study, and refine the approach to bring real-world improvements while generating knowledge through social engagement in an ethical way to make a positive change (Coghlan & Shani, 2021). Moreover, Stark (2014) mentioned that action research is more than just a research methodology, as it acts as an instrument of change, aiming to transform lives of individuals through their own actions and efforts.

The literature consistently highlights that reflection is fundamental to action research, as it allows the approach to fulfil its dual mandate, which is addressing a real-life problem through practical interventions while simultaneously contributing to knowledge (Costello, et al., 2015). In this research, reflection was central to fulfilling the dual mandate of action research, ensuring that smart nudging interventions designed to reduce the anthropogenic indoor air emissions related to household energy consumption and improve indoor air quality in homes were both practically effective and academically informative. The pre-intervention interviews were conducted to identify and assess the existing behaviours and habits of home occupants, their attitudes, perceptions, energy usage patterns, and their context. Simultaneously, Passive

sensor-based monitoring through sensor data was conducted to assess the energy usage patterns and indoor air quality levels in the house. Both the data gathered from the pre-intervention interviews and the sensor data were used to design the smart nudging interventions. The objective data from sensors complemented the qualitative data from the pre-intervention interviews, forming a main part of the reflective process in action research.

After the intervention period, the real-time minute-by-minute data on temperature, CO₂, relative humidity, and TVOC were analysed over a month using a pre- and post-intervention comparison to assess the engagement analytics and identify the impact of smart nudging interventions in changing behaviours. The engagement analytics were analysed alongside the qualitative insights from the post-intervention interviews, which were conducted to assess the experiences and perceptions of the home occupants and their behaviour changes to internally validate the research findings. Moreover, an external validation was conducted by comparing the research findings with the existing empirical research and by comparing the findings across the houses. This reflective process informed iterative refinements to the smart nudging interventions including amendments to the logics of the smart nudging interventions, etc.

In action research, inputs from the industry partner, which is Covatic, a leading software company in the UK, at both the intervention design stage and after the post-intervention period contribute to reflection and practical improvements. This is because action research is built on iterative cycles of designing, testing, observing, and reflecting. Therefore, this iterative process helped to refine the smart nudging interventions and the smart nudge design, interpret outcomes accurately, and generate transferable knowledge, thereby fully meeting the dual mandate of action research.

The industry partner, Covatic, played a crucial role in the development of the mobile app used in this study. The mobile app was used to deliver the smart nudging interventions. Their technical expertise supported the incorporation of the smart nudge design including the logics of the smart nudging interventions into the app, ensuring that the app effectively delivered the smart nudging interventions to the home occupants. Covatic's involvement extended beyond developing the mobile application, as they also contributed to validating the smart nudge design including the logics of the smart nudging interventions by providing feedback to make the smart nudge design practical and impactful in the real-world settings.

This chapter aims to provide a comprehensive and theoretical overview of methodology by detailing the overall research approach, strategies, and techniques that will be used to conduct

the research, data collection and analysis methods, and linking them with research objectives to achieve the aim of this research, ultimately leading to filling the research gap and providing a contribution to the existing research. To provide a clear roadmap for how each research objective is addressed, Table 9 below shows each research objective in relation to the particular methods employed and identifies the specific chapters where these discussions can be found.

Research objectives	Methods	Chapters
1) To define and examine the existing body of knowledge on anthropogenic air emissions and behavioural economics, including strategies to effectively nudge individuals towards reducing anthropogenic air emissions in home energy consumption and improving indoor air quality through the application of digital technology.	Literature review	Chapter 2 – Literature review
2) To develop a smart nudge design based on the literature review, complete with a process flow diagram and clearly articulate the steps involved in implementing the smart nudge design. 3) To compose smart nudging interventions within the newly designed smart nudge design, ensuring they are tailored to influence user behaviour, make informed decisions, reduce anthropogenic air emissions related to household energy use, and improve indoor air quality.	Literature review synthesis and design formulation	Chapter 4 – Smart nudge design
4) To conduct testing, analysis, and validation of the different smart nudging interventions by utilising the engagement analytics of the users and assessing user interviews through an action research methodology.	Research design, Qualitative analysis, Quantitative analysis, triangulation, external validation	Chapter 3- Methodology Chapter 5 – Results, and Discussion
5) To propose an effective smart nudge design aimed at reducing anthropogenic air emissions related to household energy use and improving indoor air quality by changing human behaviours and consolidating findings from the literature review, design development, testing phases, and expert reviews to formulate an actionable design for behavioural change.	Synthesis of research findings, expert review	Chapter 6 – Proposed smart nudge framework

Table 9: Mapping of research objectives to methods and thesis chapters

The first research objective involves conducting a comprehensive literature review, which is presented under Chapter 2: Literature review. Chapter 4: Smart nudge design aims to achieve objectives 2 and 3 by presenting the steps of developing the smart nudge design and the logics of composing smart nudging interventions by synthesising literature review findings. Chapter 3: Methodology, which presents the research design of the study, intends to achieve objective 4 by describing the action research methodology. Chapter 5 includes the data analysis and validation of the results by assessing quantitative data (engagement analytics of the users) and qualitative data (user interviews) targeted at achieving objective 4. Moreover, Chapter 5 aims to achieve objective 4 by presenting the results of the study and providing a critical discussion of the findings. Chapter 6 involves formulating an actionable smart nudge design that aims at reducing anthropogenic air emissions that occur from household energy use and improving indoor air quality by nudging human behaviours towards achieving sustainable consumption behaviours, aiming to achieve objective 5.

3.2 Research philosophy.

Philosophers of science and methodologists have been having a long-standing epistemological debate, which is centred on two different and competing philosophical stances, namely, positivism and interpretivism, to find the best one to conduct research in the built environment (Amaratunga, et al., 2002). Similarly, Saunders, et al. (2007) stated that “*The debate is often framed in terms of a choice between either the positivist or the interpretivist research philosophy*”. Positivism is associated with quantitative research and experimental methods, including developing and testing hypothetical-deductive generalisations and explaining causal relationships or fundamental laws. Interpretivism is associated with qualitative research and naturalistic methods to identify human experiences, behaviours, beliefs, and attitudes holistically in context-specific settings, especially by explaining a particular social phenomenon rather than finding causal relationships or fundamental laws (Amaratunga, et al., 2002).

Pragmatism is a research philosophy that does not fall under any one system of philosophy or reality, as it uses pluralistic approaches to derive knowledge about the research questions. Hence, it can be applied to mixed-methods research that includes both positivism (quantitative) and interpretivism (qualitative). Pragmatism values flexibility and adaptability in research design and provides the opportunity to use multiple data collection methods and data analysis methods that are fit for the research. Therefore, Pragmatism is used in this research, as it includes mixed methods that use both quantitative data collection (engagement analytics) and qualitative data collection (user interviews) and uses different data analysis methods to provide the best understanding of the research questions, namely, 1) ‘Can smart nudging interventions induce behavioural changes that improve indoor air quality parameters to reach the recommended thresholds in houses?’ 2) ‘What is the most effective smart nudging intervention in reducing indoor air emissions related to household energy consumption and improving indoor air quality holistically in the residential settings?’ 3) ‘How do individuals perceive the effectiveness of smart nudging interventions across the different indoor air quality parameters in achieving the safe thresholds?’.

Action research involves a process of addressing real-world problems through active participation and conducting research. Furthermore, action research aligns with the pragmatism’s core belief that knowledge is gained from practical engagement (or “learning by doing”) (Stark, 2014). Therefore, pragmatism is the best fit for this action research. The reason is that both researcher and research participants engage in learning by doing, as the action

research is collaborative and participatory. The researcher learns through direct involvement in the real-world problem solving, while home occupants learn through reading and understanding smart nudging interventions, which are designed to support them to reflect on their own behaviours, learn through their own behaviours, and adopt best practices to reduce high energy consumption and improve indoor air quality in their homes.

3.3 Research approach

3.3.1 Reasoning approach

The main two research approaches are the ‘deductive approach’ and the ‘inductive approach’. The deductive approach develops a theory or hypothesis based on the pre-existing theories and then designs a research strategy to test the theory or hypothesis (Melnikova, 2018). The inductive approach collects data, analyses data, and develops a theory based on the data analysis. The deductive approach owes more to positivism, while inductive approach owes more to interpretivism, even though such categorisation is potentially misleading and has no real practical value (Saunders, et al., 2007). On the other hand, there is another research approach, which is named ‘abductive approach’. An abductive approach *“is to be seen as different from a mixture of deductive and inductive approaches. An abductive approach is fruitful if the researcher’s objective is to discover new things — other variables and other relationships”* (Dubois & Gadde, 2002). The abduction approach is related to generating new concepts and developing theoretical models rather than confirming existing theories. Moreover, in studies based on abduction approach, the original framework or the model is successively modified, partly because of unanticipated empirical findings of the research, but also of theoretical insights gained during the research process (Dubois & Gadde, 2002).

This study follows an abductive approach and aligns with the action research and pragmatism. The abductive approach plays a main role in action research, as it helps the researchers to reflect on how they gain knowledge by moving from discovery stage to verification stage through experience, understanding, and judgment and ensuring that the research is both exploratory and evidence-based (Coghlan & Shani, 2021). This study involves a participatory and iterative process of 1) designing the smart nudge design based on the knowledge gained from literature review in this study, 2) composing the logics of smart nudging interventions by synthesising the findings from literature review and pre-intervention interviews with the home occupants to understand the occupancy periods, daily routines of the occupants, and their existing behaviours and perceptions, 3) testing the smart nudging interventions, 4) assessing the sustainable behavioural change by conducting a pre- intervention and post-intervention

comparison using quantitative data to ensure if there are significant changes after delivering the smart nudging interventions, 5) conducting post-intervention interviews to capture user experiences and changes in behaviours, 6) internally validate the findings within each house individually by triangulating the quantitative engagement analytics with qualitative insights from post-intervention interviews, 7) conducting external validation by comparing research findings with existing empirical studies and by comparing the results across the houses (3 plots), and 8) refining the smart nudge design and smart nudging interventions based on the research findings, research limitations, and supplementary academic sources, and by obtaining feedback from the industry partner. Therefore, this abductive approach ensures that the proposed smart nudge design is not a mere application of smart nudging but an evolved and a holistic design reflecting real-world behavioural dynamics. This ongoing reflective, participatory, and iterative process between theory, data, and experience reinforces the abductive approach, pragmatism, and action research methodology by solving a real-world sustainability challenge related to home energy consumption and indoor air quality.

3.3.2 Methodological approach

The methodological choice in this research is the ‘mixed- method’. The mixed method approach is more appropriate to this type of research as it integrates both qualitative and quantitative approaches, thereby delivering more comprehensive and reliable interpretations through an in-depth analysis for each house separately. Qualitative research explores, interprets, and understands the nature of individuals or groups, human experiences, behaviours, perceptions, and social phenomena in-depth (El-Gohary, 2021). Therefore, interviews are conducted before the intervention period to identify and evaluate existing behaviours, attitudes, energy usage patterns, and the current situation of the home occupants. This qualitative data provides an in-depth understanding of how home occupants interact with their living environment before smart nudging interventions are introduced. Simultaneously passive sensor-based monitoring through sensor data (real-time data) is conducted to identify electricity usage patterns and indoor air quality levels before smart nudging interventions are deployed. This quantitative data provides an objective measure of indoor air quality levels and electricity usage patterns, complementing the subjective insights from the interviews. The data collected from pre-intervention interviews is used to compose smart nudging interventions for the occupants. The smart nudging interventions are tailored to encourage more sustainable behaviours, reduce air emissions, and improve indoor air quality.

The quantitative process is “*directed towards the development of testable hypotheses and theory which are generalisable across settings and in contrast this methodology is more concerned with how a rich, complex description of the specific situations under study will evolve*” (Amaratunga, et al., 2002). Therefore, testable hypotheses are developed, and quantitative data collection is conducted throughout the intervention period. Real-time data are monitored to identify the impact of smart nudging interventions on changing occupant behaviour, reducing air emissions, and improving indoor air quality throughout the intervention period.

At the end of the intervention period, follow-up interviews (post-intervention interviews) are conducted to assess whether the occupants have perceived any changes in their behaviours. The follow-up interviews are beneficial for understanding the subjective experiences, perceptions, and attitudes of the occupants, which can provide valuable insights into the effectiveness of smart nudging interventions from the occupants’ perspective. The qualitative data from the interviews provides the opportunity to triangulate with the quantitative data, ensuring the validity and reliability of the research findings. In addition, mixed methods allow for enhanced generalisability of the research findings.

3.4 Research strategy

The research strategy which was adopted in this study is ‘multiple-case studies design’. Case study is identified as “*a strategy for doing research which involves an empirical investigation of a particular contemporary phenomenon within its real-life context using multiple sources of evidence*” (Robson, 2002, cited in Saunders, et al., 2007, p.139). Multiple- case studies are used to understand the similarities and differences between the cases and to analyse the research data both within each case and across the cases (Gustafsson, 2017). As part of the multiple-case studies design, three low- carbon homes (Project 80, Eco Drive in Handsworth, Birmingham) have been selected.

Project 80 consists of 12 low-carbon homes. Project 80 is developed by the Midland Heart Housing Association and constructed to meet the UK government’s 2025 Future Homes Standard (FHS) with a target of delivering an 80% reduction in CO₂ emissions from the 2013 Building Regulations design. The Eco Drive development, which is the first at-scale demonstrator for the Future Homes Standard (FHS), has been designed and built by increasing insulation in walls, increasing the levels of airtightness, and improving ventilation by using new technology such as Mechanical Ventilation with Heat Recovery (MVHR), Air Source Heat

Pumps (ASHP), and photovoltaic (PV) systems to enhance energy efficiency and improve indoor air quality. To assess the performance of these novel technologies, energy and indoor air quality sensors have been installed in the homes.



Figure 7: Project 80; Eco drive, Handsworth

Achieving the UK’s target of net-zero emissions by 2050 requires not only innovative house designs with low carbon technologies but also significant changes in occupant behaviour, as the occupant’s lifestyle is a key factor in achieving net-zero emissions. The multiple-case studies design is appropriate for this study because it offers a real-life context, where real people are living in newly built low carbon homes equipped with low-carbon technologies designed to reduce household air emissions and improve indoor air quality. Moreover, it provides the opportunity to critically and exclusively evaluate occupant behaviour and assess how sustainable behavioural change contributes to reducing anthropogenic air emissions and improving indoor air quality, without considering the confounding variables present in older or retrofitted houses.

Case study design aligns with abductive approach “*as it supports a depth of interaction between the researcher and the field and between data and theory*” (Conaty, 2021). Therefore, this multiple case study research resonates with abductive approach and provides a holistic understanding of the observed phenomena related to smart nudging interventions and their impact on reducing air emissions associated with household energy consumption and improving indoor air quality. Furthermore, a case study is more suitable for answering the research questions of this study as it supports exploring the effectiveness of different smart nudging interventions across different indoor air quality parameters separately within the same experimental setting to identify how an intervention performed with a parameter and the factors influencing the performance through integrating mixed methods. Moreover, this multiple-case

studies design provides recommendations to improve smart nudging interventions by analysing the engagement analytics and user experiences, behaviours, perceptions, and underlying practices identified through abductive reasoning and validating or refuting the research hypothesis.

This multiple-case studies design uses a combination of purposive and convenience sampling. Research participants are initially identified through the purposive sampling technique, which involves specific settings, persons, or events that are selected deliberately with a warrant inclusion of participation to provide important information that cannot be gained from other choices to answer research questions and achieve research objectives (Taherdoost, 2016). As a result, Project 80 is selected in this study. Following this, convenience sampling is used to recruit research participants from the Project 80. Convenience sampling is a sampling technique in which research participants are selected based on their availability and ease of access (Golzar & Tajik, 2022). Although the Project 80 development consists of 12 low carbon homes, the research includes three low-carbon homes as three cases, which are referred to as 'plots' (plot 5, plot 10, and plot 12), due to anonymity of data. These houses have been selected based on the research participants' availability, willingness or consent to participate in the research interviews, monitor and collect sensor data (real-time data), and onboard the mobile application to trial the smart nudging interventions.

The smart nudging interventions selected in this study are feedback, social comparison, and loss-aversion. According to the literature review presented in section 2.3.3.1 in Chapter 2, the time of application of feedback and social comparison is after the action has taken place. For example, sending the feedback or social comparison after a home occupant cook is highly relevant, as it targets a teachable moment when the home occupant is more likely to reflect and take recommended actions or best practices, such as improving ventilation or turning the extractor fan on. According to the section 2.3.4.6 in Chapter 2: Literature review, previous studies comparing different interventions in the same research (the studies of Dominicis et al. (2019), Kazukauskas et al. (2021), and Ruokamo et al. (2022)) have mainly focused on feedback and social comparison. In addition, according to the literature review findings, social comparison and feedback are the most used interventions in the residential energy sector. In considering the studies that used 'framing', loss-aversion appeared to deliver more significant results in the existing studies, highlighting the effectiveness. Loss-aversion can be applied throughout the action. Therefore, selecting these three smart nudging interventions can be more

timely and contextually appropriate to prompt reflection, improve learning, and nudge towards achieving a specific sustainable behaviour.

The three plots have similar household characteristics, as they are 3-bedroom houses (2 ½ storey houses), designed to achieve lower airtightness combined with natural ventilation, Air Source Heat Pumps (ASHPs) for heating and hot water cylinders for hot water, PV panels, and wastewater heat recovery (WWHR) (Mateo-Garcia, et al., 2023). In addition, the three plots show similar demographics such as family size, cultural background, income, and education level. More specifically, each plot comprises of two adults and two children, with children under the age of 10 and adults aged 30 and 45 years. Plot 10 includes a child with a disability. All the plots share similar cultural backgrounds, predominantly Somali and this helps to maintain the cultural consistency across the case studies. Therefore, this study design maintains similar household characteristics and demographic characteristics to control for confounding variables or external factors. This uniformity allows for a clear assessment of how each smart nudging intervention influences behaviours across the four indoor air quality parameters. In addition, this uniformity helps to isolate the impact of interventions to focus on intervention-driven behaviour changes. In addition, the existing empirical research has deployed the smart nudging intervention, which is ‘social comparison’ in similar households to compare its effectiveness between neighbouring households. For examples, the studies of Liu et al. (2022), Myers & Souza (2020), Canale et al. (2021) etc. Therefore, to deploy social comparison, the selected households should show similar household characteristics.

More importantly, this case study uses a within-subject repeated measures research design. In a within-subject research design, “*each individual is exposed to more than one of the treatments being tested*” (Charness, et al., 2012). The internal validity of a within-study design is not based on a random assignment. In addition, a within-subject study can provide a substantial boost in statistical power as it allows the same plot to interact with different interventions (Charness, et al., 2012). However, a within-subject study design that exposes the same plot to three smart nudging interventions can introduce confounding variables. Therefore, counterbalancing or varying the order in which smart nudging interventions are delivered (random order of presentation) to each plot helps to manage any confounding variables. This will help to fill the research gaps (shown in section 2.4 in Chapter 2 – Literature review) identified in this domain.

This within-subject study analyses the three plots individually as multiple-case studies to answer the research questions, achieve research aim and objectives, and to understand

thoroughly how each plot responds to the three types of smart nudging interventions. More specifically, this research design allows to investigate deeply how each intervention achieves the safe thresholds of each indoor air quality parameter by enhancing the reliability of the findings. In addition, this design enables a detailed understanding of unique responses and context-specific effects of each plot separately. Therefore, this approach is important in identifying the effectiveness of tailored and targeted smart nudging interventions.

The intervention period for this case study runs for a month. One month intervention period is selected based on the research findings of the existing empirical studies (shown in Table 2-7 in Chapter 2- Literature review). The existing empirical research indicated that smart nudging interventions showed effectiveness over various timeframes such as one month, one year, two years, etc. The existing empirical research shows that the design of the interventions matters more than the intervention period. However, this research design allows the researcher to collect and analyse data at specific time points, such as one week and one month after the intervention start date, to comparatively assess the short-term and sustained impacts of the smart nudging interventions on reducing air emissions associated with household energy use and improving indoor air quality.

However, this one-month intervention period has limitations. Most notably, the one-month intervention period does not capture seasonal variations in occupant behaviours or environmental conditions, such as changes in heating demand, ventilation practices, or external air quality across different times of the year. Therefore, the research findings might not be fully generalisable across seasons. Moreover, the research findings derived from a one-month intervention period may not be generalisable to longer-term living conditions or household circumstances, as home occupants routines can fluctuate due to work patters, school holidays, or other life events.

3.5 Data collection methods

The major approaches of data collection are ‘primary data’ (information collected or generated by a researcher) and ‘secondary data’ (information gathered from the primary data). The primary data collection methods include observations, interviews, and questionnaires. Secondary data collection methods include documents such as government publications, earlier research, census, personal records, etc. (Kumar, 2011). This mixed-methods multiple case study design uses both primary data, such as semi-structured interviews, passive sensor-based

monitoring of real-time indoor air quality data, and secondary data, such as comprehensive literature review, as the data collection methods.

3.5.1 Literature review

This study commenced with a comprehensive review of previous literature that is relevant to the research aim and objectives. Existing literature was retrieved from professional and academic journals, conference papers, research reports, and books to obtain all necessary information, understand the background of the research, and identify the knowledge gaps. Additionally, this research followed the ‘Preferred Reporting Items for Systematic Reviews and Meta-Analyses’ (PRISMA) guidelines, which were initially published in 2009 to assess the effectiveness of different smart nudging interventions in the household energy sector. The PRISMA 2020 statement, which includes 27 item checklists, “*replaces the 2009 statement and includes new reporting guidance that reflects advances in methods to identify, select, appraise, and synthesise studies*” (Page, et al., 2021). The explicit statement was developed based on the PICO technique or process, which is an acronym presenting the population of the study (P), intervention (I), comparison (C), and outcome (O) (Roever, 2018). The criteria used in this study are:

- Population – householders
- Intervention – smart/digital nudging interventions delivered through different information delivery mediums or digital platforms.
- Comparison – no treatment/baseline period/between treatments.
- Outcome – energy consumption reduction, air emissions reduction, and improving indoor air quality.

This study systematically searched two electronic databases, namely Scopus and Science Direct, for the period between 2010 to 2023. To identify many appropriate and eligible studies, the search terms and strategies were broadened and modified with informatics and boolean operators. The search strings selected were:

- To represent the population - { (“homes” or “households” or “users” or “residential”) and (“energy” or “electricity”) and (behaviour” or “behavioural”) }.
- To represent the intervention – { (“feedback” or “real-time” or “comparison” or “framing” or “information”) }.
- To represent the digital platform – (“digital” or “smart” or “technology”).

- To represent the outcomes – (“consumption” or “reduction” or “saving” or “air” “quality” or “emissions”).
- To represent the study type – (“field”, “survey”, “trial”).

Firstly, in the selection process, all the duplicates in the two databases were removed using Excel electronically. Scopus facilitates CSV export, but Science Direct does not allow CSV export. As a result, all the documents in Science Direct were exported to RIS format, and thereby, those documents were exported to CSV file format using Zotero software. The Excel sheets of Scopus and Science Direct were merged to remove the duplicates. Secondly, the screening process was conducted by reviewing the titles and abstracts of the documents (‘records’) to decide the eligibility of those documents to be included in the study. Thirdly, the ‘reports’ or full-text articles were screened, and the relevant articles were evaluated for final inclusion. The eligible papers were put in a table, read, and combined into a single word document for a comprehensive review. The selection criteria (eligibility criteria) are explained below.

- the studies should be published on or after 2010 to ensure that the study findings or empirical data are current and up-to-date, and the period selected was between 2010 to 2023.
- all the studies must be full text papers, not abstracts.
- the studies must clearly describe the digital or smart nudging interventions and their delivery mediums (digital platforms).
- the studies should explicitly describe the research findings related to user engagement or user behaviours and the reduction of household energy consumption, air emissions, and indoor air quality.

Some research papers were excluded from this study based on 1) empirical research has not investigated the effectiveness of digital/smart nudging interventions in the household energy sector; 2) studies have not used digital/smart nudging interventions in reducing household energy consumption and air emissions; 3) studies have not used digital/smart technology; and 4) systematic review papers were excluded.

The total number of records identified was 3569, and 2303 records were excluded before screening due to being duplicates. Therefore, 1266 records were reviewed, and 105 reports were sought for retrieval. Reports that were assessed for eligibility are 62. Finally, the studies

included in this study were 23. The below Figure 8, which is the PRISMA flow chart, shows the summary of the process.

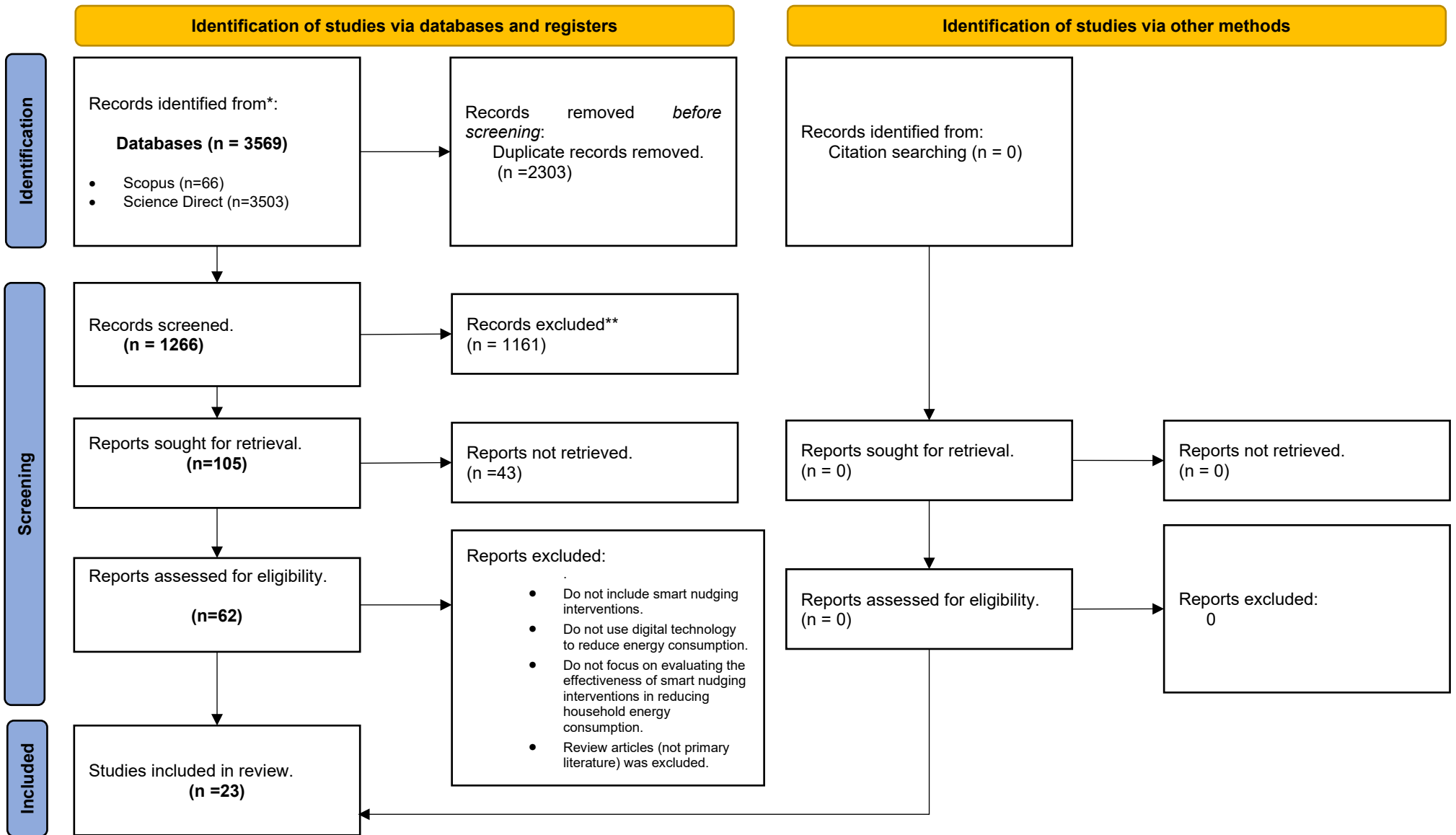


Figure 8: PRISMA flow diagram

3.5.2 Passive sensor-based monitoring

Passive sensor-based monitoring is a method of data collection where sensors automatically record environmental conditions without emitting signals or requiring direct researcher involvement. This method is unobtrusive and non-reactive and reduces researcher influence (Rama, et al., 2025). Passive sensor-based monitoring is particularly useful for collecting objective data on behaviours and environmental conditions over time, which is difficult to capture through direct observation. This study involves monitoring and collecting sensor data (real-time data) about indoor air quality related to household energy use and observing participants' behaviours.

This Passive sensor-based monitoring method helps to gather objective data on participants' energy consumption behaviours, indoor air quality, and interactions with the interventions without involving the researcher in the data collection process. In addition, this method allows for the gathering of accurate and detailed information on participants' actual behaviours in their natural environment, providing the opportunity to assess the effectiveness of smart nudging interventions aimed at reducing air emissions associated with household energy consumption and improving indoor air quality holistically. Therefore, passive sensor-based monitoring through real-time data is an effective method to capture real-time and objective data on participant behaviour in the domain of household energy consumption, reducing air emissions, and improving indoor air quality.

Passive sensor-based monitoring might reduce observer bias, which is caused by the researcher's presence and subjective interpretations influencing both the behaviour of home occupants and the data collection (Uwamusi & Ajisebiyawo, 2023). In this study, observer bias is mitigated by relying mainly on objective, minute-by-minute real-time sensor data through the Uhoo smart air monitoring, which reduces the need for direct observation and avoids subjective influence. Moreover, combining quantitative data with semi-structured interviews helps to reduce the impact of observer bias on the research findings.

Passive sensor-based monitoring can lead to the Hawthorne effect, as there can be changes in the home occupants' normal behaviours attributed to the knowledge that their behaviours are being watched or studied (Oswald, et al., 2014). To minimise the Hawthorne effect, home occupants were monitored over a month, allowing them to become more accustomed to the presence of sensors. As monitoring becomes part of their daily routine, initial behaviour changes driven by awareness of observation tend to diminish. Moreover, the Hawthorne effect

can be partially mitigated through the use of minute-by-minute sensor data and short temporal comparison windows such as 15-minute and 30-minute windows. Although the Hawthorne effect cannot be completely eliminated in this research context, its influence was held constant within each comparison window, as home occupants' awareness of monitoring did not change between the two time points.

3.5.2.1 Monitoring indoor air quality

In this study, 'Uhoo smart air monitor' sensors were installed in the living room and kitchen of all 3 plots to monitor and collect real-time indoor air quality data associated with participants' energy consumption behaviours. The living room and kitchen were selected for sensor deployment as they represent the main locations of indoor air emission-generating and occupancy-driven activities such as cooking, heating use, and prolonged presence (Petrou, et al., 2024). As a result, monitoring these two locations enables accurate detection of indoor air emission levels and allows direct attribution of before and after behaviour changes associated with smart nudging interventions.

The Uhoo smart air monitor allows monitoring temperature, relative humidity, Carbon Dioxide (CO₂), Total Volatile Organic Compounds (TVOC), Particulate matter (PM_{2.5}), Carbon monoxide (CO), air pressure, Nitrogen dioxide (NO₂), and ozone. However, to ensure effective and manageable monitoring of data using Uhoo smart air monitors and to avoid overloading home occupants with excessive information, four parameters, namely, temperature, CO₂, TVOC, and relative humidity, were selected. The main reason was that these four parameters were easier to link with occupant activities and more related to the energy consumption behaviours, facilitating the design of targeted and personalised interventions and integrating them into the mobile application.

More specifically, CO₂ concentrations increase predictably with occupancy levels and ventilation behaviour, making CO₂ a reliable proxy for occupant presence and air exchange patterns in homes (Ibrahim, et al., 2024). In UK homes, poor heating behaviours such as not running heating frequently enough or setting temperatures below or above the recommended threshold of 18-21⁰C, contribute significantly to poor thermal comfort by pushing indoor air temperature and relative humidity levels outside the safe thresholds (Al-Hafith, et al., 2024). Moreover, occupant behaviours such as not opening windows or not using extractor fans while cooking can trap moisture indoors and contribute to poor relative humidity levels, leading to condensation and mould growth. National data show that 5% of homes had damp problems in

2023, with poor ventilation practices, showing that occupant behaviours significantly influence indoor humidity and comfort (GOV.UK, 2025). In UK homes, occupant activities such as cooking, cleaning, use of household products, etc release higher levels of TVOCs. These higher TVOC levels can remain elevated for longer periods, showing that occupant behaviours directly contribute to reduce the indoor air quality (Warburton, et al., 2025). The Uhoo dashboard, which allows us to monitor real-time data, is shown in Figure 9.

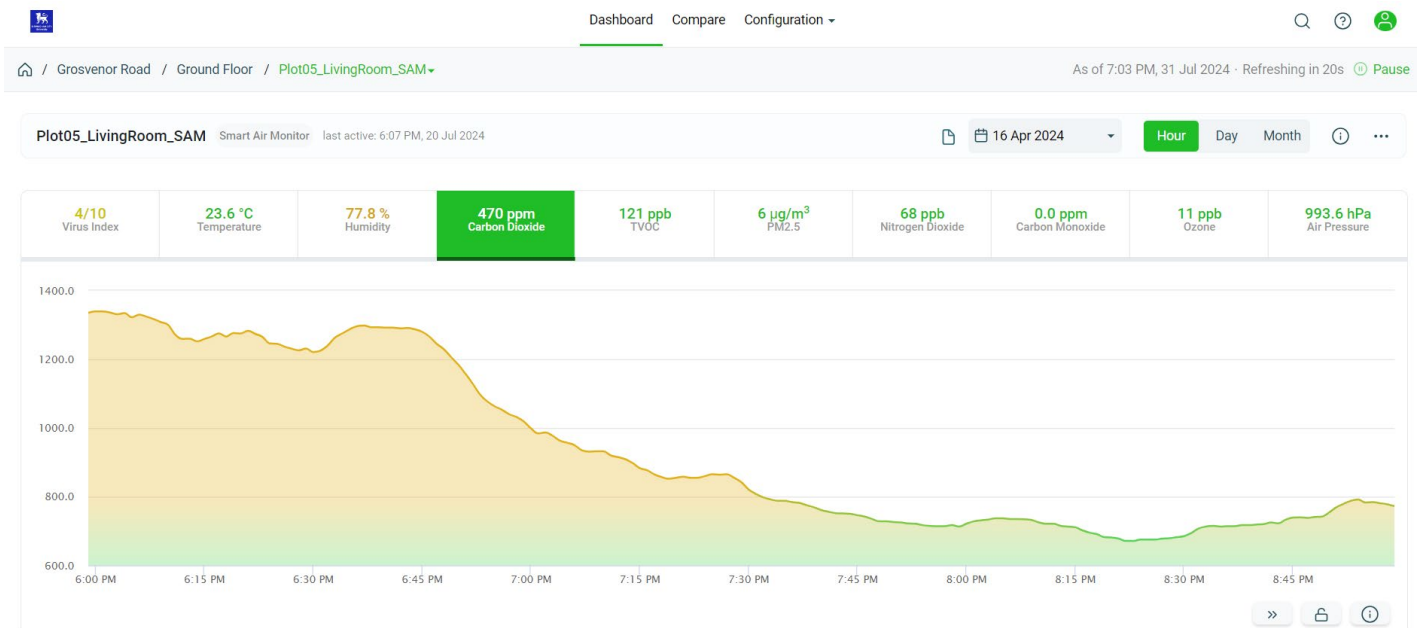


Figure 9: Uhoo dashboard (plot5, living room)

3.5.2.2 Digital home user app – “I am zero”

The mobile application, which was developed by Covatic (a software company in the UK and the industry partner) as a tool to nudge occupant’s behavioural changes, includes the Midland Heart’s digital home user guide that allows users to read and learn about how their low carbon house works related to ventilation, heating, hot water systems, renewable energy, thermal comfort, and overheating, as shown in the below Figure 10, and delivers smart nudging interventions as push notifications for targeted activities associated with indoor air quality parameters (temperature, CO₂, TVOC, and relative humidity) if these parameters exceed specific thresholds. For example: if the CO₂ level of a plot exceeds 1000ppm, a smart nudging intervention in the form of a push notification is sent at the next hour by monitoring and recording the last-minute data of that previous hour.

The rationale for taking the last-minute real-time data of the previous hour (for example, 3.59pm data is being used to send the push notification at 4.00pm) as a reference point for

sending push notifications is 1) to ensure that the push notification or the smart nudging intervention is timely and accurate despite the fluctuating environmental conditions such as CO₂ levels; 2) to provide the current and immediate measure of the indoor air quality conditions to assess the immediate impact of the push notifications; and 3) to simplify and facilitate the implementation process of the intervention by creating a clear, practical, and straightforward procedure for when data should be collected and when push notifications should be sent. The thresholds used for each indoor air quality parameter are described in Table 10.

Indoor air quality parameters	Thresholds
Temperature	18°C-21°C (Public Health England, 2013, cited in Public Health England, 2014, p.4)
CO ₂	400-1000 ppm in the occupied period (ASHRAE, 2022; Institute of Air Quality Management, 2021; RESET, 2019)
TVOC	0- 400 ppb (Bugayong, 2022)
Relative humidity	Between 30%rh-60%rh (ASHRAE, 2016; WHO, 2009)

Table 10: Indoor air quality parameters and their thresholds

Table 10 shows the thresholds for each indoor air quality parameter selected in this study. The threshold for temperature is 18°C-21°C. The threshold for maintaining safe CO₂ levels is 400-1000ppm in the occupied period. The threshold for managing safe TVOC levels is less than 400ppb. The threshold for TVOC levels is indicated using parts per billion because the Uho smart air monitor portal provides the TVOC levels only in ppb. The threshold for relative humidity is between 30%rh-60%rh.

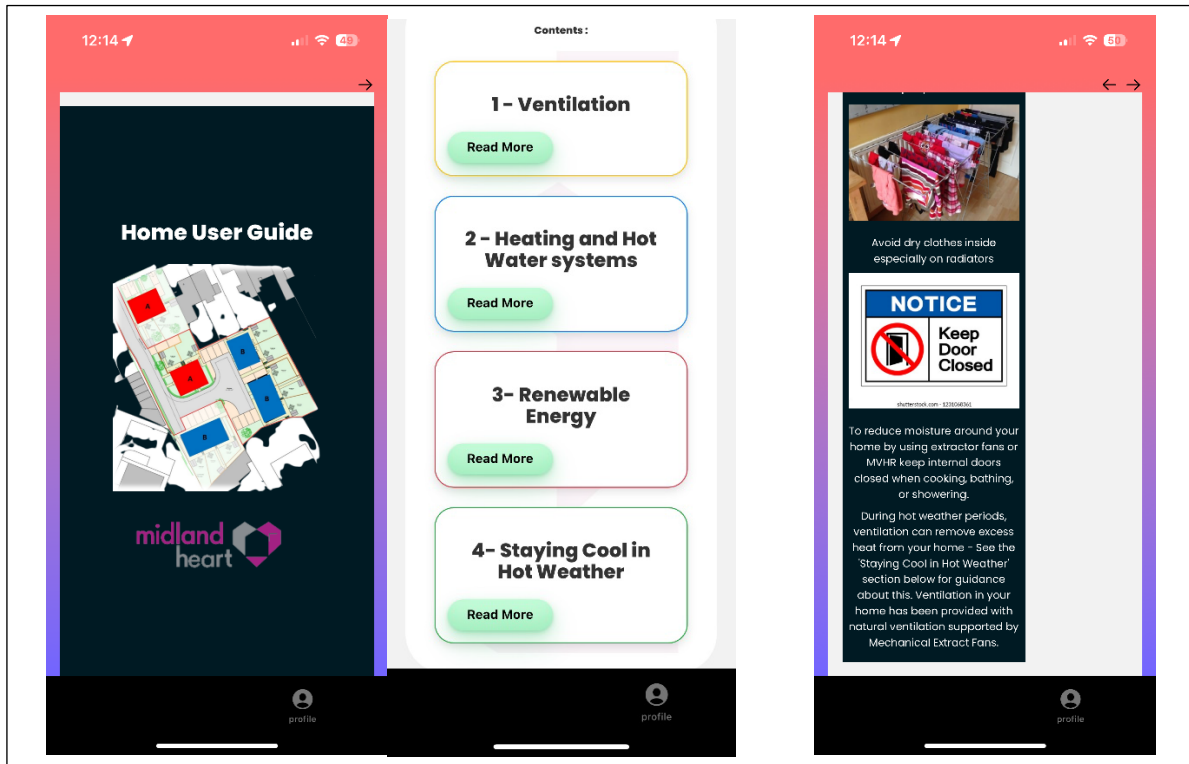


Figure 10: Digital home user guide displayed in the mobile application

3.5.3 Semi-structured interviews

Interviewing is the most commonly used data collection method for collecting information from participants (Kumar, 2011). In this study, semi-structured interviews are used to gather information, or in-depth insights, about the research participants' behaviours, perceptions, and experiences related to smart nudging interventions. Firstly, the semi-structured interviews are conducted before the intervention period to understand participants' behaviours, feelings, beliefs, situation, and experiences in their own words, which is crucial to tailoring personalised interventions. The interview questions are described below.

- Interview question 1: Can you describe a typical day in your household, including what times you are usually at home?
- Interview question 2: How often do you cook at home? Could you describe your cooking behaviours, such as using extractors, and whether you typically open windows or doors?
- Interview question 3: How much do you know about the carbon emissions associated with your daily activities, like cooking or heating?

- Interview question 4: What do you normally do when you detect your house is stuffy? Do you know why this is? and what measures, if any, do you currently take to improve it in your home?
- Interview question 5: What do you normally do when you generate lots of steam in the kitchen or bathroom?
- Interview question 6: How often do you open windows?
- Interview question 7: Do you have a tumble dryer? How do you dry your clothes?
- Interview question 8: What temperature do you normally have your thermostat in?
- Interview question 9: Have you ever used a mobile app or any other tool that provides feedback on your energy consumption or environmental impact? If so, could you tell me about your experience with it?
- Interview question 10: How do you think personalised messages on your energy usage could potentially influence your behaviour?

Additionally, semi-structured interviews are conducted after the intervention period to assess whether participants have perceived a change in behaviours, allowing for the evaluation and validation of the effectiveness of smart nudging interventions from the participant's own perspective. Therefore, the use of semi-structured interviews allows for a comprehensive understanding of participants' experiences, complementing the quantitative data collected from the sensor data and allowing for the richness of the research findings. The interview questions are described below.

- Interview question 1 – Have you observed any changes in your daily activities or habits that have affected your energy usage, such as closing kitchen doors, opening windows, or using extractors while cooking?
- Interview question 2 – Have you observed any changes in your thermostat settings?
- Interview question 3 – Have you had the chance to explore the mobile app for learning about carbon emissions and monitoring digital user guides since we last spoke? If so, what has been your experience with it?
- Interview question 4 - Have you become more aware of the carbon emissions associated with your daily activities, such as cooking, or heating, since our last discussion? Have you taken any steps to reduce the carbon emissions?

- Interview question 5 - Can you provide an update on any efforts you have made to improve indoor air quality in your home? Have you noticed any changes in ventilation or mould issues?
- Interview question 6 - Can you share your experiences with personalised messages?
- Interview question 7 - What specific personalised message do you believe played the most significant role in promoting changes? And why do you think it is effective?

3.6 Data analysis methods

Furthermore, the unit of analysis in this research is each household (plot), with a focus on smart nudging intervention impact on occupant behaviour within each plot. The three identical plots from Project 80 serve as separate cases, providing a consistent context in terms of house design and occupant demographics. All the smart nudging interventions are applied in all three homes, and outcomes are measured by conducting a pre- and post-intervention comparison and research interviews while isolating the intervention-driven behaviour changes.

3.6.1 Quantitative data analysis

The quantitative data analysis aims to identify the most effective type of smart nudging intervention out of the three smart nudging interventions, namely, feedback, social comparison, and loss aversion, in achieving the overall reduction of indoor air emissions related to household energy use and improving indoor air quality parameters (temperature, CO₂, TVOC, and relative humidity) holistically when the levels of these parameters exceeded the predefined thresholds. Moreover, the quantitative data analysis aims to answer the first and second research questions. The quantitative data analysis is conducted using minute-by-minute data, as the indoor air quality parameters associated with the occupant activities are collected on a minute-by-minute basis using Uhuo smart air monitors. The analysis of the real-time data collected is initially conducted over one-week period from the intervention start date to capture the immediate responses from the home occupants and assess the immediate impact of the smart nudging interventions. Following this, an extended one-month analysis (one month from the intervention start date) is conducted to evaluate sustained engagement and determine if the home occupants maintained their interest over a longer period of time.

Quantitative data analysis is conducted in two-time windows, namely, 15-minute and 30-minute windows on a weekly and a monthly basis. In the 15-minute window, the indoor air quality data at the delivery of the smart nudging intervention, which is the last-minute data of the previous hour, and the data after 15 minutes of the delivery of the smart nudging

intervention are assessed to identify whether the indoor air quality parameter has reached a safe threshold. Similarly, in the 30-minute window, the indoor air quality data at the delivery of the smart nudging intervention, which is the last-minute data of the previous hour, and the data after 30 minutes of the delivery of the smart nudging intervention are evaluated to find whether the indoor air quality parameter has reached a safe threshold. The rationale for this analysis based on 15-minute and 30-minute windows is: 1) it helps capture the immediate changes in the indoor air quality parameters that happen because of the quick actions or behaviour changes of the home occupants, 2) it helps to avoid unrelated fluctuations in the indoor air quality parameters associated with the activities of the home occupants by isolating the impact of the smart nudging interventions, 3) to identify which timeframe is sufficient to capture behavioural changes by allowing adequate time for the home occupants to act, 4) to identify which timeframe allows sufficient time for the air quality parameters to manifest after the occupant's actions, and 5) to identify the types of smart nudging interventions that showed the better effectiveness in achieving safe thresholds of each indoor air quality parameter in each plot.

The quantitative data analysis for this study is conducted using the SPSS software. Moreover, the data analysis is conducted individually for each plot and each indoor air quality parameter within the plots, as this is a within-subject design across multiple cases and interventions are personalised for each plot and thereby, allowing to gain better insights through a broader case study in action research. The hypothesis for the quantitative analysis is described below.

- H_0 (Null hypothesis): There is no significant difference in the effectiveness of the three smart nudging interventions across each indoor air quality parameter in each plot.
- H_1 (Alternative hypothesis): At least one smart nudging intervention is significantly more effective than others for a specified indoor air quality parameter in a plot.

Quantitative data analysis is conducted in six stages. The stages are shown in Figure 11. The Stage 1 assesses the descriptive statistics of the three smart nudging interventions for each indoor air quality parameter of each plot on a weekly and monthly basis within the 15-minute and 30-minute windows to identify the potential effectiveness. Stage 2 assesses the optimal or right time window to evaluate the effectiveness of the smart nudging interventions. Stage 3 assesses the impact of the intervention(s) for each indoor air quality parameter in each plot on a weekly and a monthly basis. Stage 4 verifies the positive instances of the effective smart nudging interventions of each indoor air quality parameter in each plot. Stage 5 assesses the most effective smart nudging intervention for each indoor air quality parameter in each plot.

The final stage, which is stage 6, assesses the inferential statistics (if applicable) to support and make the findings more credible and meaningful and to determine the observed effects are statistically significant or occurred due to random variations. The stages are explained in detail below.

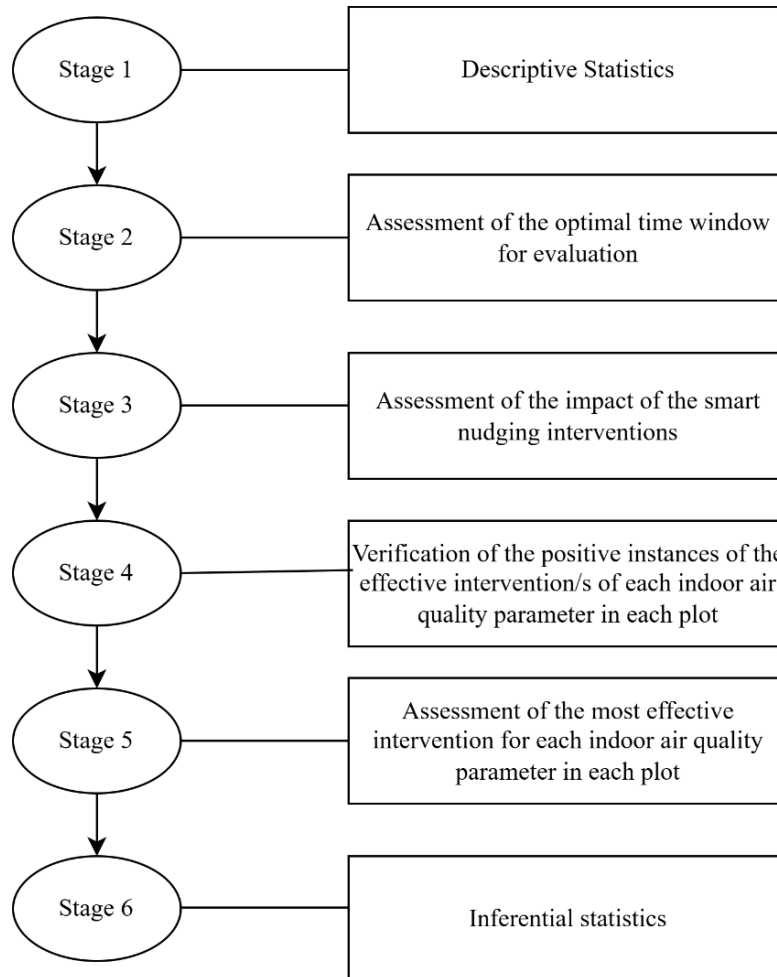


Figure 11: Stages of quantitative data analysis

3.6.1.1 Descriptive statistics

Descriptive statistics are conducted as they “*summarize the data to describe how the sample looks like*” (Kotronoulas, et al., 2023). The descriptive information can be presented using a special measure known as ‘measures of central tendency’, which indicates the central position of the data in a particular data set and helps illustrate how the data tend to cluster around a middle value, more specifically the ‘arithmetic mean’ (Kotronoulas, et al., 2023). Descriptive statistics are conducted in this research to gain an initial understanding of the data by assessing the means of the variables. In addition, the standard deviations are assessed to understand the variability of the data (observations) around the means (Ayeni, 2014).

The data are cleaned and organised using Microsoft Excel in a structured format that is suitable for SPSS, and thereby, that format is imported into SPSS for analysis. After loading the data sheets into SPSS, the types of selected variables are defined accordingly. For example, the smart nudging interventions are marked as 1, 2, and 3 and the nudge type is defined as 'numeric' and 'nominal' in SPSS. Additionally, new variables are created to calculate the impact. For example: 'CO₂ difference = CO₂ level after 15min – CO₂ level last minute of the previous hour'. Those variables are defined as 'numeric' and 'scale' in SPSS. In some instances, this difference between the sensor data is mentioned as a 'reduction' (examples: CO₂ reduction, Temperature reduction, TVOC reduction, and Humidity reduction) to assess the effectiveness of the interventions in reducing higher levels above the safe thresholds in a plot. For example, if the CO₂ difference shows a negative value, which means that the nudge type has made a positive impact and is effective in changing behaviours. On the other hand, in some instances, this difference between the sensor data is presented as an 'increase' to assess the effectiveness of the interventions in increasing lower levels below the safe thresholds. For example, if the temperature difference shows a positive value, which means that the nudge type has made a positive impact and is effective in increasing the lower temperatures below 18⁰C and bringing to a safe threshold.

3.6.1.2 Assessment of the optimal time window for evaluation

The assessment of the optimal time window after descriptive statistics is necessary because it ensures the time window that reliably captures the impact of a smart nudging intervention or home occupant's action after observing how that intervention behaves or maintains consistency across the 15-minute and 30-minute windows. The optimal time window is assessed by using existing literature or empirical findings of this study or both.

3.6.1.3 Assessment of the impact of the smart nudging intervention/interventions

This stage assesses the impact of the smart nudging interventions using their mean differences, number of positive impact instances, and the number of no/negative impact instances. The rationale for analysing the mean difference, positive impact instances, and no/negative impact instances of a smart nudging intervention is that it helps to assess whether the smart nudging intervention consistently leads to improvements and to understand its overall effectiveness or impact.

The impact is shown using a legend, namely, positive impact, no/negative impact, neutral impact, and not conclusive/uncertain impact. A positive impact is considered if the number of

positive impact instances are higher than the number of no/negative impact instances and the mean difference, which highlights that the overall impact is positive and indicates an improvement in the indoor air quality parameters. A no/negative impact is considered if the number of no/negative impact instances are higher than the number of positive impact instances and the mean difference, which highlights that the overall impact is negative and shows no improvement in indoor air quality parameters. A neutral impact is considered based on the equal number of positive impact instances and number of no/negative impact instances. An uncertain/not conclusive impact is determined if there is a contradiction between the mean difference and number of positive or no/negative impact instances. For example, if the mean difference is negative, indicating a positive impact, but the number of no/negative impact instances are higher than the number of positive impact instances. A further assessment is performed to assess the positive instances related to the interventions that showed a positive impact, neutral impact, and uncertain impact, except for the no/negative impact through verification.

3.6.1.4 Verification of the positive instances of the interventions

This stage is conducted after assessing the intervention(s) related to each indoor air quality parameter in each plot on a weekly and monthly basis in the 30-minute window. A verification is conducted to assess whether the identified positive instances of a smart nudging intervention/s are real and observable or showed significant improvements rather than random or inconsistent changes. This strengthens the evidence of the true or best effectiveness of the intervention/s.

3.6.1.5 Assessment of the most effective intervention

This stage is performed to identify the most effective smart nudging intervention related to each indoor air quality parameter in each plot separately. This step concludes the true or best effectiveness of the smart nudging interventions.

3.6.1.6 Inferential statistics

Inferential statistics are conducted to analyse the data. Inferential statistics are used to determine the most effective type of smart nudging intervention in achieving safe thresholds by comparing the mean differences (mean differences such as CO₂ reduction, temperature increase, etc.) of each smart nudging intervention. The inferential statistics *“aims to test hypotheses to return a probability about whether or not a hypothesized effect, relationship, or*

difference is likely true” (Kotronoulas, et al., 2023). The inferential statistics comprise of null hypothesis (HO) and alternative hypothesis (H1) (Kotronoulas, et al., 2023).

The repeated measures ANOVA is used to determine which type of smart nudging intervention shows a significant impact on achieving the safe thresholds for each indoor air quality parameter in each plot. Repeated measures ANOVA violates the main ANOVA assumption of ‘independence’, as repeated measures are correlated observations that are observed from the same plot (Muhammad, 2023). Therefore, repeated measures ANOVA is selected based on the research design, as this research is a within-subject design, and the analysis is conducted focussing on one indoor air quality parameter of a single plot that is exposed to all three types of smart nudging interventions for over the intervention period. Therefore, this implies that the same plot (subject) is exposed to three interventions multiple times. Furthermore, the results of repeated measures ANOVA are specific or tailored to each indoor air quality parameter of a single plot.

The assumptions of repeated Measures ANOVA are 1) the continuous dependent variable should be approximately normally distributed, 2) the categorical independent variable should have three or more levels, 3) absence of outliers, and 4) sphericity (Muhammad, 2023). More importantly, Muhammad (2023) states that all assumptions should be met to perform a repeated measures ANOVA. The Shapiro-Wilk test is suitable to test normality for both smaller ($N < 50$) and larger sample sizes ($N > 50$). If the p-value of the Shapiro-Wilk test is larger than 0.05 ($P > 0.05$), it can be concluded that the data are normally distributed, thereby, achieving the assumption of normality (Mishra, et al., 2019). The Mauchly’s test is performed to determine if the sphericity assumption is met (Muhammad, 2023). The hypotheses for the repeated measures ANOVA are described below.

- Null hypothesis (HO): There is no significant difference in the mean differences (difference = sensor data after 30min – sensor data at the last minute of the previous hour) of the repeated measures across the three types of smart nudging interventions.

$H_0 = \mu_1 = \mu_2 = \mu_3$, where μ_1 , μ_2 , and μ_3 represents the mean differences for each type of smart nudging intervention.

- Alternative hypothesis (H1) – There is a significant difference in the mean differences (difference = sensor data after 30min – sensor data at the last minute of the previous hour) of the repeated measures across the three types of smart nudging interventions.

$H_1 = \mu_1 \neq \mu_2$ or $\mu_1 \neq \mu_3$ or $\mu_2 \neq \mu_3$, where at least one type of smart nudging intervention shows a different mean difference in achieving the safe thresholds.

Friedman's test, which is the non-parametric alternative of the repeated measures ANOVA, is performed if the normality assumption is violated (Muhammad, 2023). The hypotheses are described below.

- Null hypothesis (H₀): The distributions of the dependent variable (difference between the sensor data = sensor data after 30min – sensor data at the last minute of the previous hour) are the same across the three types of smart nudging interventions.
- Alternative hypothesis (H₁) – At least one of the smart nudging interventions has a different distribution of the dependent variable (difference between the sensor data = sensor data after 30min – sensor data at the last minute of the previous hour).

The paired samples T-test is “used to determine whether the change in means between two paired observations is statistically significant” (Mishra, et al., 2019). Paired samples T-test is conducted at instances where only two smart nudging interventions are present for the comparison. The paired variables must be continuous variables and normally distributed (Mishra, et al., 2019). The assumption of normality is checked using the Shapiro-wilk test. The paired t-test accounts for the fact that the same indoor air quality parameter of the same plot is exposed to both smart nudging interventions. The data can be reported using the p-value. If the p-value is less than 0.05, it shows a significant difference between the paired groups (Kotronoulas, et al., 2023). The hypotheses are as follows.

- Null hypothesis (H₀): There is no difference in the mean differences (difference between the sensor data = sensor data after 30min – sensor data at the last minute of the previous hour) across the two types of smart nudging interventions.
- Alternative hypothesis (H₁) – There is a significant mean difference (difference between the sensor data = sensor data after 30min – sensor data at the last minute of the previous hour) between the two smart nudging interventions.

The Wilcoxon signed rank test is the non-parametric alternative to the paired sample t-test. The Wilcoxon signed rank test can be performed when the distribution of differences within pairs deviates from the normal distribution (Oyeka & Ebu, 2012). The hypotheses are as follows.

- Null hypothesis (H0): There is no difference in the medians of the paired differences (difference between the sensor data = sensor data_{after 30min} – sensor data_{at the last minute of the previous hour}) between the two types of smart nudging interventions.
- Alternative hypothesis (H1) – There is a significant difference in the medians of the paired differences (difference between the sensor data = sensor data_{after 30min} – sensor data_{at the last minute of the previous hour}) between the two types of smart nudging interventions.

3.6.2 Qualitative data analysis

A thematic analysis is conducted to analyse interviews performed before the intervention period and after the intervention period. The interviews are recorded and transcribed automatically using Microsoft Teams, and the transcriptions are stored safely in the BCU OneDrive. Transcripts of all interviews are systematically coded using NVivo, a qualitative data analysis software. Initial codes are generated to capture important features of the data, which will be collated into potential themes. These themes are reviewed and improved to ensure that they accurately reflect the data and address the research questions. Pre-intervention interviews are used to assess the home occupants' existing behaviours, perceptions, occupancy period, knowledge about air emissions related to household energy consumption, and experiences related to interventions to tailor personalised and context-specific smart nudging interventions. Post-intervention interviews are used: 1) to understand whether home occupants have perceived changes in their behaviours related to household energy consumption, 2) to understand their experiences related to learning through digital home user guide and smart nudging interventions, 3) to understand their experiences related to the deployment of smart nudging interventions, 4) to identify the most effective smart nudging intervention, and 4) to triangulate the research findings from quantitative data with qualitative data.

3.6.2.1 Pre-intervention interviews

The themes of pre-intervention interviews are 'understanding existing behaviours', 'occupancy period', 'knowledge about air emissions associated with household energy use', and 'interventions for sustainable behavioural change'. The two codes, namely, 'reducing stuffiness' and 'heating,' are collated under the theme, which is 'understanding existing behaviours'. The code, which is 'reducing stuffiness', has eight sub-codes, namely, 'regular cooking', 'irregular cooking', 'opening kitchen windows', 'closing kitchen door', 'using extractors', 'drying clothes', 'opening non-kitchen doors', and 'opening non-kitchen windows'. These sub-codes intend to identify the frequency of cooking, existing cooking

behaviours of the householder such as opening the kitchen window, closing the kitchen door, and using extractor fans, the way the householder dries their clothes, the frequency of opening non-kitchen doors and non-kitchen windows if the householder detects stuffiness in the house, and practices for managing steam in the bathroom. The code, which is 'heating', has only one sub-code, namely, 'thermostat temperature'. intends to identify the typical thermostat temperature of the house. Therefore, the first theme attempts to identify the current behaviours of the householders holistically.

The codes, namely, 'all-day occupancy', 'morning occupancy', and 'evening occupancy', are categorised under the theme 'occupancy period'. These codes target to capture householder's primary duration of occupancy in their house. The theme, which is 'knowledge about air emissions associated with household energy use' include only one code, which is 'air emissions awareness'. This code aims to capture householder's understanding of air emissions, their sources, and impact. The theme, which is 'interventions for sustainable behavioural change', has two codes, namely, 'previous app experience' and 'perceptions about personalised messages'. These codes intend to understand householder's prior experience with air quality monitoring apps, their usability perceptions, the extent to which that app influenced their behaviours, and the householder's thoughts on the potential impact of personalised messages. The mind map is created to visualise the relationship between themes, codes, and sub-codes of the pre-intervention interviews, as shown in Figure 12.

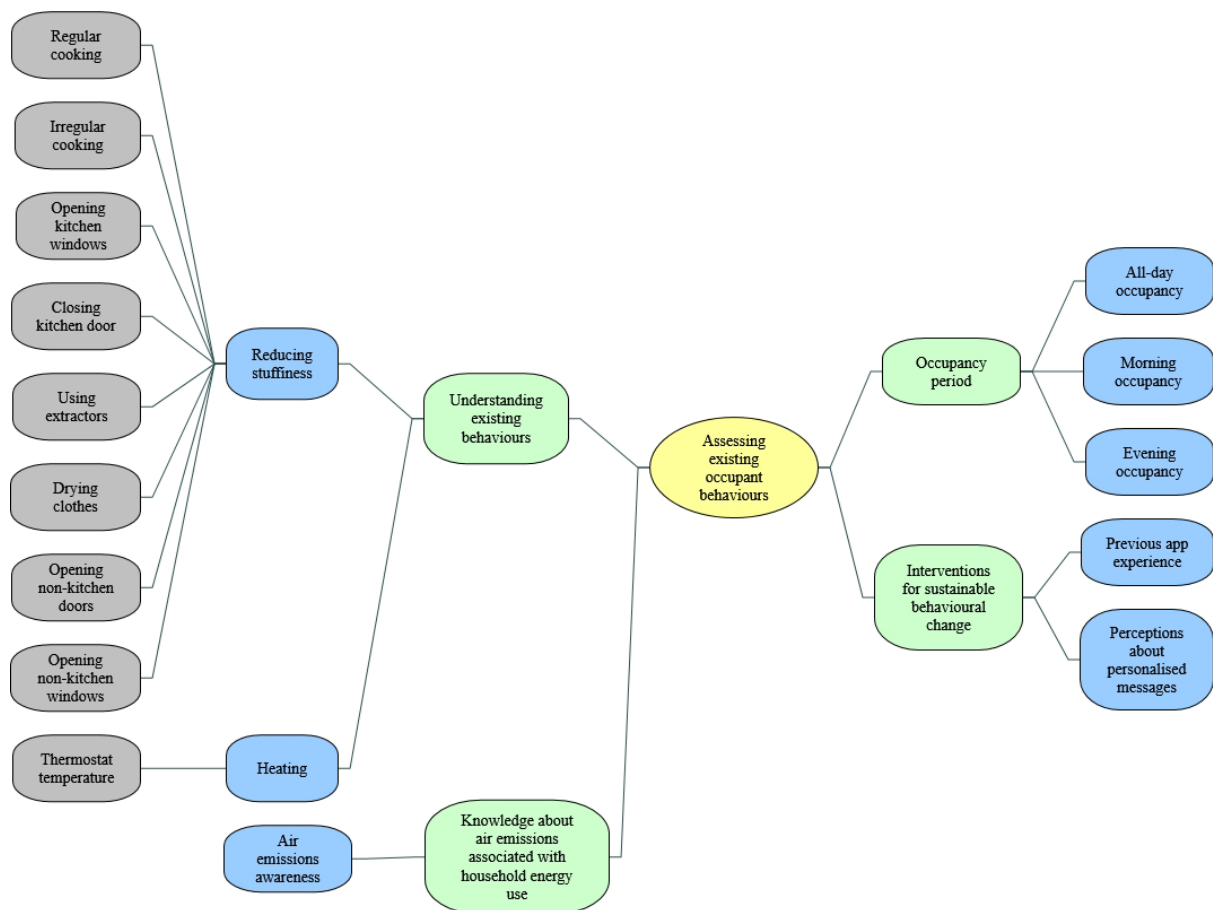


Figure 12: Pre-intervention interviews - mind map

The findings from the pre-intervention interviews were used to create the smart nudge design and compose the smart nudging interventions. The following sections show how findings from each theme inform the composing of smart nudging interventions aimed at nudging individuals towards achieving sustainable behavioural change.

- The findings under the first theme, which is ‘understanding existing behaviours’, guide the design of personalised push notifications or smart nudging interventions by highlighting best practices to adopt and change the current unsustainable behaviours of each householder. For example, 1) if the householder cooks regularly, uses the extractor fans, and does not close the kitchen door, the push notification could suggest the householder shut the kitchen door to reduce high humidity, as it limits the spreading of steam and moisture to the other areas of the house and helps to contain the humidity within the kitchen, 2) if the householder keeps the thermostat temperature at 30⁰C, which is higher than the recommended threshold, the push notification could suggest the householder maintain the temperature between 18-21⁰C to save on energy costs and improve indoor air quality, and 3) if the sensors detect high CO₂ levels in the house,

the push notification could suggest the householder open windows to ventilate the house and improve the indoor air quality.

- The findings under the second theme, which is the ‘Occupancy period’, attempt to identify the correct time periods to send the personalised push notifications. For example, if the householder is available from 4.00pm to 9.00am the following day, the push notifications were set to send from 4.00 pm to 10.00pm and from 7.00am to 9.00am to increase the likelihood of timely engagement and reduce negative perceptions.
- The findings under the third theme, which is the ‘knowledge about air emissions associated with household energy use’, identify the importance of input digital user guides to the mobile application that include general energy-saving tips and Indoor Air Quality improving tips. In addition, the findings investigate the importance of educating the householders through the personalised push notifications. Moreover, this highlights the importance of notifying the householder about how they can reduce high humidity, high CO₂ etc. in the household by highlighting the personalised best practices to adopt. Furthermore, digital user guides and personalised push notifications intend to serve as self-learning methods by providing the householders with detailed information and visual aids.
- The findings under the fourth theme, which is the ‘interventions for sustainable behavioural change’, attempt to identify if the householders are familiar with indoor air-quality apps, their perceptions, and how they interacted with those apps to pinpoint areas that were less favourable to design a more user-friendly and engaging app. Moreover, this last theme attempts to investigate the perceptions and check if the householders are open to receiving the personalised push notifications.

3.6.2.2 Post-intervention interviews

Figure 13 shows the mind map that includes the themes, codes, and sub-codes generated from the post-intervention interviews. The post-intervention interviews have four themes, namely, ‘assessing behavioural change’, ‘learning about air emissions associated with household energy use’, ‘experience with smart nudging interventions’, and ‘identifying the most effective smart nudging intervention’. The two codes under the theme, which is ‘assessing behavioural change’ are ‘reducing stuffiness’ and ‘heating’. The code, which is ‘reducing stuffiness’, has four codes, namely, ‘opening kitchen windows’, ‘closing kitchen door’, ‘using extractors’, and ‘opening non-kitchen doors and windows’. The code, which is ‘heating’ has only one sub-code, namely, ‘changing thermostat temperature’. The two codes under the theme, which is ‘learning about air emissions associated with household energy use’, has two codes, namely, ‘indoor air quality awareness’ and ‘reading user guides’. The theme, which is ‘experience with smart nudging interventions’ has only one code, namely, ‘personalised messages’. Similarly, the theme, which is ‘identifying the most effective smart nudging intervention’ has only one code, namely, ‘type of personalised message’.

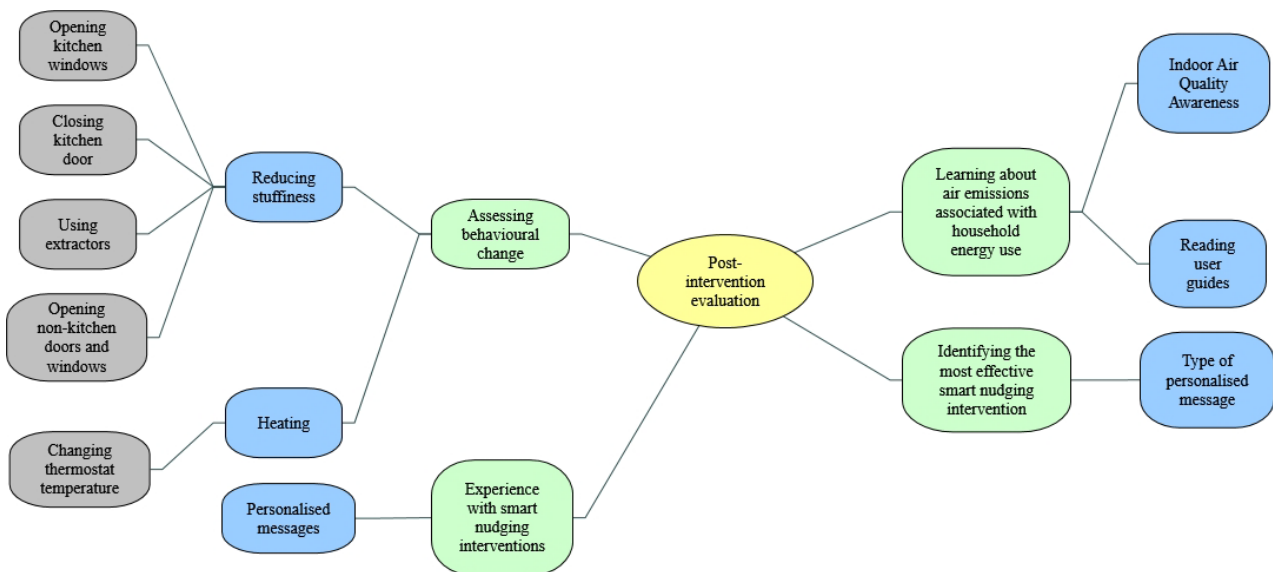


Figure 13: Post-intervention interviews - mind map

The sub-codes under the first code, which is ‘Reducing stuffiness’, attempt to identify whether the householders have adopted sustainable behaviours to reduce high humidity levels, high CO₂ levels, and high TVOC levels in their homes. For example, if the householder opens doors and windows more frequently than before, it denotes a sustainable behavioural change. The sub-code under the code ‘Heating’ investigates whether the householders have maintained the thermostat temperature between the recommended threshold, which is 18-21⁰C. The code,

which is ‘Indoor Air Quality awareness’, intends to assess whether the householders have read the personalised push notifications or messages, understood the negative impacts, learned from them, and acted to mitigate those negative impacts. The second code, which is the ‘Reading user guides’, checks whether the householders read the digital user guides and learnt about improving Indoor Air Quality. The code, namely, ‘Personalised messages’, attempts to assess the experience of a householder in dealing with personalised push notifications. Moreover, this code helps to understand the pros and cons of personalised push notifications and areas of improvement. The code, namely, ‘Type of personalised message’. This code mainly attempts to assess the most effective smart nudging intervention in making a sustainable behavioural change and, thereby, assists to validate findings of the quantitative analysis. Overall, these themes, codes, and sub-codes attempt to assess whether householders have read, understood, learned, and made a sustainable behavioural change to reduce air emissions associated with household energy use, improve indoor air quality holistically.

3.7 Validation and design development

The internal validation of this study is ensured by triangulating the quantitative findings or engagement analytics with qualitative findings from the post-intervention interviews for each indoor air quality parameter within each house separately. The external validation is ensured by comparing the research findings with existing empirical studies and comparing the research findings across the three plots. The smart nudge design and smart nudging interventions are refined using the research empirical findings, identifying research limitations, and referring to the supplementary academic sources to develop a proposed smart nudge design.

The validation of the ‘smart nudge design’ ensures that the model achieves the nudging goal of reducing anthropogenic air emissions related to household energy consumption and improving indoor air quality through changing occupant behaviours in a real-world context. Therefore, expert reviews or the feedback from the industry partner, which is Covatic, play an important role in both the development and the validation, as the feedback helps to modify the refined smart nudge design through identifying potential weaknesses and suggesting improvements.

The presumption of Future Home Standard (FHS) measures in Project 80 does not undermine the validity of the research findings. This is because all three case study plots show identical house designs and similar demographics. As a result, the plots were assessed under the same baseline to ensure that observed differences are attributed to the smart nudging interventions

or intervention-driven behaviour change rather than housing variations. However, while the research findings are specific to these low-carbon homes and may not generalise to the existing housing stock, they provide a forward-looking evaluation relevant to future low-carbon homes. Once the Future Homes Standard is formally implemented, the external validity of the research findings is likely to increase, as the study effectively evaluated the smart nudging interventions in homes representative of the future regulatory environment.

3.8 Ethical considerations

In relation to the BCU Research Ethical Framework, there are important ethics that need to be considered. As this research focuses on both quantitative and qualitative data, areas such as obtaining informed consent, data storage, and security are important. In relation to the ethics policy of the university, signed consent forms were obtained when collecting confidential data, and suitable measures were adopted when storing the data, such as storing data on “one drive” and on encrypted devices. In order to avoid the language barriers of the recruiters, all the work was carried out in English only.

If the recruiters or research participants cannot provide consent or raise doubts during the process, the data would not be retained. Plagiarism was addressed seriously by proper referencing and credits were given to the original sources of information in relation to best academic practices. Furthermore, ethical considerations were carefully applied when engaging households with any disabilities. This included providing accessible information, ensuring informed and ongoing consent, providing flexibility in participation, offering flexible timing, and minimising any physical or emotional burden. Participation was entirely voluntary, with the right to withdraw at any stage.

Additionally, data collection through a software application (“I am zero”), developed by Covatic, stores the data in an encrypted database on the user's mobile phone. This software application processes data on the device and returns a true or false value to the backend based on the result of that analysis. That result is only associated with a “framework ID”, which is a random string (an example is “63d11f31f521169153951b3b”) and is only used to link related reports. There is no mechanism to enable the linkage between a framework ID and a person. When the app is uninstalled, all the personal data that was stored is deleted. Therefore, the collected data is not exposed to any external parties that could endanger individuals. Data is treated as confidential with no unapproved third parties gaining the access to the data.

3.9 Chapter summary

The action research methodology combines pragmatism, abductive approach, three multiple-case studies with purposive and convenience sampling techniques, and mixed methods to achieve the aim and objectives of this study and answer research questions. The primary data collection methods used in this study are passive sensor-based monitoring and semi-structured interviews. The secondary data was collected through a comprehensive literature review. The quantitative data analysis methods included statistical tests such as descriptive statistics, repeated measures ANOVA, paired sample t-test, Friedman test, and Wilcoxon-signed rank test. Qualitative data analysis included a Thematic analysis.

A triangulation approach was employed to ensure the internal validity of the study, where both qualitative and quantitative research findings were integrated and compared. Comparison: 1) between the research findings of this study and the research findings of the existing empirical studies and 2) across the three plots, was used to enhance the external validity of the study. The smart nudge design and the logics of smart nudging interventions were refined by focusing on the research empirical findings, research limitations, and supplementary academic sources, successively leading towards the development of the smart nudge design. Expert reviews or the feedback from the industry partner, which is Covatic, was obtained for the development and the validation of the proposed smart nudge design. Therefore, this chapter included the entire research methodology of this study from inception to completion.

4 Chapter – Smart nudge design

4.1 Introduction

This chapter provides the formulation of the smart nudge design. Although Karlsen & Andersen (2019) extended the digital nudge design of Schneider et al. and introduced a new smart nudge design using a use case that is focused on the transportation sector, no smart nudge design has been proposed to the household energy sector. The concept of smart nudge design was first introduced by Karlsen and Andersen in 2019. Therefore, this research builds on Karlsen and Anderson's work by merging the 'smart nudge components', introduced by Karlsen and Andersen (2022), into the smart nudge design to create a new smart nudge design that addresses the limitations that were identified in the existing empirical research (as described in the chapter 2 – literature review). The limitations identified in the existing empirical research are generalisability of the research findings, overreliance on self-reported data that may lead to reporting bias and inaccuracies of data, less user-friendliness, and limited frequency of delivering smart nudging interventions (once a month, once a week, or two-weekly) that may not effectively prompt immediate behaviour changes in users. These limitations will be addressed, and the research will provide solutions to overcome these limitations by creating more user-friendly, structured, and timely personalised smart nudging interventions.

4.2 Formulation of the smart nudge design

Initially, the smart nudge design of Karlsen and Andersen (2019) included eight steps (as described and shown in the Chapter 2: Literature review), namely: 1) define the goal; 2) understand the users; 3) understand the situation; 4) select the targeted activity; 5) select relevant information; 6) design a smart nudge; 7) present a nudge; and 8) evaluate the nudge. However, adapting Karlsen and Andersen's smart nudge design, which was originally proposed for the transportation sector, to the residential energy sector presents challenges:

- The first step in the original smart nudge design was 'Define the goal'. The goals such as "choosing more environmentally friendly transport" are clear, easy to track or measurable, action-oriented, and often supported by public infrastructure and policy in the transportation sector. In contrast, achieving goals such as reducing indoor air emissions related to household energy use and improving indoor air quality can be more critical and less immediate, as the indoor air pollutants generate from daily activities of the occupants are not noticeable or visible and thereby, many occupants

might not feel the urgency to change their unsustainable behaviours. In addition, the nudging goal of reducing air emissions and improving indoor air quality aligns with diverse behaviours, preferences, perceptions, and values of households, making it more challenging to change the behaviours of the occupants.

- The second step of the original smart nudge design, which is ‘understand the users’ involves challenges in adapting to the residential energy sector. Unlike commuting choices, which are often routine and observable, energy consumption in homes is different based on the unique lifestyles of the occupants and is often influenced by personal preferences, emotions, habits, etc. Therefore, it is important to carefully understand the occupant and personalise the approach through interviews after obtaining the informed consent from the occupant to avoid ethical and privacy concerns.
- The third step of the original smart nudge design, which is ‘understand the situation’ involve challenges in adapting to the residential energy sector. In transportation, contextual factors such as weather, traffic, time of the day are available and easier to integrate. In contrast, the residential energy sector needs to understand the house characteristics or property details to design smart nudging interventions, which might raise privacy concerns.
- The fourth step of the original smart nudge design is ‘Select the targeted activity’. Selecting a targeted activity for the transportation sector can be less critical, as clear and distinct choices can be found in transportation such as choosing between walking or driving. Targeting the right indoor air quality parameters to reduce indoor air emissions related to household energy use and improve indoor air quality should involve robust research to identify the suitable indoor air quality parameters that are related to energy consumption, observe and understand occupant behaviours and their context to make the smart nudging interventions more impactful.
- The 6th step, ‘Design a smart nudge’ can be more challenging in the household energy sector than the transportation sector, as the nudges might be perceived as interfering with comfort, privacy, and autonomy based on the occupants’ existing behaviours that are deeply tied to personal comfort, such as heating preferences, not using the extractor fan to avoid the noise in the kitchen, and ventilation habits. Therefore, balancing influence with user acceptance is more sensitive in the residential settings.

In addition, the original smart nudge design proposed by Karlsen and Andersen (2019) shows some limitations. The main limitation of the smart nudge design introduced by Karlsen and Andersen (2019) lies in the Step 6: Design a smart nudge, as there is no specific structured format or logic for designing the intervention. This lack of a clear structure or a logic can lead to inconsistencies and confusions in how smart nudging interventions are developed and presented, potentially affecting their effectiveness. Without a proper logic or a structured format, the design process of the interventions might lack the practical, motivational, and actionable elements in a balanced and impactful way. This may show challenges for replication and scalability across different contexts. On the other hand, this design did not clearly show how the intervention can be redesigned if the user did not follow it in the Step 8: Evaluate the nudge. The Step 8 suggested that the nudging intervention might be adapted by targeting a different activity, using different information, or changing the timing of the delivery but did not mention a structured format or a logic for making those changes systematically. Therefore, these limitations highlight the requirement of a new extended smart nudge design to nudge the individuals.

The new smart nudge design formulated in this study involves additional steps: 1) to enhance personalisation and the effectiveness of the smart nudging interventions, 2) to overcome the challenges of adapting the smart nudge design from the transportation sector to the residential energy sector, and 3) to address the limitations of the smart nudge design introduced by Karlsen and Andersen (2019). In addition, these steps aim to address the identified research limitations in the existing empirical research (shown in Chapter 2: Literature review), thereby contributing to the advancement of knowledge in this domain. Figure 14 shows how the new smart nudge design was formulated by highlighting the new steps that were added to the design or steps that were modified in relation to the original design.

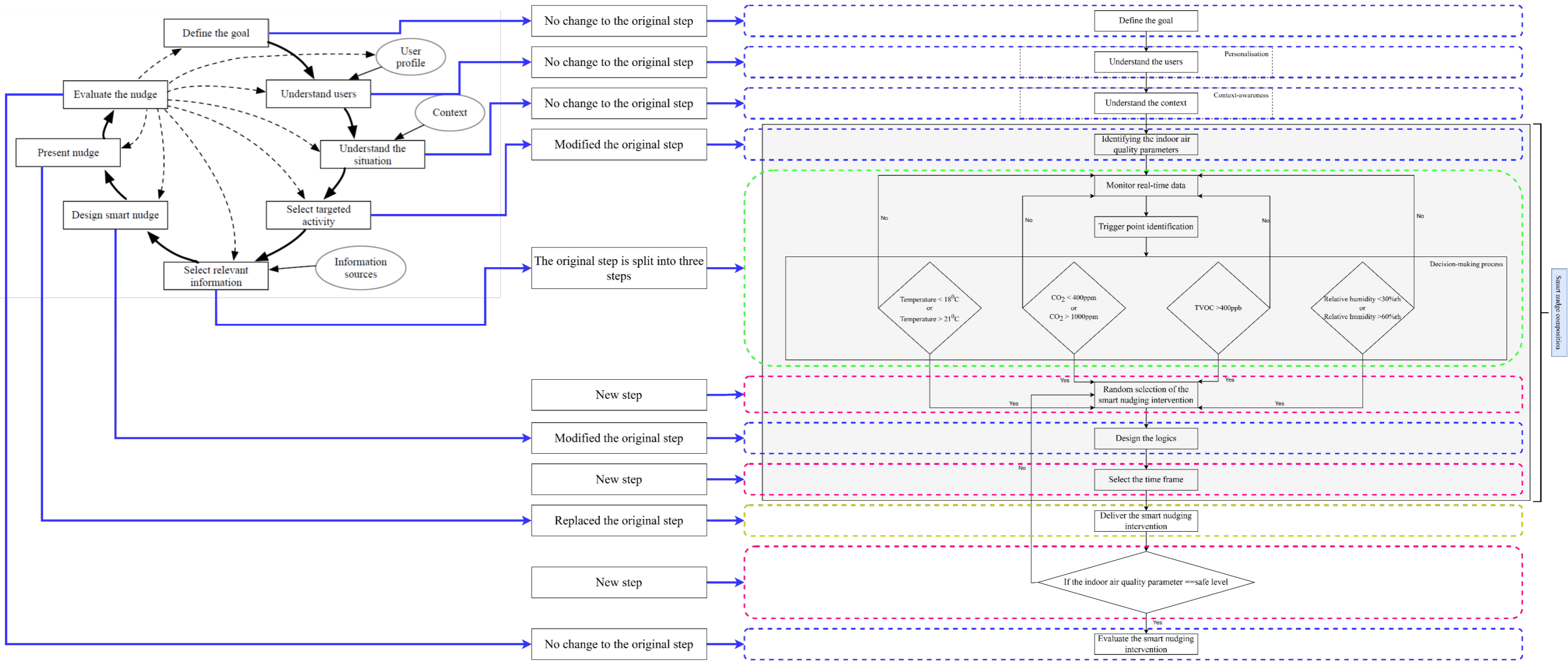


Figure 14: Formulation of the new smart nudge design

Figure 14 shows the original steps, modified steps, and the additional steps of the new smart nudge design that build onto the original design.

- Step 1 – Define the goal – no change to the original step.
- Step 2 – Understand the users - no change to the original step.
- Step 3 - Understand the situation/context - no change to the original step.
- Step 4 – Select targeted activity - modified as ‘Identify the indoor air quality parameters’ in the new design.
- Step 5 – Select relevant information – broken down into three steps in the new design, namely, ‘monitor real-time data’, ‘trigger point identification’, and ‘decision-making process’.
- Step 6 – Design smart nudge – modified the original step and introduced as ‘design the logics’ in the new design. This step includes the logic formulations of the smart nudging interventions to avoid the limitations identified in the smart nudge design introduced by Karlsen and Andersen (2019).
- Step 7 – Present nudge - replaced with ‘deliver the smart nudging intervention’ in the new design.
- Step 8 – Evaluate the nudge – no change to the original step. However, the wording was changed as ‘evaluate the smart nudging intervention’.
- New steps added to the original design - ‘random selection of the smart nudging intervention’, ‘select the time frame’, and ‘assess the indoor air quality parameter’.

This structured approach ensures that each step is purposefully designed to achieve the nudging goal, providing a clear pathway for the implementation and evaluation of the personalised smart nudging interventions that are tailored to deliver personalised recommendations. Therefore, the new smart nudge design includes 13 steps, instead of 8, and the steps are described below.

- 1) Define the goal – this first step involves identifying the nudging goal. The nudging goal is to reduce anthropogenic air emissions related to household energy consumption and improve indoor air quality through a sustainable behavioural change among home occupants. Identification of the nudging goal helps to understand what behaviour, decision, and specific indoor air quality parameter related to an occupant’s activity the smart nudging intervention aims to steer home occupants towards. Moreover, the nudging goal helps in identifying, structuring, and following the necessary steps to

achieve the desired outcomes systematically. Although defining this nudging goal is challenging in the residential energy sector, the use of a structured approach and the steps outlined in the new smart nudge design can help mitigate this challenge.

- 2) Understand the users – this second step involves ‘personalisation’ and refers to the process of gaining demographic information about the home occupants, including their habits, behaviours, and preferences. This research will gain information such as family size (number of households including children), daily cooking times, occupancy periods, selected thermostat settings of the house. This will help tailor personalised smart nudging interventions that resonate with the targeted home occupants. Thus, it will increase the user engagement to reduce air emissions related to household energy consumption and improve indoor air quality, as home occupants feel the interventions are more relevant and applicable to their specific situations. Although personalisation can be challenging in the residential energy sector due to the unique lifestyles of the home occupants and other ethical and privacy concerns, pre-intervention interviews can help to mitigate this challenge by obtaining the informed consent from the occupants and conducting interviews to understand their household preferences, behaviours, etc. before designing the smart nudging interventions. Moreover, the challenges of personalisation in the residential energy sector can be mitigated by identifying the areas of improvement of occupants, such as their knowledge gaps related to air emissions, household issues such as condensation, etc. and occupants’ interactions with digital technology. The above section 3.6.2.1 under Chapter 3 described how the pre-intervention interviews informed the formulation of the smart nudging interventions.
- 3) Understand the context – this step allows for understanding the context of the home occupants, such as house characteristics (type of the house, number of rooms, size of the house, and location) and local weather conditions. This step is crucial for tailoring effective smart nudging interventions, as it allows for understanding potential barriers and facilitators in the decision-making process. For example: if the house is designed to achieve a lower airtightness, combining natural ventilation, the smart nudging interventions can suggest the home occupant open the windows for a few minutes while cooking to improve the indoor air quality. The challenge of understanding the context (house or property characteristics and design) without raising privacy concerns was addressed by collaborating with the Midland Heart Project 80 Group and using their

user guides. In addition, three similar plots were used in this study, as described in Chapter 3: Action Research Methodology.

- 4) Identify the indoor air quality parameters – understanding the indoor air quality parameters for which smart nudging interventions are designed is important for ensuring their effectiveness and relevance. Moreover, it helps identify the most appropriate timing and information that needs to be included in the design of the interventions to influence behaviours positively and maximise the benefits of the interventions. The indoor air quality parameters are temperature, CO₂, TVOC, and relative humidity. These indoor air quality parameters help to achieve the nudging goal holistically.
- 5) Monitor real-time data – monitoring minute-by-minute real-time data related to the indoor air quality parameters allows for the identification of emerging patterns and areas of improvement. In addition, continuous monitoring offers immediate insights into the creation of timely interventions that match the conditions that change over time to pinpoint certain areas where air quality can be improved, ultimately achieving the nudging goal. The real-time indoor air quality data is monitored using UHoo Smart Air sensors.
- 6) Trigger point identification – identifying whether the indoor air quality parameters have exceeded their specific thresholds and provide a clear and actionable metric for making timely interventions. The thresholds for each indoor air quality parameter are decided based on the literature, as shown in above Table 10: Indoor air quality parameters and their thresholds.
- 7) Decision-making process – the diamond boxes shown in Figure 14 represent the decision-making process, where the next step depends on the identification of last-minute data of the hour related to the indoor air quality parameters that exceed the thresholds. If the last-minute data of the hour has not exceeded the threshold, no intervention will be applied, but it will be subjected to continuous monitoring. However, if the last-minute data has exceeded the threshold, then it will proceed to the next step, and a smart nudging intervention will be applied.
- 8) Random selection of the intervention – selecting the smart nudging interventions randomly avoids ‘order bias’ and thus allows for a more accurate and balanced assessment of the effectiveness of each intervention in achieving the nudging goal.

Additionally, it prevents home occupants from becoming accustomed to or resistant to a particular intervention, thereby maintaining the element of surprise and gradually increasing the impact of interventions. The smart nudging interventions selected in this research are feedback, social comparison, and loss aversion.

- 9) Design the logics – The logics of the smart nudging interventions are designed to nudge the users to achieve the safe thresholds of the indoor air quality parameters. The logics are designed using the smart nudging components, and this is described in the below sections 4.2.1 and 4.2.2.
- 10) Select the time frame – an hourly time frame is selected for delivering interventions to ensure timely and actionable responses based on the recent data. By checking the last-minute data of each hour, such as data collected at 4.59p.m. and scheduling to send the smart nudging interventions promptly at the start of the next hour if the data exceeds the threshold, such as at 5.00pm., avoids the random fluctuations or variations that affect the indoor air quality parameters. Moreover, it ensures the possibility of addressing quick actions without delays and avoiding an overload of alerts for home occupants.
- 11) Deliver the interventions – this step involves delivering push notifications at the correct time based on the time frame scheduled in step 10. The interventions are delivered during the occupancy periods identified through the pre-intervention interviews.
- 12) Assess the indoor air quality parameter – this step ensures that the indoor air quality parameter has reached its safe levels. If it has not reached its safe levels, then it will proceed to step 8, and a different intervention will be selected to nudge the home occupant until it reaches its safe levels.
- 13) Evaluate the smart nudging intervention – this step will assess the effectiveness of the intervention if the indoor air quality parameter has reached its safe level in the above step 12.

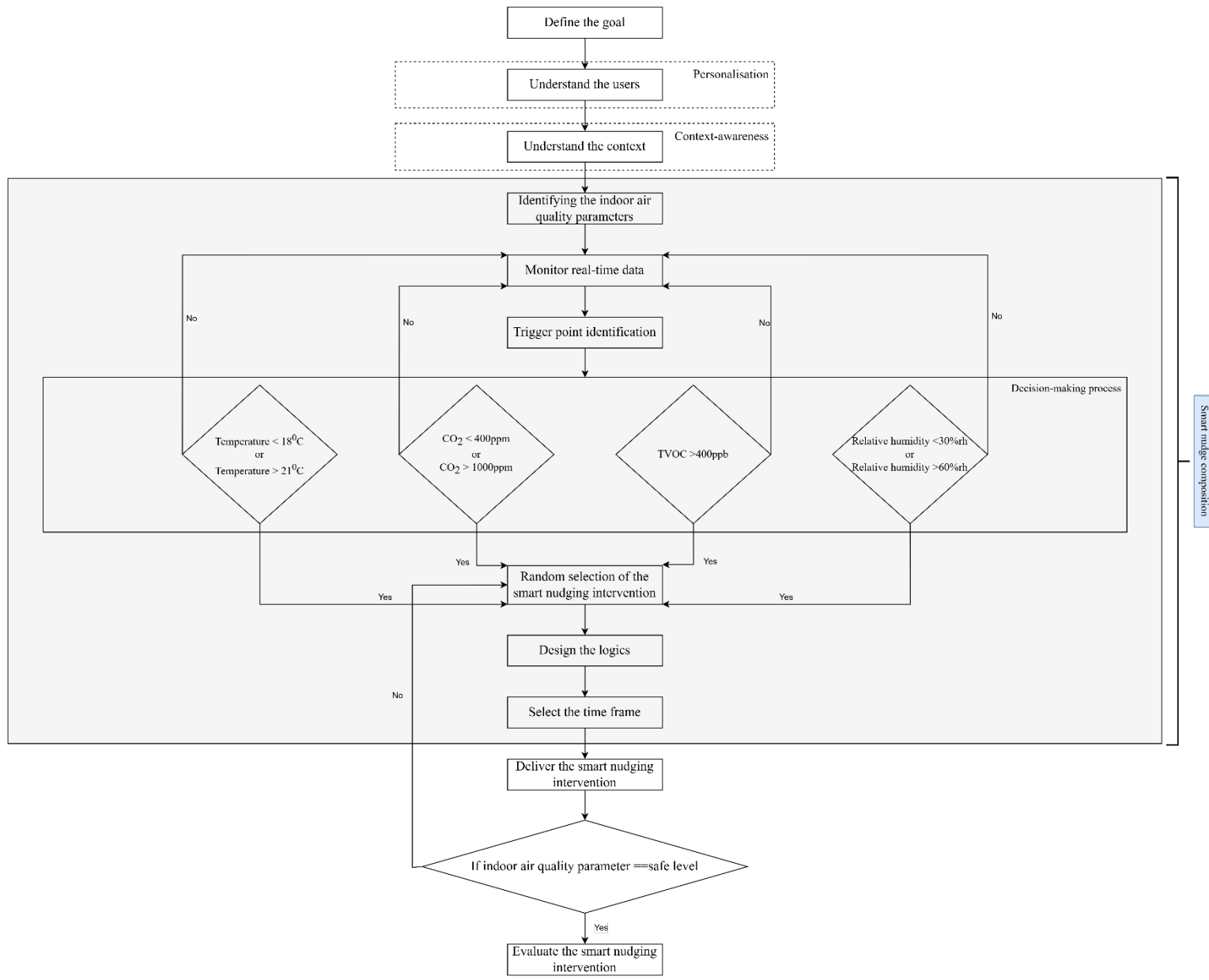


Figure 15: Smart nudge design

4.2.1 Smart nudge composition

Karlsen and Andersen (2022) explained smart nudge components as “*Smart nudge = {A, I, C, T, P}*”. The components of a smart nudge or smart nudging intervention are Activity (A), Influence (I), Contents (C), Time frame (T), and Presentation (P). Activity (A) refers to a specific activity selected for achieving the nudging goal. Influence (I) refers to the information or the motivational factors provided for the user to choose and engage with an activity that helps achieve the nudging goal. Content (C) refers to the practical information provided for the user. Time frame (T) refers to the most suitable time for the nudge. Presentation (P) refers to how the nudge is presented for the user (Karlsen & Andersen, 2022).

The smart nudge composition includes 7 steps from the 4th step to the 10th step and introduces the components involved in designing or creating the smart nudging interventions. This initial smart nudge composition is modified in the new smart nudge design. The modifications are described below.

- The Activity (A) includes 4 steps from the 4th step to 7th step. The steps begin with identifying the indoor air quality parameters related to household energy consumption, monitoring real-time data related to the identified parameters, trigger point identification, and decision-making process. Therefore, instead of selecting an activity to achieve the nudging goal, the new smart nudge composition identifies which indoor air quality parameter related to household energy use exceeds the pre-defined threshold using real-time monitoring and then uses it as the base to compose the smart nudging intervention and nudge the householder towards achieving the nudging goal.
- The smart nudge components - influence (I), Content (C), and Presentation (P) - are included in the 8th and 9th steps. The 8th step and 9th step focus on providing information for the householder in three different ways that relate with the three smart nudging interventions, which are feedback, social comparison, and loss-aversion, to achieve the nudging goal by achieving the safe threshold of the indoor air quality parameter. More specifically, these three smart nudge components are embedded in the logic formation of each smart nudging intervention.
- The Time frame (T) includes in the 10th step of the smart nudge design. This step determines the best time to deliver the smart nudging intervention.

4.2.2 The logic formation

The logic formation is the 9th step in the new smart nudge design, and this 9th step covers three smart nudge components, namely, influence (I), Content (C), and Presentation (P). In the 2008 book “Nudge”, Thaler and Sunstein highlighted that the nudges could affect the decision-making of individuals differently.

The nudges or the smart nudging interventions selected for this study are ‘Feedback’, ‘Social comparison’, and ‘Loss-aversion’. Feedback improves decision-making by providing individuals with information about their behaviours or actions, helping them to understand, adjust and make better decisions. Social comparison improves decision-making by providing comparative information to evaluate themselves against others to encourage conformity. Loss-aversion improves decision-making by highlighting the emotional weight of avoiding potential losses over similar gains. The three logics of each type of smart nudging interventions are devised for creating well-structured smart nudging interventions to ensure that they can be easily implemented in the mobile application as push notifications.

Table 11 presents the structure of the logics for each smart nudging intervention. The logic of feedback includes the steps, namely, 1) urgency, 2) personalisation, 3) personal performance information, 4) emoji, 5) emotions, 6) best practice, 7) incentive, and 8) value, respectively. The logic of social comparison includes the steps: 1) urgency, 2) personalisation, 3) peer behaviour information, 4) emoji, 5) emotions, 6) best practice, 7) incentive, 8) exclusivity, and 9) value, respectively. The logic of loss-aversion includes 7 steps, namely, 1) urgency, 2) personalisation, 3) potential loss information plus best practice, 4) incentives, 5) emoji, 6) emotions, and 7) value, respectively. The 1st, 2nd, 4th, 5th, 6th, and 7th steps are similar in feedback and social comparison logics. Social comparison includes an additional step at the end, making it 9 steps in total. However, the 3rd step of each of the smart nudging intervention is different. The steps are explained in detail in the below sections.

Steps	Feedback	Social comparison	Loss-aversion
1	Urgency	Urgency	Urgency
2	Personalisation	Personalisation	Personalisation
3	Personal performance information	Peer behaviour information	Potential loss information + best practice
4	Emoji	Emoji	Incentives
5	Emotions	Emotions	Emoji
6	Best practice	Best practice	Emotions
7	Incentive	Incentive	Value
8	Value	Exclusivity	
9		Value	

Table 11: The structure of the logics of each smart nudging intervention

4.2.2.1 Inclusion of trigger words in logics

Each logic includes trigger words or power words to get the immediate attention of the home occupants and, therefore, prompt immediate actions to achieve the nudging goal. In addition, appropriate emojis are used in the logics to make the interventions more appealing. The power words: words of ‘urgency’ to prompt immediate actions of home occupants, words of ‘personalisation’ to make the interventions more engaging and relatable, words of ‘emotions’ to induce emotions, words of ‘exclusivity’ to make users special and important, and words of ‘value’ to denote the value of their actions. The power words were selected by assessing their alignment with the logical flow of the content, and the words are explained below.

- Words of urgency - “now”, “Act now”, “Act fast”, “important”, “alert”, “today”, and “don’t loss” (Chugh, 2017; Kotter, 2008).
- Words of personalisation – “you”, and “your” (Chugh, 2017).
- Words of emotions – “enjoy”, “comfort”, “happy”, “smart”, “improve”, and “secure” (Chugh, 2017; Strauss & Allen, 2008).
- Words of exclusivity – “member”, “be part of”, and “join the club” (Chugh, 2017).
- Words of value – “save”, “money”, “unlock”, and “savings” (Chugh, 2017).

4.2.2.2 Type of personalised information in logics

In reviewing the steps of each of the three logics of smart nudging interventions shown in above Table 11, the third step, which is the type of personalised information that each logic of the smart nudging interventions provides, is different in each logic and stands out as the main difference or primary concern. The reason is that feedback, social comparison, and loss-aversion influence decision-making through the nature of the information or the type of information they provide for the individuals (Thaler & Sunstein, 2008). More specifically, the core of the three logics of the three smart nudging interventions will differ mainly from the type of personalised information they provide for the home occupants.

The logics of feedback, social comparison, and loss-aversion include ‘personal performance information’, ‘peer behaviour information’, and ‘potential loss information’, respectively, under the third step in each logic as presented in Table 11. For example, the logic of the feedback nudge will include only the home occupant’s personal performance information as “...CO₂ level is at 1200ppm...”, the logic of the social comparison nudge will include comparative information as "...current CO₂ level is 1200ppm, while your neighbours maintain

it between 400-1000ppm, which is safe....”, and the logic of the loss-aversion nudge includes potential loss information as “...CO₂ level is at 1200ppm. If you do not ..., you will lose the chance...”. Thus, this makes the nudging interventions different from each other.

4.2.2.3 Inclusion of best practices in logics

As per the above Table 11, the logics include the ‘best practices’. Best practices for each indoor air quality parameter are devised and included in logic formation. Table 12 shows the best practices.

Indoor air quality parameter	Threshold	Best practice
Temperature	18°C-21°C (Public Health England, 2013, cited in Public Health England, 2014, p.4)	Maintain thermostat at 18°C-21°C (Public Health England, 2013, cited in Public Health England, 2014, p.4).
CO ₂	400-1000ppm (ASHRAE, 2022; Institute of Air Quality Management, 2021; RESET, 2019)	Opening windows (Deng, et al., 2021; Elwell & Few, 2021; Park & Choi, 2019; Sharpe, et al., 2016, Gunes & Undar, 2024).
TVOC	0-400ppb (Bugayong, 2022)	Reducing the use of diffusers, air fresheners, and scented candles, window opening (Kim, et al., 2024; Warburton, et al., 2023; Gunes & Undar, 2024).
Relative humidity	30%rh - 60%rh (ASHRAE, 2016; WHO, 2009)	Using extractors when cooking, opening windows, closing the kitchen door (Chen, et al., 2023; NHBC, 2023).

Table 12: Indoor air quality parameters, thresholds, and best practices

Table 12 shows the indoor air quality parameters, their thresholds, and best practices that help the home occupants to improve indoor air quality and maintain consistency by not exceeding the specified thresholds. The threshold for temperature is between 18-21⁰C. The Public Health England (2013, cited in Public Health England,2014) recommends maintaining indoor temperatures between 18°C and 21°C for most people, including elderly people and children, especially in living areas for comfort, health, and energy efficiency.

In indoor environments, a CO₂ concentration of 400-1000ppm is considered safe and acceptable. High indoor CO₂ levels above 1000ppm can be observed in these low-carbon homes. The sudden spikes in indoor CO₂ levels can be decreased by opening windows occasionally, especially during periods of high occupancy or when ventilation demand is higher. This conclusion is supported in the study of Sharpe et al. (2016), as the study mentioned that “CO₂ levels were generally lowest during the summer season, attributed most likely to a

greater prevalence of window opening". In addition, the study by Deng, et al. (2021) showed that high indoor CO₂ levels are one of the main drivers that prompt home occupants to open windows to increase ventilation and improve indoor air quality. Similarly, the studies by Elwell and Few (2021), Park and Choi (2019), and Gunes and Undar (2024) showed that window opening plays a critical role in controlling indoor CO₂ levels by improving ventilation.

The threshold for maintaining safe TVOC levels is 0 - 400ppb. The study of Gunes and Undar (2024) showed that higher TVOC levels can be reduced by opening windows. The studies by Kim, et al. (2024) and Warburton, et al. (2023) showed that reducing the usage of diffusers, air fresheners, and scented candles and opening windows can lower indoor TVOC levels.

The threshold for maintaining safe relative humidity is 30%rh – 60% rh. The study by Chen, et al. (2023) showed that relative humidity can be reduced by using extractors when cooking. NHBC (2023) stated that it is necessary to open the kitchen window and/or use the extractor fan and close the kitchen door for about 20 minutes after cooking, bathing or washing to reduce high relative humidity in the house.

4.2.2.4 Inclusion of incentives in logics

Thaler and Sunstein (2008) have mentioned that *"by properly deploying both incentives and nudges, we can improve our ability to improve people's lives and help solve many of society's major problems"*. Therefore, this research included incentives in the three logics. The incentives are presented as "reduce bills" for temperature control and "better health" for CO₂, TVOC, and relative humidity, as this research provides a holistic approach to reduce air emissions associated with energy consumption behaviours and improve indoor air quality at homes.

The logics of each smart nudging intervention and the smart nudge design are visualised in below Figures 16,17, and 18. Figure 19 shows an example of a push notification that was formulated using the logic of feedback to improve relative humidity levels.

1) Logic - Feedback nudge (push notification)

Alert! Today your thermostat is set at 25°C, which means high electricity bills (). Be smart by maintaining thermostat at 18°C-21°C and reducing bills. Unlock savings!

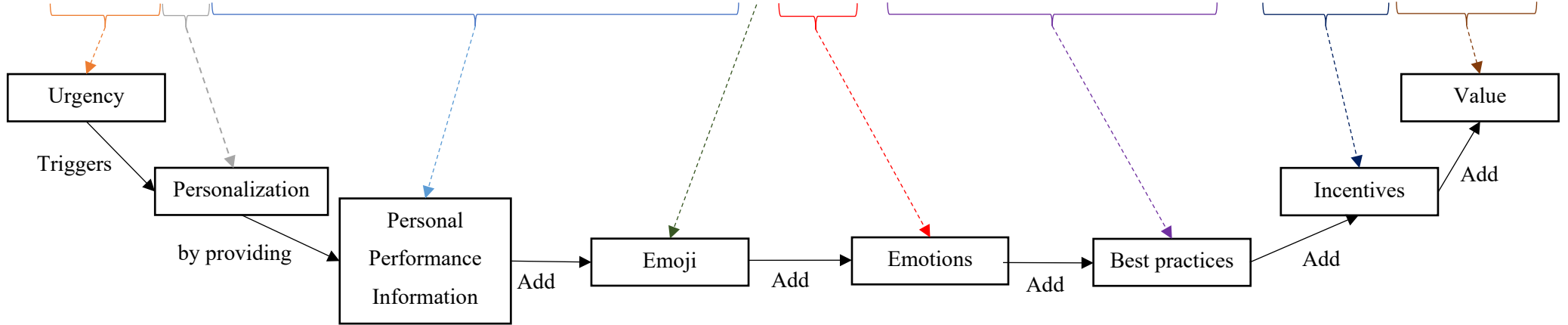


Figure 16: Logic of feedback

2) Logic - Social comparison nudge (push notification)

Alert! Your thermostat's still at 24°C. Your neighbours keep it at 21°C, which means low electricity bills (). Be smart by maintaining thermostat at 18-21°C and reducing bills. Be part of money-saving neighbours!

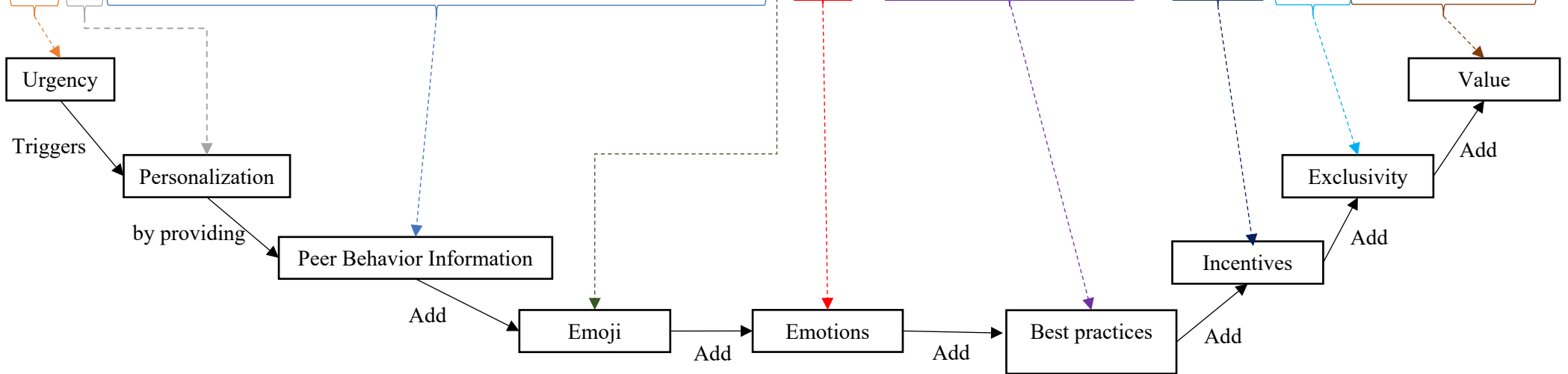


Figure 17: Logic of social comparison

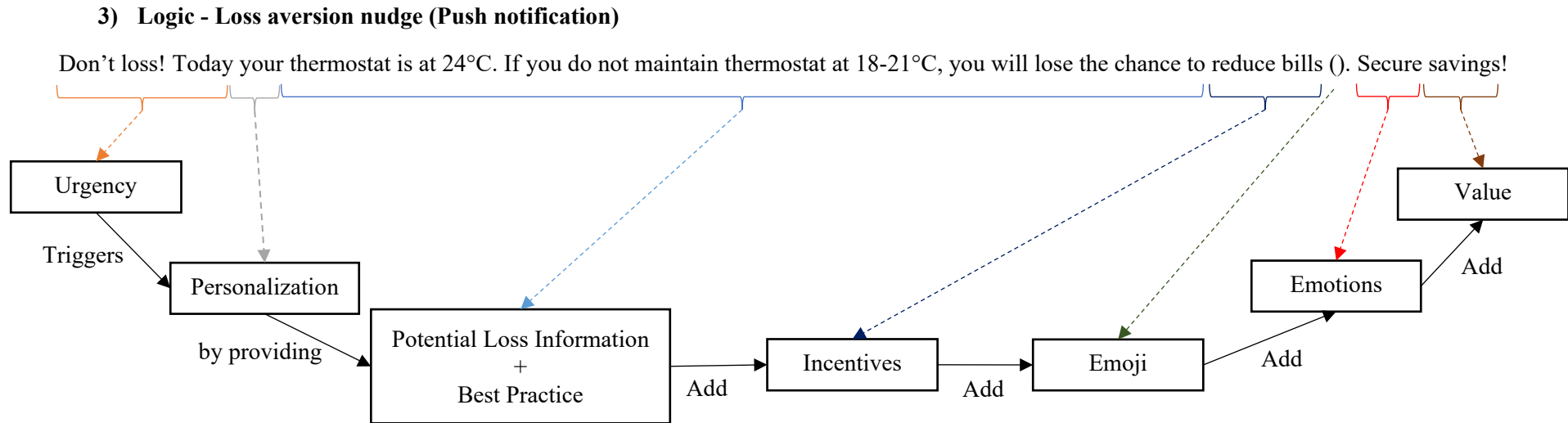


Figure 18: Logic of loss-aversion



Figure 19: Push notification - Feedback to improve relative humidity

4.3 Bridging research limitations in existing empirical research

Each step of the new smart nudge design is designed to overcome the research limitations of the existing empirical research identified in Chapter 2 – Literature review. The steps from 1-7 ensure that the new smart nudge design overcomes the research limitations of self-reported data, such as reporting biases and inaccuracies of data, as those limitations may have affected the overall effectiveness of the smart nudging interventions deployed in studies such as Burchell et al. (2016) and Ghesla et al. (2020). The 8th step of the smart nudge design uses three smart nudging interventions in a random order to avoid the order bias, habituation, as most of the studies have focused on a single smart nudging intervention, which research participants may become accustomed to over time and lose interest over time. This may have affected the overall effectiveness of the interventions used in the studies such as Lynham et al. (2016) and Shafqat et al. (2019).

The 9th step of the smart nudge design ensures that the logics of the smart nudging interventions are more personalised, context-specific, and more appealing to the home occupants. This can prompt immediate behavioural changes in home occupants by nudging them to learn and adopt the best practices and maintaining interest over time. The existing empirical research shows a research limitation, which is the limited frequency of delivery that may hinder the overall effectiveness of the interventions deployed in the studies such as Burchell et al. (2016), Mogles et al. (2017), Henry et al. (2019), and Myers and Souza (2020). Therefore, the 10th step and 11th step ensure that the smart nudging interventions are designed to overcome this research limitation of limited frequency of delivery by delivering timely interventions to the home occupants. Moreover, the existing research showed that the interventions were not user friendly and may have affected the overall effectiveness of the interventions used in the studies of Burchell et al. (2016), Ghesla et al. (2020), Shafqat et al. (2019), and Cappa et al. (2020). Therefore, this new smart nudge design ensures the user-friendliness by avoiding participant's direct inputs.

The logics of the smart nudging interventions developed in this study can be adapted to any context, regardless of the diversity of households or contextual factors. This adaptability is possible because the logics are both personalised and context-aware, taking into account household characteristics, demographics, and environmental conditions. The trigger words, best practices, and incentives embedded in the logic formulations are directly applicable to any context, with only the personalised information adapted for each context. As a result, this

research fills a void in the existing literature by introducing a novel smart nudge design with logic formulations for the household energy sector.

4.4 Chapter summary

The new smart nudge design extends the smart nudge design of Karlsen and Andersen (2019) and combines the smart nudge components introduced by Karlsen and Andersen (2022) to address the knowledge gap and research limitations of the existing empirical studies, which were identified in the Chapter 2 – Literature review and to provide more user-friendly, timely and personalised smart nudging interventions. The three smart nudging interventions are feedback, social comparison, and loss-aversion. The new smart nudge design includes 13 steps: define the goal, understand the users, understand the context, identify the indoor air quality parameters, monitor real-time data, trigger point identification, decision-making process, random selection of the smart nudging intervention, design the logics, select the time frame, deliver the interventions, assess the indoor air quality parameter, and evaluate the indoor air quality parameter.

The logics of each smart nudging intervention are devised for creating smart nudging interventions in a well-structured and logical manner, ensuring that those logics can be easily implemented in the mobile application and nudge home occupants to take immediate actions. The logics of the smart nudging interventions mainly differ from the type of personalised information they provide for the home occupants. In addition, these logics include trigger words to motivate home occupants, best practices to guide and induce sustainable behavioural change, and incentives to prompt immediate actions. Therefore, this research provides a contribution to the existing research by proposing a new extended smart nudge design for reducing anthropogenic air emissions related to the household energy sector and improving indoor air quality.

5 Chapter – Results and Discussion

5.1 Introduction

This chapter presents the findings from the data collected in this study and provides an in-depth analysis of the research findings, highlighting their significance, implications, and contributions to the field. The multiple-case studies design includes three plots, and each plot is treated as an individual case study. This within-subject research design includes repeated measures of three smart nudging interventions taken over a week and a month from the intervention start date.

The quantitative data analysis focuses on assessing whether the smart nudging interventions can achieve safe thresholds of each indoor air quality parameter within each plot. In addition, it focuses on assessing the most effective smart nudging intervention in reducing indoor air emissions related to household energy use and improving indoor air quality holistically by considering the overall impact across all the indoor air quality parameters. This quantitative data analysis uses a within-subject comparison to evaluate the impact of the smart nudging interventions in making a sustainable behavioural change by subtracting the baseline level at the time the smart nudging intervention was delivered from the post-intervention levels measured at 15-minute and 30-minute windows.

The qualitative analysis based on pre-intervention interviews aims to assess the existing behaviours, perceptions, choices, daily routines of the home occupants to support the designing of the smart nudging interventions or composing the logics of smart nudging interventions. The qualitative data analysis assesses whether the individuals have perceived a change by understanding their behaviours, perceptions, and experiences during the post-intervention period and to internally validate and triangulate the quantitative research findings. Finally, this chapter summarises the research findings related to the three types of smart nudging interventions that were deployed across each indoor air quality parameter in each plot and linking them to the research questions and research objectives.

5.2 Quantitative findings

The quantitative findings are presented in 6 stages for each indoor air quality parameter, namely, CO₂, relative humidity, TVOC, and temperature. The stages are explained below.

- First stage - Descriptive statistics

The descriptive statistics of each indoor air quality parameter includes the mean difference, number of times the smart nudging intervention was sent or number of instances, and standard deviation. The mean difference is calculated by subtracting each before value from the after value of each instance, adding all the differences, and dividing by the number of instances. For example, the difference of each instance is calculated using the formula:

“Difference = IAQ parameter after 15 min – IAQ parameter last minute data of the previous hour” or
“Difference = IAQ parameter after 30 min – IAQ parameter last minute data of the previous hour”.

When considering CO₂, relative humidity, TVOC, and temperature above 21⁰C, a positive mean difference shows a negative impact or an increase, while a negative mean difference indicates a positive impact or a reduction. However, when considering the parameter, which is the temperature below 18⁰C, a positive mean difference indicates a positive impact, while a negative mean difference indicates a negative impact. The standard deviations are calculated to identify the variability of the data around their means.

- Stage 2 - Assessment of the optimal time window for evaluation

This stage presents the optimal time window to reliably capture the real impact of a smart nudging intervention on nudging the home occupant towards achieving sustainable behaviours and improving the indoor air quality parameter. In addition, this step is used to understand how the smart nudging intervention maintains consistency across the 15-minute and 30-minute windows.

- Stage 3 - Assessment of the impact of the smart nudging interventions

This stage presents the impact of the smart nudging interventions based on their mean differences, number of positive impact instances, and number of negative impact instances. The impact is categorised as:

- positive impact - the number of positive impact instances should be higher than the number of no/negative impact instances and the mean difference should indicate a positive impact or an improvement.
- No/negative impact - the number of positive impact instances should be lower than the number of no/negative impact instances and the mean difference should indicate a no/negative impact or no improvement.
- Neutral impact – equal number of positive and negative impact instances regardless of the mean difference.

- Not conclusive/Uncertain impact - contradiction between the impact shown through the mean difference and the number of positive or no/negative impact instances.
- Stage 4 – Verification of the positive impact instances

This stage presents the findings related to the verification of the positive impact instances of interventions. The positive impact instances of the interventions that showed a positive impact, neutral impact, and an uncertain impact in the optimal time window of each indoor air quality parameter are assessed to verify whether the observed positive impact instances show significant improvements rather than random changes.
- Stage 5 – Assessment of the most effective intervention

This stage compares and presents the real effectiveness of the smart nudging interventions and shows the intervention that showed the highest (real) effectiveness for each indoor air quality parameter. More importantly, the significant positive impact rate is calculated by verifying the real positive impact instances against the total positive instances of a smart nudging intervention to ensure the real effectiveness of the intervention. This step is conducted after verifying the real positive impact instances in the stage 4.
- Stage 6 – Inferential statistics (if applicable)

Findings relating to the inferential statistics are presented to identify whether the observed improvements of indoor air quality parameters are likely due to chance or represent real improvements.

5.2.1 CO₂

5.2.1.1 Descriptive statistics

Table 13 shows the descriptive statistics related to CO₂ in each plot. The descriptive statistics of the smart nudging interventions delivered are analysed on a weekly and monthly basis and are presented within the 15-minute and 30-minute windows in each plot. However, if any smart nudging intervention was not delivered during any period in any plot, that row is left blank. The potential effectiveness of each smart nudging intervention is highlighted using three colours: green for a positive impact/reduction, red for a no/negative impact/increase, and grey for a not conclusive outcome (or the availability of only a single instance) based on the mean differences.

	Time period	Type of smart nudging interventions	Mean difference of the smart nudging interventions	Number of times (instances) the intervention was sent	Standard deviations	Overall CO ₂ reduction (potential effectiveness)		Remarks	
						Yes	No		
Plot 5	15-minutes window	One week	Feedback	-11	4	174.10	✓		Positive impact/Reduction
			Social comparison	+69	1	-			Not conclusive impact
			Loss-aversion	+58	3	161.50		✓	Negative impact / Increase
		One month	Feedback	-11	4	174.10	✓		Positive impact / Reduction
			Social comparison	+69	1	-			Not conclusive impact
			Loss-aversion	-6.20	5	161.96	✓		Positive impact / Reduction
	30-minutes window	One week	Feedback	-43.25	4	188.19	✓		Positive impact / Reduction
			Social comparison	+58	1	-			Not conclusive impact
			Loss-aversion	-124.33	3	187.86	✓		Positive impact / Reduction
		One month	Feedback	-43.25	4	188.19	✓		Positive impact / Reduction
			Social comparison	+58	1	-			Not conclusive impact
			Loss-aversion	-121.80	5	134.24	✓		Positive impact / Reduction
Plot 10	15-minutes window	One week	Feedback	-44	1	-			Not conclusive impact
			Social comparison	-	-	-	-	-	-
			Loss-aversion	-89	1	-			Not conclusive impact
		One month	Feedback	-13	5	48.99	✓		Positive impact / Reduction
			Social comparison	+39.50	2	89.80		✓	Negative impact / Increase
			Loss-aversion	-29.33	3	51.79	✓		Positive impact / Reduction
	30-minutes window	One week	Feedback	-2	1	-			Not conclusive impact
			Social comparison	-	-	-	-	-	-
			Loss-aversion	-181	1	-			Not conclusive impact
		One month	Feedback	-259.40	5	339.34	✓		Positive impact / Reduction
			Social comparison	-213.00	2	287.09	✓		Positive impact / Reduction
			Loss-aversion	-79.67	3	124.28	✓		Positive impact / Reduction
Plot 12	15-minutes window	One week	Feedback	-	-	-	-	-	-
			Social comparison	-	-	-	-	-	-
			Loss-aversion	-	-	-	-	-	-
		One month	Feedback	-260.33	3	200.40	✓		Positive impact / Reduction
			Social comparison	-23.50	2	61.52	✓		Positive impact / Reduction
			Loss-aversion	+27	1	-			Not conclusive impact
		One week	Feedback	-	-	-	-	-	-
Social comparison	-		-	-	-	-	-		

30- minutes window	One month	Loss-aversion	-	-	-	-	-	-
		Feedback	-411	3	306.99	✓		Positive impact / Reduction
		Social comparison	+2.50	2	120.92		✓	Negative impact / Increase
		Loss-aversion	+70	1	-			Not conclusive impact
Legend								
	Positive impact / Reduction - Potential effectiveness		No or Negative impact / Increase - Potential effectiveness				Not conclusive impact	

Table 13: Descriptive statistics - CO₂

The standard deviations of smart nudging interventions in each plot indicate a high variability of CO₂ data around their mean differences. In addition, no statistical tests or inferential statistics are performed due to the small number of instances present in some smart nudging interventions. For example: the number of instances of feedback, social comparison, and loss-aversion are 4, 1, and 5, respectively, within the 30-minute window in plot 5 over the month. This shows that statistical tests cannot be reliably performed due to the small number of instances, particularly if the number of instances is as low as 1 or 4. Therefore, the presence of small number of instances and high variability in the data limit statistical reliability, making it difficult to derive firm conclusions in a better way. However, the visual interpretations using line graphs show changes in CO₂ levels after the delivery of the interventions across instances, supported by post-intervention interviews, can determine the effectiveness of the interventions despite the lack of statistical tests.

5.2.1.1.1 Plot 5

As per Table 13, the descriptive statistics related to plot 5 within the 15-minute-window show that the mean difference of feedback is -11, the standard deviation is 174.10, and the number of instances is 4 on a weekly and monthly basis. This mean difference indicates that feedback shows a potential effectiveness in reducing high CO₂ levels after the delivery of the interventions. Social comparison shows a mean difference of +69 in both weekly and monthly, showing no potential effectiveness in reducing high CO₂ levels. However, the impact of social comparison is not conclusive, as it has only one instance. In addition, no standard deviation is calculated, as it is not possible to calculate the standard deviation using a single instance. The loss-aversion shows mean differences of +58 and -6.20 on a weekly and a monthly basis, respectively. The mean difference of loss-aversion on a weekly basis suggests an increase in high CO₂ levels (>1000ppm) after delivering the interventions and thus showing no potential effectiveness compared to feedback. However, loss-aversion shows a potential effectiveness in reducing high CO₂ levels monthly, as it shows a negative mean difference, which is a reduction.

Loss aversion shows a standard deviation of 161.50 with 3 instances and 161.96 with 5 instances on a weekly and a monthly basis, respectively.

Descriptive statistics for CO₂ levels within the 30-minute window show mean differences of feedback and social comparison as -43.25 and +58 in both weekly and monthly. Feedback shows a standard deviation of 188.19 with 4 instances on a weekly and a monthly basis. Social comparison has only a single instance in both weekly and monthly. Loss-aversion shows mean differences of -124.33 and -121.80, respectively, on a weekly and monthly basis, indicating potential effectiveness. Loss-aversion shows standard deviations of 187.86 with 3 instances and 134.24 with 5 instances, respectively, on a weekly and a monthly basis. In comparing the both time windows, the data suggests that loss-aversion did not show potential effectiveness in the 15-minute window in weekly, but it showed potential effectiveness in the 30-minute window over the week. However, only feedback and loss-aversion show potential effectiveness in reducing high CO₂ levels on a weekly and a monthly basis in plot 5 within the 30-minute window.

It is worth noting that both feedback and social comparison were only delivered during the first week from the intervention start date and they were not delivered after the first week of the intervention period. This might have happened due to the random selection of the smart nudging interventions and/or because CO₂ levels were not elevated above the safe threshold, resulting a few instances for both feedback and social comparison. This can be confirmed, as loss-aversion was delivered 3 and 5 times in weekly and monthly, respectively. Therefore, CO₂ was elevated above the safe threshold of 1000ppm in only 2 instances after the first week, and in those 2 instances, loss-aversion was delivered instead of feedback and social comparison due to the random selection of smart nudging interventions.

5.2.1.1.2 Plot 10

As per the Table 13, the 15-minute and 30-minute windows of plot 10 shows that the social comparison was not delivered during the first week of the intervention period. Feedback and loss-aversion show only one instance each during the first week. Therefore, no standard deviations are calculated, as the calculation of variability around their means is not possible using single instances. These data suggests that CO₂ levels were elevated above the safe threshold of 1000ppm only in two instances during the first week. Feedback and loss-aversion show mean differences of -44 and -89, respectively, indicating reductions in high CO₂ levels after the intervention delivery. Similarly, in considering the 30-minute window of plot 10 on a

weekly basis, feedback and loss-aversion show mean differences of -2 and -181 with single instances each, indicating reductions in high CO₂ levels. However, the potential effectiveness of feedback and loss-aversion is not conclusive in both time windows, as those interventions have single instances. In addition, it seems that the reduction in CO₂ levels during the first 15 minutes (-44) suggests an immediate effect over the week, but by 30 minutes (-2), the CO₂ levels likely rebounded due to an increase of the CO₂ levels again by closing the window or sensor error or other environmental factors, reducing the overall impact.

Feedback, social comparison, and loss-aversion show mean differences of -13, +39.50, and -29.33, respectively, on a monthly basis in the 15-minute window. Feedback shows a standard deviation of 48.99 in 5 instances. Social comparison shows a standard deviation of 89.80 in 2 instances. Loss-aversion shows a standard deviation of 51.79 with 3 instances. However, only feedback and loss-aversion show potential effectiveness in reducing high CO₂ levels on a monthly basis within the 15-minute window in plot 10.

In considering the 30-minute window, feedback, social comparison, and loss-aversion show mean differences of -259.40, -213, and -79.67, indicating potential effectiveness in reducing high CO₂ levels. Feedback shows a standard deviation of 339.34 with 5 instances. Social comparison shows a standard deviation of 287.09 with 2 instances. Loss-aversion shows a standard deviation of 124.28 with 3 instances. In comparing both time windows, the data suggests that social comparison did not show potential effectiveness within the 15-minute window in monthly, but it showed potential effectiveness in the 30-minute window over the month.

5.2.1.1.3 Plot 12

According to Table 13, the descriptive statistics for CO₂ levels in plot 12 within the 15-minute window show that the mean differences of feedback, social comparison, and loss-aversion are -260.33, -23.50, and +27, respectively, on a monthly basis. Feedback shows a standard deviation of 200.40 with 3 instances. Social comparison shows a standard deviation of 61.52 with 2 instances. Loss-aversion was delivered only once. Therefore, loss-aversion has only a single instance and the impact is not conclusive. Only feedback and social comparison show potential effectiveness in reducing high CO₂ levels in plot 12 within the 15-minute window.

In considering the 30-minute window, the descriptive statistics show that only feedback with a mean difference of -411 indicates a potential effectiveness in reducing high CO₂ levels above 1000ppm. Feedback shows a standard deviation of 306.99 with 3 instances. Social comparison

and loss-aversion show mean differences of +2.50 and +70, respectively. Social comparison has shown a standard deviation of 120.92 with 2 instances. Loss-aversion was delivered only once. Therefore, the impact of loss-aversion is not conclusive. In comparing both time windows, the descriptive statistics show that social comparison showed potential effectiveness in the 15-minute window, but it showed no potential effectiveness in the 30-minute window. In addition, no smart nudging intervention was delivered over the first week of the intervention period. This might have happened due to no instances of showing elevated CO₂ levels above 1000ppm during the week.

5.2.1.2 Assessing the optimal time window for CO₂ reduction evaluation

5.2.1.2.1 Discussion of the findings

The results show no clear consistency across the 15-minute window and 30-minute window in each plot (see Table 13). This lack of consistency of the findings can be related to: 1) lack of sufficient time given in the 15-minute window for the householder to act and show a significant impact, 2) 15-minute timeframe might not account for delays in action that occur at the last few minutes of this timeframe, and 3) reduction of CO₂ levels might take time to manifest and show the real impact. For example:

- a) Plot 5 - the loss-aversion did not show any potential effectiveness in the 15-minute timeframe on a weekly basis. However, loss-aversion showed potential effectiveness in the 30-minute window on a weekly basis.
- b) Plot 10 - social comparison did not show any potential effectiveness in the 15-minute window on a monthly basis. However, it showed a potential effectiveness in the 30-minute window on a monthly basis.
- c) Plot 12 - social comparison showed potential effectiveness in the 15-minute window over the month. However, social comparison did not show any potential effectiveness in the 30-minute window over the month.

Generally, opening windows for 5 to 15 minutes can reduce high CO₂ levels, as empirical research showed that reductions in high CO₂ levels can be observed within a very short period of time after the occupant's action. These findings are in line with the research conducted by Hsu et al. (2024). The study of Hsu et al. (2024) found that in the first 15-minutes after opening the cross windows, the CO₂ levels were reduced quickly. However, after 30-minutes, the CO₂ levels were stabilised, and no further reduction occurred. In addition, the study of Muelas et al. (2022) showed that opening windows for 5-15 minutes reduced CO₂ levels, as opening

windows fully for 6 minutes reduced CO₂ levels from 1015 ppm to around 780ppm. In addition, the study of Su et al. (2023) showed that CO₂ levels were reduced from 1303ppm to 515ppm within 30-minutes by providing adequate ventilation. Therefore, comparatively, 30-minute window can be a better timeframe of study because it allows for a reasonable period of time to consider for the delay in action or allows sufficient time for the householder to act, showing the real impact by allowing adequate time for the CO₂ reduction to manifest, and capture immediate behavioural change by minimising random fluctuations.

To further assess the optimal time window, the CO₂ data at the time the smart nudging intervention was sent, as well as at the 15-minute and 30-minute post-delivery, were obtained for each instance. Figures 20, 21, and 22 show the comparison of three levels of CO₂, namely, CO₂ level at the time the intervention was sent, CO₂ level after 15 minutes, and CO₂ level after 30 minutes in each instance across the three plots.

Figure 20 shows the comparison of CO₂ levels in plot 5. In considering the plot 5, this study findings indicate that a 15-minute window is insufficient, as most instances, such as the 2nd, 3rd, 4th, 5th, 7th, 8th, and 10th instances, did not show any reduction in higher CO₂ levels above 1000ppm. In contrast, the 30-minute window shows reductions in many instances except the 2nd, 4th, 5th, and 7th instances. More specifically, the 1st, 3rd, 6th, 8th, 9th, and 10th instances show that 30-minute window is more accurate to show reductions of high CO₂ levels. On the other hand, the 2nd, 4th, 5th, and 7th instances show that the occupant has not taken any action to decrease the high CO₂ levels.

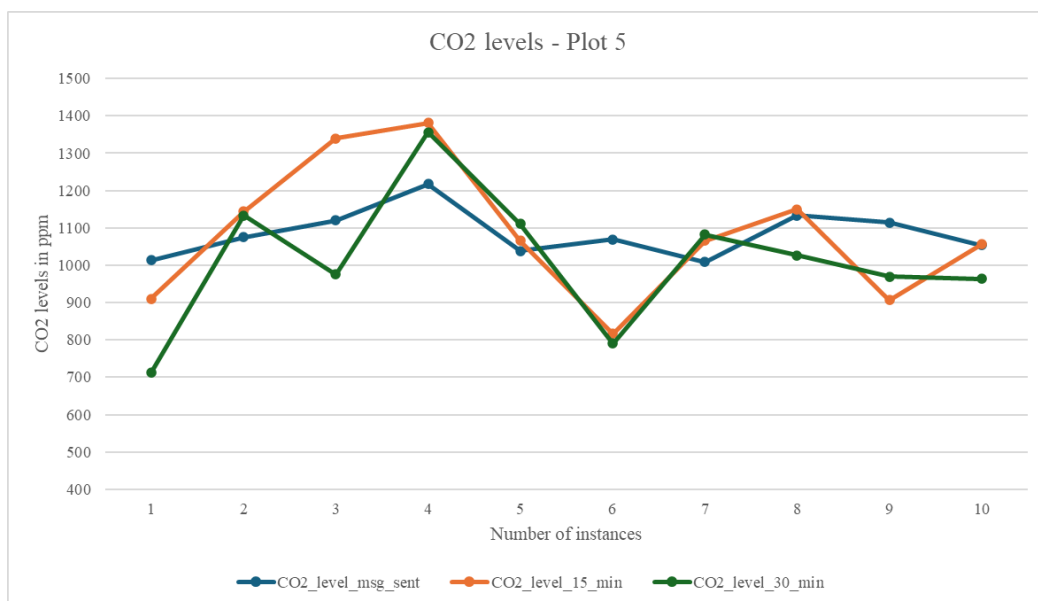


Figure 20: Comparison of CO₂ levels in plot 5

Figure 21 shows the comparison of three levels of CO₂ in plot 10. This study findings show that most instances out of 10 instances in the 15-minute window, such as the 4th, 5th, 6th, 7th, 9th, and 10th instances, did not show any reduction in higher CO₂ levels above 1000ppm. In contrast, the 30-minute window shows CO₂ reductions in many instances out of 10 instances except the 1st, 3rd, 9th, and 10th instances. More specifically, the 2nd, 4th, 5th, 6th, 7th, and 8th instances show that the 30-minute window is more accurate to show reductions of high CO₂ levels. On the other hand, it seems that the home occupant has not taken any action to reduce high CO₂ levels in the 3rd, 9th, and 10th instances.

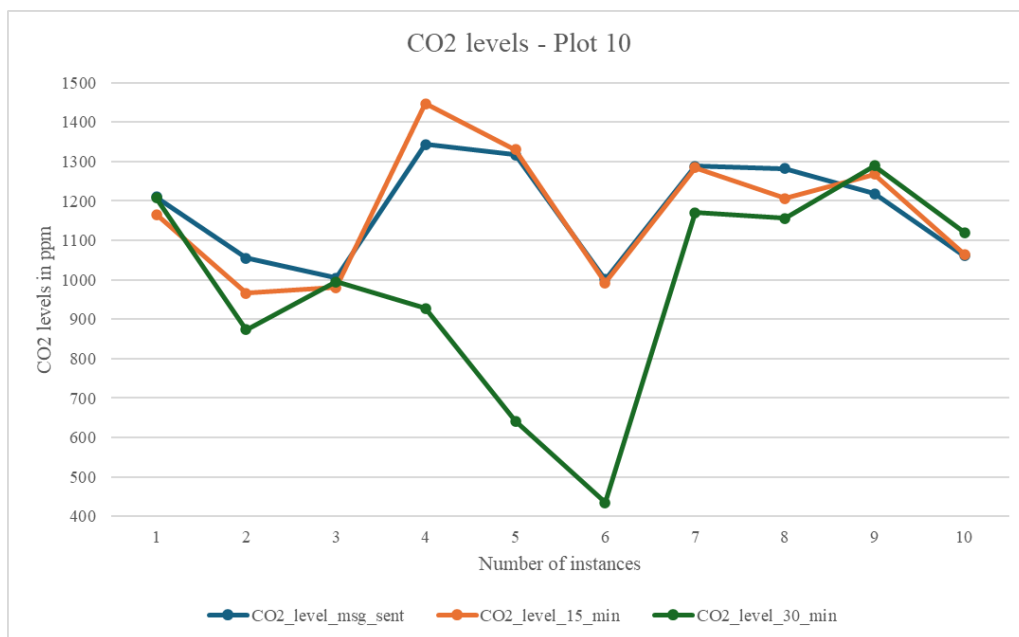


Figure 21: Comparison of CO₂ levels in plot 10

Figure 22 shows the comparison of three CO₂ levels in plot 12. The results of this study show that two instances out of 6 instances in both the 15-minute window and 30-minute window, such as the 2nd instance and 3rd instance, show no reductions in higher CO₂ levels above 1000ppm. These data suggests that the home occupant has not taken any action to reduce high CO₂ levels in the 2nd and 3rd instances. Both 15-minute and 30-minute windows show CO₂ reductions in many instances out of 6 instances, namely, the 1st, 4th, 5th, and 6th instances. However, the CO₂ levels were reduced more significantly over the 30-minute window compared to the 15-minute window. For examples: 1) the CO₂ levels were reduced from 1518ppm to 946ppm in the 1st instance and 2) the CO₂ levels were reduced from 1051ppm to 447ppm in the 6th instance.

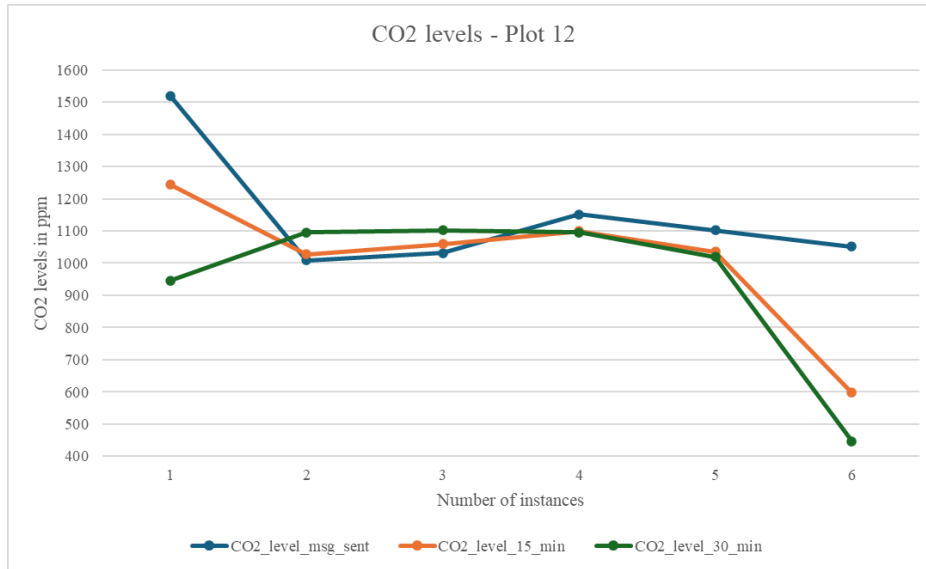


Figure 22: Comparison of CO₂ levels in plot 12

In conclusion, from the analysis conducted, it can be inferred that the 30-minute window provides more accurate results for evaluation than 15-minute window. The main reason is that the 30-minute window can capture no/delayed action beyond the 15-minute window or actions occurring at the last few minutes of the 15-minute window, the real impact of smart nudging interventions by allowing adequate time for the CO₂ levels to reduce and manifest, and avoid random fluctuations and isolate the home occupant's action or change in behaviour. Therefore, 30-minute window was selected for further study.

5.2.1.3 Assessment of the impact of the smart nudging interventions

Table 14 shows the impact (positive impact or neutral impact or no/negative impact or uncertain impact) of each intervention across each plot on a weekly and a monthly basis in the 30-minute window.

	Time period	Smart nudging interventions	Mean difference	Number of instances/times the intervention was sent	Positive impact instances	No/Negative impact instances	Actual Impact comparison
Plot 5	One week	Feedback	-43.25	4	2	2	Yellow
		Social comparison	+58.00	1	0	1	Grey
		Loss-aversion	-124.33	3	2	1	Green
	One month	Feedback	-43.25	4	2	2	Yellow
		Social comparison	+58.00	1	0	1	Grey
		Loss-aversion	-121.80	5	4	1	Green
Plot 10	One week	Feedback	-2.00	1	1	0	Grey
		Loss-aversion	-181.00	1	1	0	Grey
	One month	Feedback	-259.40	5	4	1	Green
		Social comparison	-213.00	2	2	0	Green
		Loss-aversion	-79.67	3	2	1	Green

Plot 12	One month	Feedback	-411.00	3	3	0	
		Social comparison	+2.5	2	1	1	
		Loss-aversion	+70	1	0	1	
Legend							
	Positive impact		Neutral impact		No/Negative impact		Not conclusive/ Uncertain impact

Table 14: Assessment of the impact of the smart nudging interventions - CO₂

According to Table 14, feedback, social comparison, and loss-aversion showed the neutral impact, not conclusive/uncertain impact, and positive impact, respectively, in both weekly and monthly in plot 5. Feedback showed a neutral impact, as it was delivered 4 times and showed a positive impact in 2 instances and a no/negative impact in 2 instances. Social comparison showed a not conclusive/uncertain impact, as it was delivered only once and did not provide sufficient data for a comparative analysis and assessment of the impact. Loss-aversion showed a positive impact over the week, as it was delivered at 3 instances and showed a positive impact in 2 instances and a no/negative impact in a single instance. In addition, loss-aversion showed a positive impact over the month, as it was delivered at 5 instances and showed a positive impact in 4 instances and a no/negative impact in a single instance. The negative mean differences of loss-aversion in both weekly and monthly further supports its positive impact, suggesting reductions in high CO₂ levels. Therefore, loss-aversion was the only intervention that showed a positive impact in both weekly and monthly. This suggests that loss-aversion had an immediate impact as well as a sustained impact over time in plot 5.

In plot 10, feedback and loss-aversion were delivered once and showed reductions in high CO₂ levels in those single instances. However, with only a single instance for each feedback and loss-aversion, there is not sufficient data to compare and assess the impact. Therefore, the impacts of both feedback and loss-aversion are not conclusive or uncertain. All the three types of smart nudging interventions showed positive impact in reducing high CO₂ levels over the month based on their negative mean differences and higher number of positive impact instances compared to the number of no/negative impact instances. Feedback was delivered 5 times and showed a positive impact in 4 instances and a no/negative impact in one instance. Social comparison was delivered twice during the month, showing a positive impact in both instances. Loss-aversion was delivered three times. Out of those three times, two instances showed a positive impact, while a single instance showed a no/negative impact.

In plot 12, only feedback showed a positive impact based on the negative mean difference, with all three instances showing positive impacts. Social comparison was delivered at two instances. Out of those two instances, only one instance showed a positive impact of, while the other

instance showed a no/negative impact, suggesting a neutral impact. Loss-aversion was delivered only once and showed a no/negative impact in that single instance. However, this result of loss-aversion is inconclusive or uncertain due to the availability of limited data to compare and assess the impact.

5.2.1.4 Verification of the positive instances of the smart nudging interventions

5.2.1.4.1 Plot 5

As shown in above Table 14, loss-aversion was highlighted as the only smart nudging intervention that showed a positive impact in plot 5 on a weekly basis. Figure 23 shows the two positive instances of loss-aversion. The 1st positive instance showed a reduction of high CO₂ levels from 1013ppm to 712 ppm. The 2nd positive instance showed a CO₂ reduction from 1120ppm to 975 ppm. Therefore, both of these two instances achieved the safe threshold of CO₂, indicating that loss-aversion showed a real positive impact.

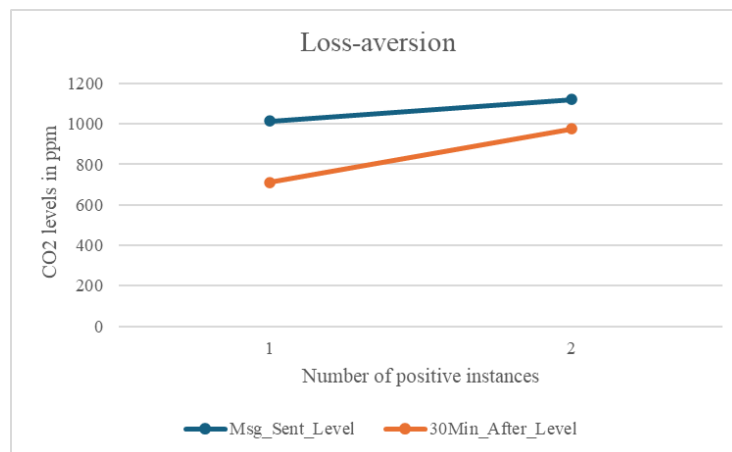


Figure 23: Plot 5 - Verification of the positive instances – weekly

Loss-aversion showed the positive impact in plot 5 over the month. All the 4 positive instances of loss-aversion achieved the safe threshold, as shown in below Figure 24. The 1st instance showed a high CO₂ reduction from 1013ppm to 712ppm. The 2nd instance showed a CO₂ reduction from 1120ppm to 975ppm. The 3rd instance showed a CO₂ reduction from 1114ppm to 969ppm. The 4th instance showed a CO₂ reduction from 1054ppm to 963ppm. Therefore, loss-aversion showed a positive impact in plot 5 over the month.

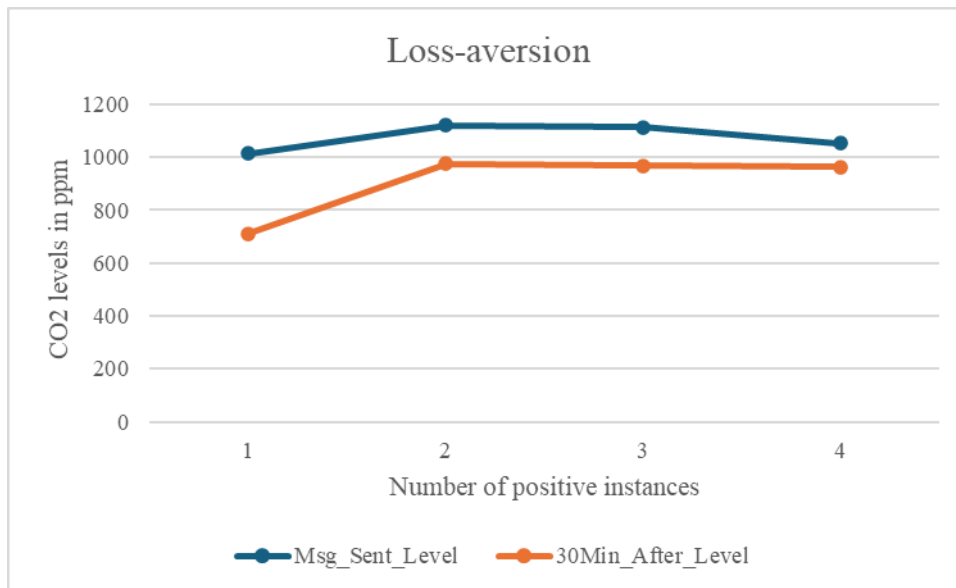


Figure 24: Plot 5 - Verification of the positive instances – monthly

5.2.1.4.2 Plot 10

According to the above Table 14, all the three smart nudging interventions showed positive impact in reducing high CO₂ levels in plot 10 over the month. Figure 25 shows the CO₂ reductions in the positive instances of each smart nudging intervention. In reviewing the positive instances of feedback, the 1st instance did not show a significant CO₂ reduction, as it indicated a CO₂ reduction from 1210ppm to 1208ppm. This might have happened due to a sensor error or a random fluctuation. The 2nd and 3rd positive instances of feedback achieved the safe threshold below 1000ppm. The 2nd instance showed a CO₂ reduction from 1317ppm to 642ppm. The 3rd instance showed a CO₂ reduction from 1001ppm to 435ppm. The 4th instance showed a CO₂ reduction from 1282ppm to 1156ppm but did not achieve the safe threshold. This might have happened due to the less ventilation, or opening the windows was not sufficient to ventilate the space. However, feedback showed a real positive impact in plot 10 over the month, as most of the instances showed significant reductions. Social comparison showed a significant CO₂ reduction only in one positive instance. The 2nd positive instance of social comparison showed a CO₂ reduction from 1344ppm to 928ppm. Similarly, loss-aversion showed a significant CO₂ reduction below the safe threshold of 1000ppm only in one instance. The 1st instance of loss-aversion showed a CO₂ reduction from 1055ppm to 874ppm. Therefore, in overall comparison, feedback shows the highest effectiveness.

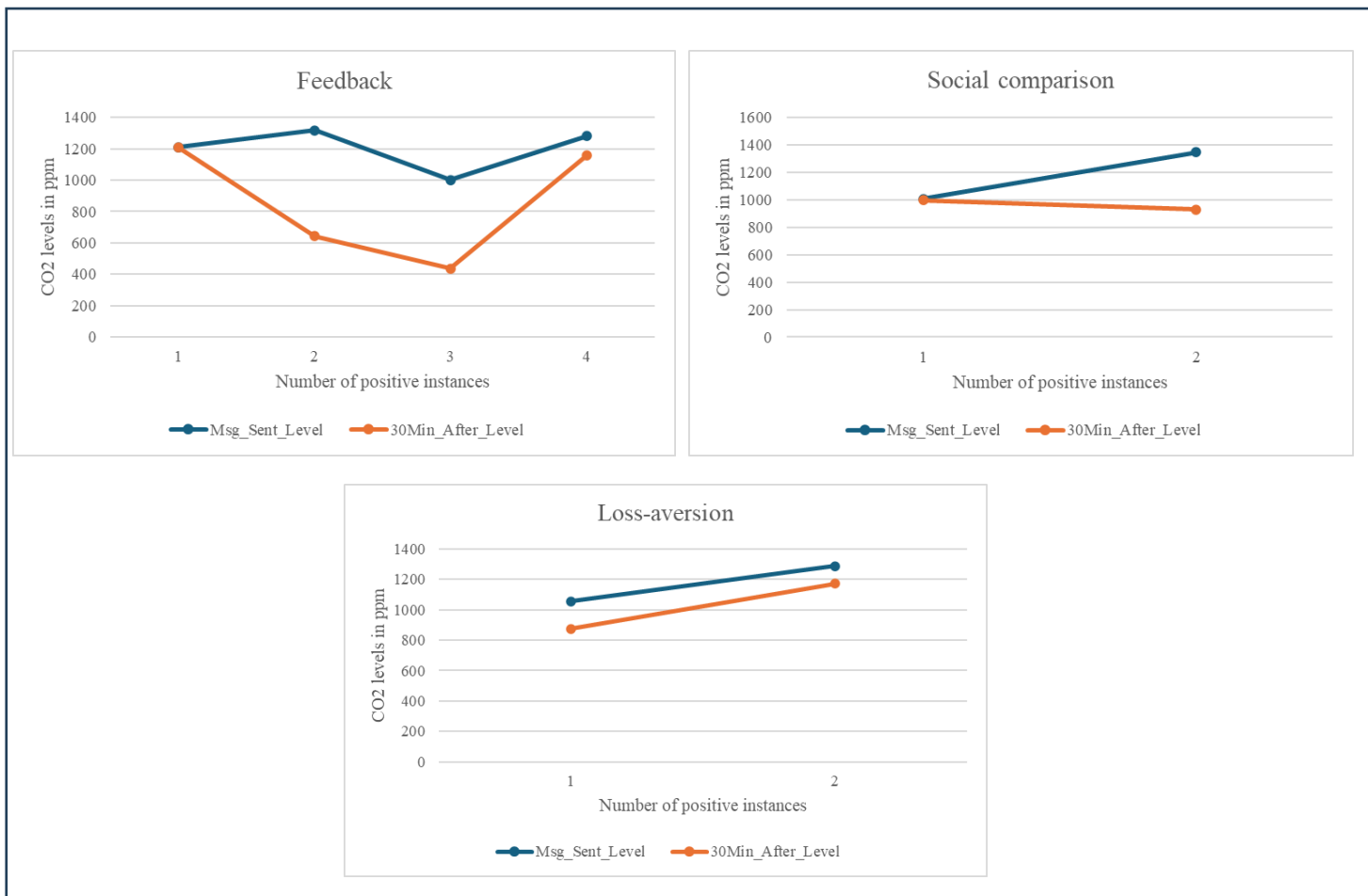


Figure 25: Plot 10 - Verification of the positive instances – monthly

5.2.1.4.3 Plot 12

As per the above Table 14, feedback showed the highest effectiveness in reducing high CO₂ levels in plot 12 over the intervention period of one month. Figure 26 shows the CO₂ reductions in the three positive instances. The 2nd instance did not show a significant CO₂ reduction, as it did not reach below the safe threshold of 1000ppm. The 2nd instance showed a CO₂ reduction from 1152ppm to 1095ppm. All the other 2 positive instances of feedback achieved the safe threshold below 1000ppm. The 1st instance showed a CO₂ reduction from 1518ppm to 946ppm. The 3rd instance showed a CO₂ reduction from 1051ppm to 447ppm. Therefore, feedback showed a positive impact in plot 12 over the month, as it showed significant reductions in multiple positive instances.



Figure 26: Plot 12 - Verification of the positive instances – monthly

5.2.1.5 Assessment of the most effective smart nudging intervention – CO2

Table 15 shows the summary of the most effective interventions in each plot. Loss-aversion is the most effective intervention in plot 5 in both weekly and monthly. Feedback is highlighted as the most effective intervention in both plots 10 and 12. In comparing the significant positive impact rate across all the three plots, loss-aversion emerged as the most effective intervention in achieving the safe threshold of CO₂.

	Time period	The most effective smart nudging intervention	Significant Positive impact rate
Plot 5	One week	Loss-aversion	100%
	One month	Loss-aversion	100%
Plot 10	One month	Feedback	50%
Plot 12	One month	Feedback	67%

Table 15: Most effective intervention – CO₂

5.2.2 Relative humidity

5.2.2.1 Descriptive statistics

Table 16 shows the descriptive statistics related to the relative humidity in each plot. The descriptive statistics related to the smart nudging interventions are analysed on a weekly and monthly basis and are shown within the 15-minute window and 30-minute window in each plot. However, if any smart nudging intervention was not sent during any period in any plot, that row is left blank. The potential effectiveness of each smart nudging intervention is presented using three colours: green for a positive impact/reduction, red for a no/negative impact/ increase, and grey for a not conclusive outcome (or availability of a single instance) based on the mean differences.

	Time period	Type of smart nudging interventions	Mean differences of the smart nudging interventions	Number of times (instances) the intervention was sent	Standard deviations	Overall humidity reduction (potential effectiveness)		Remarks	
						Yes	No		
Plot 5	15-minutes window	One week	Feedback	-2.21	7	4.73	✓		Positive impact/Reduction
			Social comparison	+0.06	5	0.27		✓	Negative impact/Increase
			Loss-aversion	-0.01	11	0.56	✓		Positive impact/Reduction
		One month	Feedback	-0.24	32	3.58	✓		Positive impact/Reduction
			Social comparison	-0.47	24	2.38	✓		Positive impact/Reduction
			Loss-aversion	-1.72	46	10.81	✓		Positive impact/Reduction
	30-minutes window	One week	Feedback	-3.49	7	7.15	✓		Positive impact/Reduction
			Social comparison	-2.80	5	5.94	✓		Positive impact/Reduction
			Loss-aversion	-0.04	11	0.98	✓		Positive impact/Reduction
		One month	Feedback	-0.59	32	4.85	✓		Positive impact/Reduction
			Social comparison	-1.53	24	4.29	✓		Positive impact/Reduction
			Loss-aversion	-0.49	46	3.89	✓		Positive impact/Reduction
Plot 10	15-minutes window	One week	Feedback	+0.90	1	-			Not conclusive impact
			Social comparison	+0.30	1	-			Not conclusive impact
			Loss-aversion	-3.00	3	3.21	✓		Positive impact/Reduction
		One month	Feedback	-0.18	5	1.36	✓		Positive impact/Reduction
			Social comparison	+0.20	2	0.14		✓	Negative impact/Increase
			Loss-aversion	-2.32	6	3.99	✓		Positive impact/Reduction
	30-minutes window	One week	Feedback	+0.60	1	-			Not conclusive impact
			Social comparison	+0.10	1	-			Not conclusive impact
			Loss-aversion	-0.77	3	0.68	✓		Positive impact/Reduction
		One month	Feedback	-0.50	5	1.10	✓		Positive impact/Reduction
			Social comparison	+0.10	2	0.00		✓	Negative impact/Increase
			Loss-aversion	-1.68	6	5.16	✓		Positive impact/Reduction
Plot 12	15-minutes window	One week	Feedback	-0.46	7	4.49	✓		Positive impact/Reduction
			Social comparison	-0.15	4	1.00	✓		Positive impact/Reduction
			Loss-aversion	+0.13	3	2.89		✓	Negative impact/Increase
		One month	Feedback	-2.29	13	7.91	✓		Positive impact/Reduction

30-minutes window	One week	Social comparison	-0.33	9	0.87	✓		Positive impact/Reduction	
		Loss-aversion	-0.10	6	1.92	✓		Positive impact/Reduction	
		Feedback	-2.96	7	8.21	✓		Positive impact/Reduction	
	One month	Social comparison	+2.85	4	6.87		✓	Negative impact/Increase	
		Loss-aversion	-0.83	3	4.78	✓		Positive impact/Reduction	
		Feedback	-3.71	13	9.33	✓		Positive impact/Reduction	
	One month	Social comparison	+1.43	9	4.67		✓	Negative impact/Increase	
		Loss aversion	-1.10	6	3.20	✓		Positive impact/Reduction	
Legend									
	Positive impact / Reduction - Potential effectiveness				No or Negative impact / Increase - Potential effectiveness				Not conclusive impact

Table 16: Descriptive statistics - Relative humidity

5.2.2.1.1 Plot 5

In reviewing the Table 16, the descriptive statistics of plot 5 show that the feedback, social comparison, and loss-aversion indicated mean differences of -2.21, +0.06, and -0.01, respectively, on a weekly basis across the 15-minute window. Feedback shows a standard deviation of 4.73 based on seven instances. Social comparison shows a standard deviation of 0.27 based on five instances. Loss-aversion shows a standard deviation of 0.56 based on 11 instances. This data suggests that social comparison does not show any potential effectiveness in reducing high relative humidity levels (>60%rh) after the delivery of the interventions, as it shows a positive mean difference. Feedback and loss-aversion show potential effectiveness in reducing high relative humidity levels in the 15-minute window on a weekly basis. However, the mean difference of loss-aversion is not significant, denoting that the overall humidity reduction is approximately zero. In contrast, feedback shows a significant mean difference.

In considering the 15-minute window of plot 5 on a monthly basis, feedback shows a mean difference of -0.24 with a standard deviation of 3.58, based on 32 instances. Social comparison shows a mean difference of -0.47 with a standard deviation of 2.38, based on 24 instances. Loss-aversion shows a mean difference of -1.72 with a standard deviation of 10.81, based on 46 instances. These negative mean differences show that the three types of smart nudging interventions show potential effectiveness in reducing high relative humidity levels in the 15-minute window on a monthly basis. In comparison, social comparison did not show any effectiveness in reducing high humidity levels on a weekly basis but shows potential effectiveness on a monthly basis.

In reviewing the 30-minute window of plot 5, feedback, social comparison, and loss-aversion indicate negative mean differences of 3.49, 2.80, and 0.04, respectively, on a weekly basis. Feedback shows a standard deviation of 7.15 based on 7 instances. Social comparison shows a standard deviation of 5.94 based on 5 instances. Loss-aversion shows a standard deviation of 0.98 based on 11 instances. The negative mean differences of each smart nudging intervention show that they indicate potential effectiveness in reducing high relative humidity levels (>60%rh). However, the negative mean difference of loss-aversion is not considerable, as it is approximately zero. Feedback, social comparison, and loss-aversion show potential effectiveness in reducing high humidity levels on a monthly basis, as they indicate negative mean differences of 0.59, 1.53, and 0.49, respectively. Feedback, social comparison, and loss-aversion show standard deviations of 4.85, 4.29, and 3.89, respectively. Moreover, feedback, social comparison, and loss-aversion include 32, 24, and 46 instances, respectively. Therefore, these results suggest that all three smart nudging interventions were consistent with high humidity reductions over the week and month within the 30-minute window.

5.2.2.1.2 Plot 10

In reviewing the 15-minute window of plot 10, as shown in Table 16, feedback and social comparison show positive mean differences of 0.9 and 0.3, respectively, on a weekly basis. These results show an increase in high humidity levels (>60%rh) after delivering the interventions and therefore, show no potential effectiveness. However, the results are not conclusive, as feedback and social comparison have one instance each. In addition, it is not possible to calculate the standard deviations of feedback and social comparison, as they have only a single instance each. On the other hand, loss-aversion shows a mean difference of -3.0, which is a considerable overall reduction with a standard deviation of 3.21, based on 3 instances. Therefore, only loss-aversion shows potential effectiveness in reducing high humidity levels after the delivery of interventions in plot 10 on a weekly basis.

In considering the 15-minute window of plot 10 on a monthly basis, feedback shows a mean difference of -0.18 with a standard deviation of 1.36 based on 5 instances. Social comparison shows a mean difference of +0.20 with a standard deviation of 0.14 based on 2 instances. Loss-aversion shows a mean difference of -2.32 with a standard deviation of 3.99 based on 6 instances. Only social comparison shows no potential effectiveness in reducing high relative humidity levels (>60%rh) after the delivery of interventions, as the mean difference shows a small increase in high humidity levels. Feedback and loss-aversion show potential effectiveness in reducing high humidity levels. In comparison, feedback shows no potential

effectiveness in weekly across the 15-minute window, but it shows a potential effectiveness on a monthly basis.

In considering the 30-minute window of plot 10 on a weekly basis, feedback and social comparison have only one instance per each. Therefore, no standard deviations are calculated for feedback and social comparison. Moreover, the potential effectiveness of feedback and social comparison is not conclusive, as they have only one instance each. The mean differences of feedback, social comparison, and loss-aversion are + 0.60, +0.10, and -0.77, respectively. Only loss-aversion shows potential effectiveness in reducing high relative humidity levels, as it indicates a negative mean difference. The standard deviation of loss-aversion is 0.68 and number of instances is 3. In reviewing the descriptive statistics related to the 30-minute window of plot 10 on a monthly basis, the results suggest that both feedback and loss-aversion indicate potential effectiveness in reducing high humidity levels, as they show negative mean differences. The mean differences of feedback and loss-aversion are -0.50 and -1.68, respectively. Feedback shows a standard deviation of 1.10 based on 5 instances. Loss-aversion shows a standard deviation of 5.16 based on 6 instances. The social comparison shows a positive mean difference of 0.10 with a standard deviation of 0 based on 2 instances. In comparison, both feedback and loss-aversion have shown consistency in humidity reductions across the 15-minute and 30-minute windows over the month, indicating a gradual decrease of high humidity levels after the delivery of the interventions.

5.2.2.1.3 Plot 12

In considering the Table 16, in plot 12, the descriptive statistics related to the 15-minute window on a weekly basis show that the feedback and social comparison indicate negative mean differences of 0.46 and 0.15, respectively. Moreover, feedback and social comparison show standard deviations of 4.49 and 1.00, respectively. Feedback has 7 instances, while social comparison has 4 instances. Loss-aversion shows a positive mean difference of 0.13 with a standard deviation of 2.89, based on 3 instances. Therefore, these results suggest that only feedback and social comparison are potentially effective in reducing high humidity levels (>60%rh) after the delivery of interventions, and loss-aversion is not potentially effective in achieving humidity reductions. In considering the 15-minute window on a monthly basis, the negative mean differences of each type of smart nudging interventions show potential effectiveness in reducing high humidity levels (>60% rh) after the delivery of interventions. The mean differences of feedback, social comparison, and loss-aversion show as -2.29, -0.33, and -0.10, respectively. Feedback shows a standard deviation of 7.91 based on 13 instances.

Social comparison shows a standard deviation of 0.87, and the result is based on 9 instances. Loss-aversion shows a standard deviation of 1.92 based on 6 instances.

In reviewing the 30-minute window of plot 12 on a weekly basis, feedback and loss-aversion show potential effectiveness in reducing high relative humidity levels, as feedback and loss-aversion indicate negative mean differences of 2.96 and 0.83, respectively. Feedback indicates a standard deviation of 8.21 based on 7 instances. Loss-aversion shows a standard deviation of 4.78 based on 3 instances. Social comparison shows a positive mean difference of 2.85, a standard deviation of 6.87 based on 4 instances. Therefore, social comparison did not show any potential effectiveness on a weekly basis. Similarly, social comparison did not show any potential effectiveness over the month, as it shows a positive mean difference of 1.43. Social comparison shows a standard deviation of 4.67 based on 9 instances over the month. Feedback and loss-aversion show potential effectiveness in reducing high humidity levels, as feedback and loss-aversion indicate negative mean differences of 3.71 and 1.10, respectively. Feedback indicates a standard deviation of 9.33 based on 13 instances. Loss-aversion shows a standard deviation of 3.20 based on 6 instances.

In comparison, social comparison could not maintain consistency, as it showed potential effectiveness in the first week of the 15-minute window but did not show any potential effectiveness in the first week of the 30-minute window. Similarly, social comparison showed potential effectiveness in the 15-minute window over the month but did not show any potential effectiveness in the 30-minute window on a monthly basis. In addition, loss-aversion did not show any potential effectiveness over the first week of the 15-minute window. However, loss-aversion showed a potential effectiveness over the first week of the 30-minute window.

5.2.2.2 Assessing the optimal time window for humidity reduction evaluation

5.2.2.2.1 Discussion of the findings

In reviewing the Table 16, the descriptive statistics show no clear consistency between the 15-minute and 30-minute windows in plots 5 and 12. This lack of consistency among the research findings may have been caused due to the: 1) lack of sufficient time given in the 15-minute window to show true improvements in high relative humidity levels or real impact of the interventions after the delivery of the smart nudging interventions and nudging the occupant to reduce high humidity levels, 2) the actions that performed during the last few minutes in the 15-minute window, and 3) impact of interventions and real improvements in high humidity levels above 60%rh likely takes time to reduce and manifest. For example,

- a) Plot 5 - Social comparison did not show potential effectiveness over the first week of the 15-minute window but was shown during the first week of the 30-minute window.
- b) Plot 12 - Social comparison showed potential effectiveness in the first week of the 15-minute window. However, it did not show any potential effectiveness in the first week of the 30-minute window.
- c) Plot 12 - Loss-aversion did not show any potential effectiveness in the first week of the 15-minute window. However, loss-aversion appeared as a potentially effective intervention in the first week of the 30-minute window.
- d) Plot 12 - Social comparison showed potential effectiveness in the 15-minute window over the month. However, social comparison did not show any potential effectiveness in the 30-minute window over the month.

These arguments are supported by the exiting literature, as the NHBC (2023) stated that it is necessary to keep the extractor fan on and/or the window open, and the door closed for about 20 minutes after cooking, bathing or washing to reduce high relative humidity levels that were generated in those processes. In addition, the study of Chen et al. (2023) showed that relative humidity levels were stabilised after 25 minutes and returned close to the initial background humidity level in homes mainly due to proper ventilation. In comparison, the 30-minute window can yield adequate time to observe true humidity reductions that occur because of the home occupant's actions and avoid misleading reductions due to random fluctuations. Therefore, 30-minute window is deemed more suitable for evaluating the high relative humidity reductions.

To further assess the optimal time window for evaluating the humidity reductions, the humidity level at the time the smart nudging intervention was delivered, as well as at the 15-minute and 30-minute post-delivery, were obtained for each instance in each plot. Figures 26, 27, and 28 show a comparison of relative humidity levels, namely, humidity level at the time the intervention was sent, humidity level after 15-minutes, and humidity level after 30-minutes over the intervention period.

Figure 27 shows a comparison of three relative humidity levels in plot 5. The high humidity levels were reduced at 47 instances out of 102 instances in the 15-minute window over the intervention period, while high humidity levels were reduced at 49 instances out of 102 instances in the 30-minute window. However, out of those 102 instances, few instances showed significant reductions in high relative humidity levels in the 30-minute window compared to

the 15-minute window. These instances are more significant than the instances in the 15-minute window. For examples: 1) the 6th instance showed a high relative humidity level reduction from 66.40% to 53% in the 30-minute window but no difference in the 15-minute window, 2) the 19th instance showed a high humidity level reduction from 91% to 78.10% within the 15-minute window, while it further dropped to 71.40% in the 30-minute window, 3) the 69th instance showed that the high relative humidity level was reduced from 83.40% to 72.40% in the 15-minute window, while it was reduced to 67.40% in the 30-minute window, 4)) the 74th instance showed a high reduction in humidity levels from 83.80% to 73.60% within the 15-minute window, while it further decreased to 68.70% in the 30-minute window, 5) the 81st instance indicated a reduction in high humidity levels from 66.40% to 61.80% within the 15-minute window, while it was reduced to 58.70% in the 30-minute window, 6) the 86th instance indicated a high relative humidity level reduction from 85.90% to 78% in the 15-minute window, while it was further reduced to 63.80% in the 30-minute window, and 7) the 93rd instance showed a high relative humidity level reduction from 72.20% to 60.70% in the 15-minute window, while it was further reduced to 60.10% in the 30-minute window. Therefore, these significant reductions in high humidity levels suggest that 30-minute window provides more significant relative humidity level reductions than the 15-minute window.

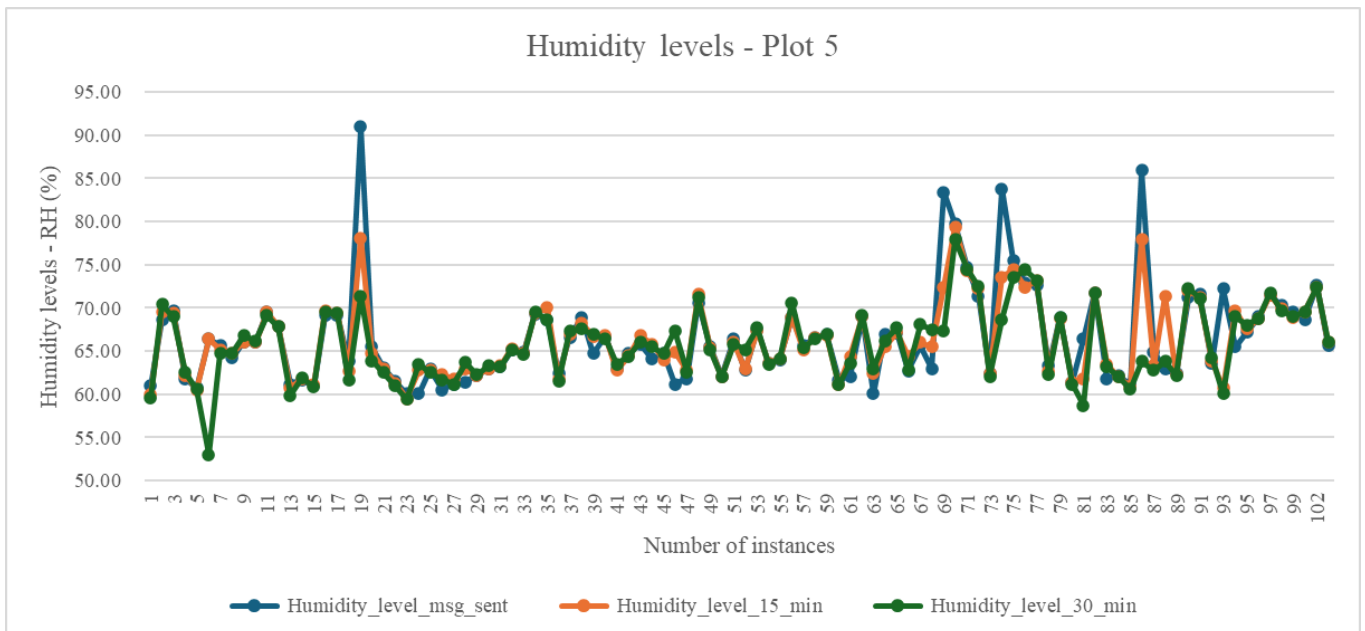


Figure 27: Comparison of humidity levels in plot 5

Figure 28 shows a comparison of relative humidity levels in plot 10. Eight instances out of the 13 instances showed humidity reductions in the 15-minute window. However, only four instances out of those 8 instances showed significant humidity reductions below 60%rh in the

15-minute window. The four instances are the 2nd, 5th, 7th, and 13th instances. Seven instances out of the 13 instances showed humidity reductions in the 30-minute window. However, out of those seven instances, only the 7th instance and 13th instance showed a humidity reduction below 60%rh in the 30-minute window. For example, the 13th instance showed the humidity reduction from 67.10% to 59.60% in the 15-minute window, and it further reduced to 55.6% in the 30-minute window. This denotes that the 30-minute window shows how the humidity level is gradually decreased and sustained by providing a sufficient time to reveal the true impact of the intervention. Other humidity reductions in the 30-minute window could not reach below 60%rh. On the other hand, the 2nd instance and 5th instance show that the humidity levels were reduced in the first 15-minutes, but humidity levels began to increase again in the next 15-minutes. This increase in humidity levels might be due to the occupant's activity such as closing the window or cooking. Moreover, some instances, namely, the 1st, 4th, 9th, 10th, and 11th instances, show no actions have been taken by the occupant to lower high humidity levels.

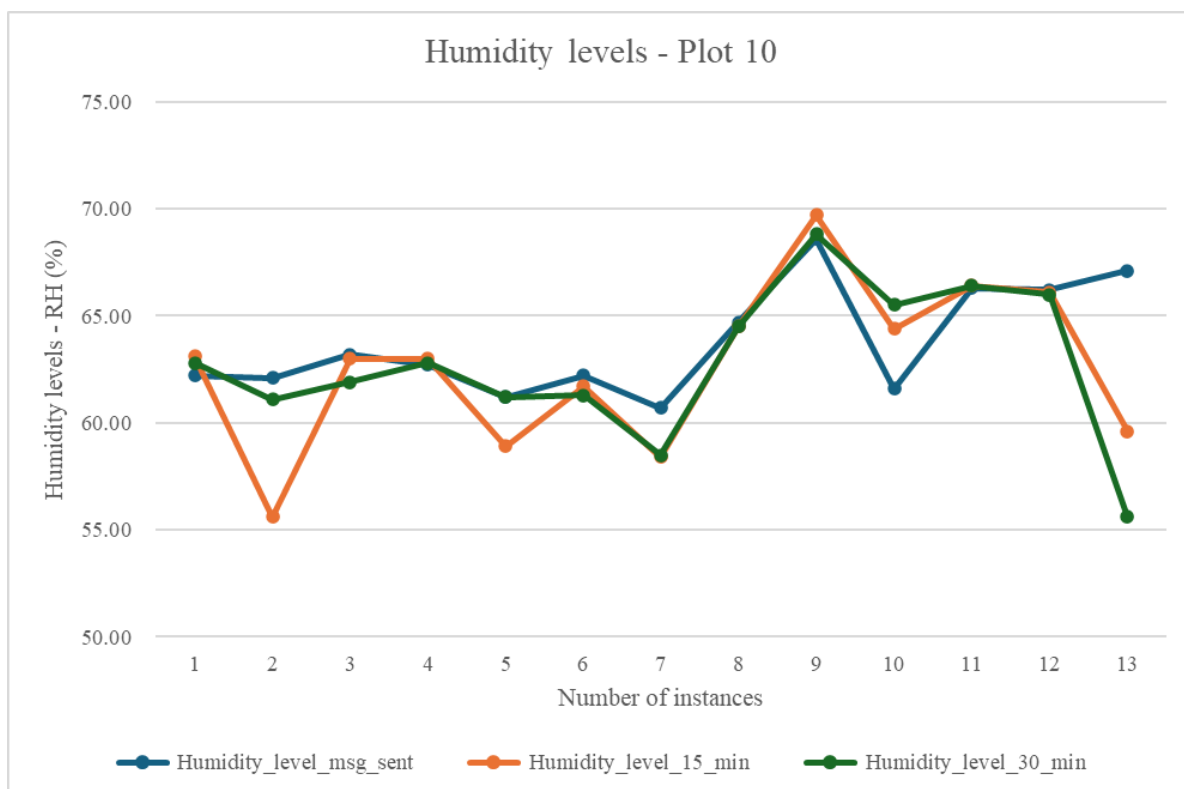


Figure 28: Comparison of relative humidity levels in plot 10

Figure 29 shows the comparison of relative humidity levels in plot 12. The high relative humidity levels were decreased at 12 instances and 16 instances out of 28 instances in the 15-minute window and 30-minute window, respectively, over the intervention period. However, out of those 16 instances, few instances indicated significant relative humidity reductions in the 30-minute window. These instances are more significant than the instances in the 15-minute

window. For examples: 1) the 1st instance showed a high relative humidity level reduction from 63.80% to 60.60% in the 15-minute window but it was reduced to 57.90% in the 30-minute window, 2) the 6th instance showed a high humidity level reduction from 87.80% to 78.00% within the 15-minute window, while it was dropped to 66.40% in the 30-minute window, 3) the 16th instance showed that high relative humidity level was decreased from 92.80% to 66.40% in the 15-minute window, while it was further decreased to 65.30% in the 30-minute window. Therefore, these findings suggest that 30-minute window is more appropriate to evaluate the humidity reductions.

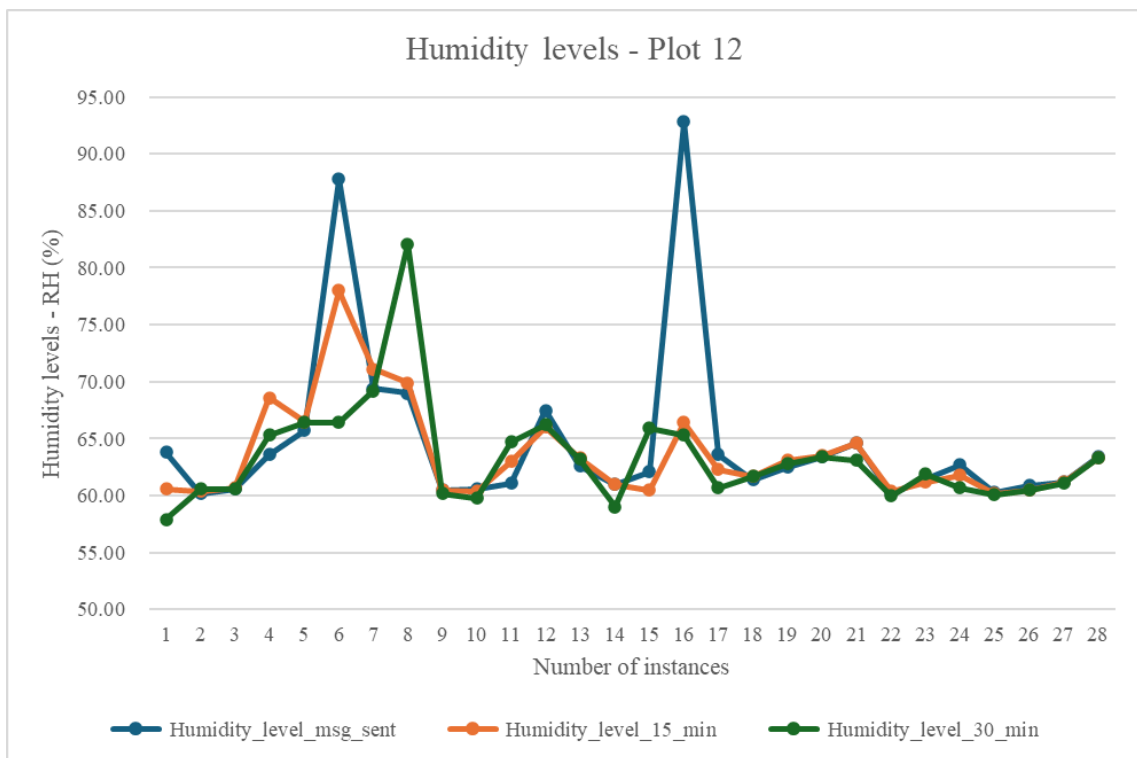


Figure 29: Comparison of humidity levels in plot 12

In conclusion, the three relative humidity levels in each plot indicate that the 30-minute window is more suitable than the 15-minute window for evaluating the impact of smart nudging interventions. The 30-minute window can detect no/delayed actions beyond the 15-minute window or actions happening at the last few minutes of the 15-minute window, the real impact of smart nudging interventions by providing sufficient time for the humidity levels to gradually decrease and sustain and avoid random fluctuations and isolate the householder’s behavioural change. Therefore, 30-minute window provides more accurate results for evaluation than 15-minute window. In addition, the observed reductions in higher relative humidity levels may have been affected by various environmental and behavioural factors such as duration of the window opening, the level of ventilation achieved, the use of extractor fans in the kitchen, and

the nature of the cooking activities. Therefore, these factors may contribute to delays in achieving the safe threshold of humidity following the home occupant actions.

5.2.2.3 Assessment of the impact of the smart nudging interventions

Table 17 shows the impact (positive impact or neutral impact or no/negative impact or uncertain impact) of each smart nudging intervention across each plot on a weekly and a monthly basis in the 30-minute window.





	Time period	Smart nudging interventions	Mean difference	Number of instances/times the intervention was sent	Positive instances	No/Negative instances	Actual Impact comparison
Plot 5	One week	Feedback	-3.49	7	6	1	Positive impact
		Social comparison	-2.80	5	4	1	Positive impact
		Loss-aversion	-0.04	11	4	7	Not conclusive/Uncertain impact
	One month	Feedback	-0.59	32	17	15	Positive impact
		Social comparison	-1.53	24	14	10	Positive impact
		Loss-aversion	-0.49	46	18	28	Not conclusive/Uncertain impact
Plot 10	One week	Feedback	+0.60	1	0	1	Not conclusive/Uncertain impact
		Social comparison	+0.10	1	0	1	Not conclusive/Uncertain impact
		Loss-aversion	-0.77	3	2	1	Positive impact
	One month	Feedback	-0.50	5	3	2	Positive impact
		Social comparison	+0.10	2	0	2	No/Negative impact
		Loss-aversion	-1.68	6	4	2	Positive impact
Plot 12	One week	Feedback	-2.96	7	3	4	Not conclusive/Uncertain impact
		Social comparison	+2.85	4	2	2	Neutral impact
		Loss-aversion	-0.83	3	2	1	Positive impact
	One month	Feedback	-3.71	13	7	6	Positive impact
		Social comparison	+1.43	9	5	4	Not conclusive/Uncertain impact
		Loss-aversion	-1.10	6	4	2	Positive impact
Legend							
	Positive impact		Neutral impact		No/Negative impact		Not conclusive/ Uncertain impact

Table 17: Assessment of the impact of the smart nudging interventions - Relative humidity

According to the Table 17, in plot 5, both feedback and social comparison showed positive impacts, as they indicated negative mean differences (or overall reductions of high humidity levels after post-delivery) and their number of positive instances are higher than the number of no/negative impact instances on a weekly and a monthly basis. Most of the instances (7 instances) of loss-aversion showed no/negative impacts, while 4 instances showed positive impacts over the week. Similarly, 28 instances of loss-aversion showed no/negative impacts, while 18 instances showed positive impacts over the month. However, the negative mean differences of loss-aversion indicated an overall reduction of high humidity levels in both weekly and monthly. As a result, the impact of loss-aversion is uncertain, as the number of no/negative impact instances was higher than the number of positive impact instances even

though the mean differences were negative and showed reductions in both weekly and monthly. This shows an inconsistent positive impact. In addition, the negative mean differences of loss-aversion might have been influenced by few extreme negative values (positive impact or reductions). Therefore, a verification of the positive instances is needed to understand the real impact of loss-aversion.

In plot 10, only loss-aversion showed a positive impact on a weekly basis due to having a negative mean difference and a higher number of positive impact instances than no/negative impact instances. The impact of feedback and social comparison remains uncertain or inconclusive due to having only one weekly instance each. Both feedback and loss-aversion showed positive impacts on a monthly basis. Only social comparison showed a no/negative impact over the month. Social comparison showed a positive mean difference, indicating an increase in high humidity levels, with all the instances showing no/negative impacts.

In plot 12, feedback, social comparison, and loss-aversion showed an uncertain/not conclusive impact, a neutral impact, and a positive impact, respectively, on a weekly basis. Feedback indicated a negative mean difference with a higher number of no/negative instances, denoting that a verification of the positive impact instances is needed to identify the true impact. Social comparison showed a neutral impact, indicating 2 positive impact instances and 2 no/negative impact instances. Feedback, social comparison, and loss-aversion showed a positive impact, uncertain/not conclusive impact, and positive impact, respectively, over the month. Social comparison showed an overall increase of high relative humidity levels, as it showed a positive mean difference. However, the number of positive instances of social comparison was higher than the number of no/negative instances. Therefore, a verification of the positive impact instances is needed to assess the true impact of social comparison.

5.2.2.4 Verification of the positive instances of the smart nudging interventions

5.2.2.4.1 Plot 5

Figure 30 shows the verification of the positive instances related to the feedback, social comparison, and loss-aversion in plot 5 on a weekly basis. According to Figure 29, feedback showed a significant reduction in high humidity levels in one instance out of the 6 positive instances. Feedback showed a significant reduction of high humidity levels from 91% to 71.4% in one instance. Similarly, social comparison showed a significant reduction in high humidity levels in one instance out of the 4 positive instances. Social comparison showed a significant reduction of higher humidity levels from 66.4% to 53% in one instance. Therefore, only these

two instances showed actions taken by the home occupant. However, all the other positive instances of both feedback and social comparison showed no considerable reductions in high relative humidity levels on a weekly basis. Therefore, the lack of significant reductions in most of the positive instances suggests that feedback and social comparison may not be consistently effective in reducing high humidity levels and achieving the immediate positive impact over the first week of the intervention period. Moreover, feedback and social comparison cannot be regarded as truly effective and reliable smart nudging interventions, as most of the positive instances were not effective. On the other hand, the positive instances of loss-aversion showed no significant reductions in high relative humidity levels. Therefore, it can be concluded that the ‘uncertain impact’ identified in Table 17 can be changed to a ‘no/negative impact’, and the negative mean difference, which is approximately to zero, had occurred due to random fluctuations. In the overall assessment, the data suggest that no smart nudging intervention showed a consistent real positive impact over the first week of the intervention period.

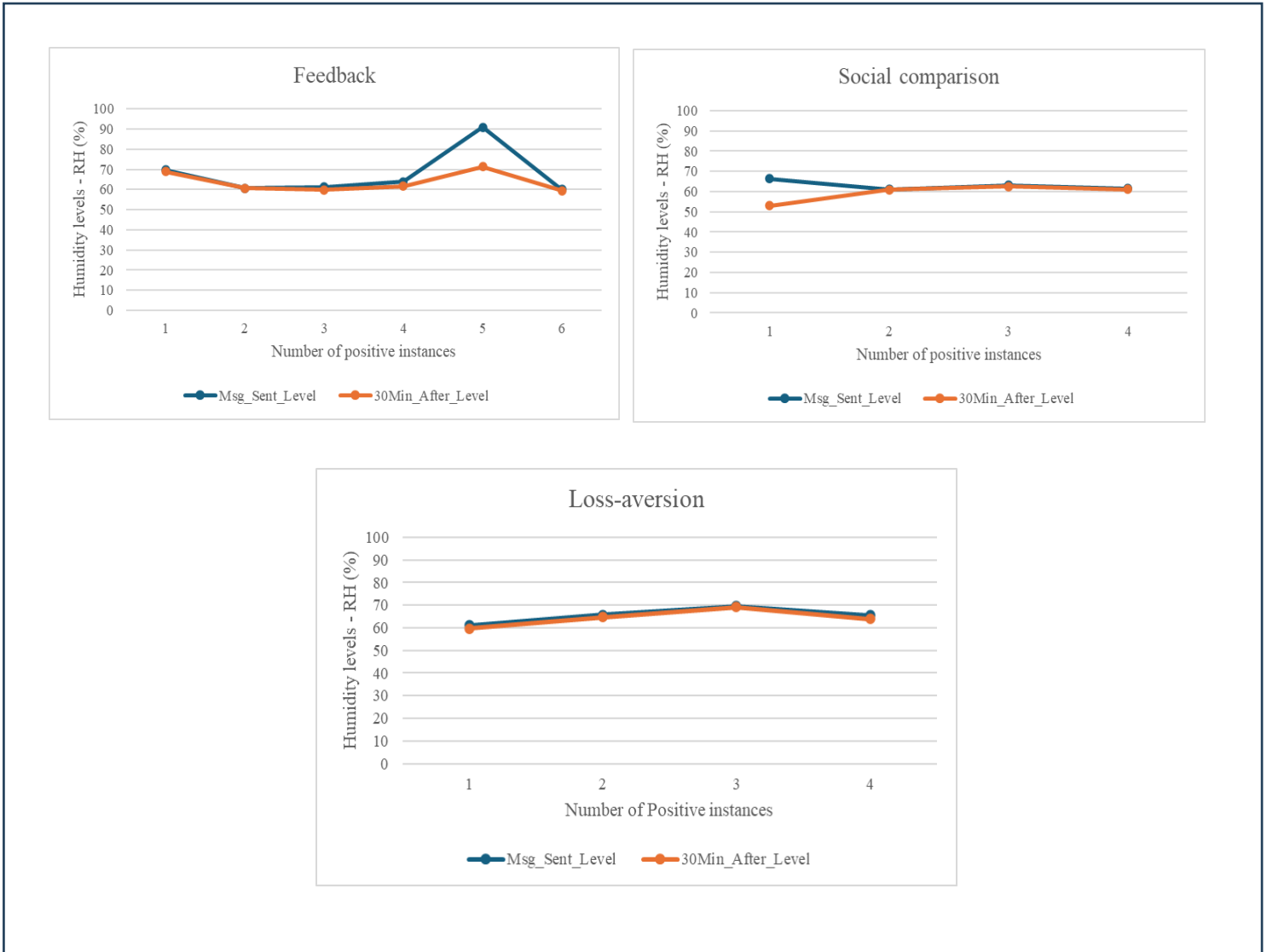


Figure 30: Plot 5 - Verification of the positive instances – weekly

Figure 31 shows the assessment of positive instances of the feedback, social comparison, and loss-aversion on a monthly basis in plot 5. According to Figure 31, feedback showed significant humidity reductions only in two instances over the month. The high relative humidity levels were reduced from 91% to 71.4% in the 5th instance. In addition, the high humidity levels were reduced from 83.4% to 67.4% in the 15th instance. Similarly, loss-aversion showed high humidity reductions in two instances. The 13th instance showed a humidity reduction from 85.90% to 63.80%, while the 17th instance showed a humidity reduction from 72.20% to 60.10%. Therefore, loss-aversion indicates a positive impact in two positive instances only, while the majority of the positive instances showed no significant humidity reductions. However, those two positive instances of loss-aversion had contributed to the appearance of the mean difference as negative, with the majority of total instances showing as no/negative instances, as shown in Table 17. Social comparison showed noteworthy reductions in three

instances. The 1st, 8th, and 10th instances of social comparison showed humidity reductions from 66.4% to 53%, 83.8% to 68.7%, and 66.4% to 58.7%, respectively. Therefore, in overall comparison, social comparison showed more effectiveness than feedback and loss-aversion, as the number of positive instances is higher than the feedback and loss-aversion over the intervention period of one month.



Figure 31: Plot 5 - Verification of the positive instances – monthly

5.2.2.4.2 Plot 10

Figure 32 shows that out of the 2 positive instances of loss-aversion on a weekly basis, no instance showed significant effectiveness in reducing high humidity levels. Therefore, these results indicate that the home occupant had not taken any action to reduce high humidity levels. Therefore, the negative mean difference had occurred due to random fluctuations.

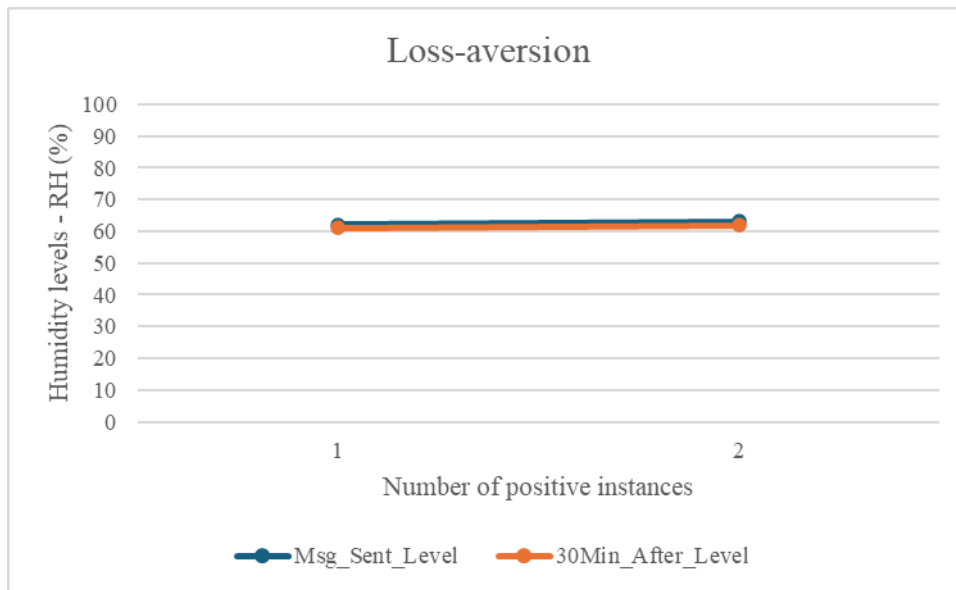


Figure 32: Plot 10 - Verification of the positive instances - weekly

Figure 33 shows the assessment of positive instances over the month in plot 10. The three positive instances of feedback showed no significant reductions. However, only one instance out of those three positive instances of feedback showed a humidity reduction from 62.2% to 58.5%. On the other hand, one positive instance out of the 4 positive instances of loss-aversion showed a significant humidity reduction from 67.10% to 55.6%, indicating that the home occupant had taken an action. However, majority of the positive instances showed no significant humidity reductions. Therefore, any of the interventions could not maintain consistent positive impact over the intervention period and thereby, both interventions are not reliable in terms of effectiveness.

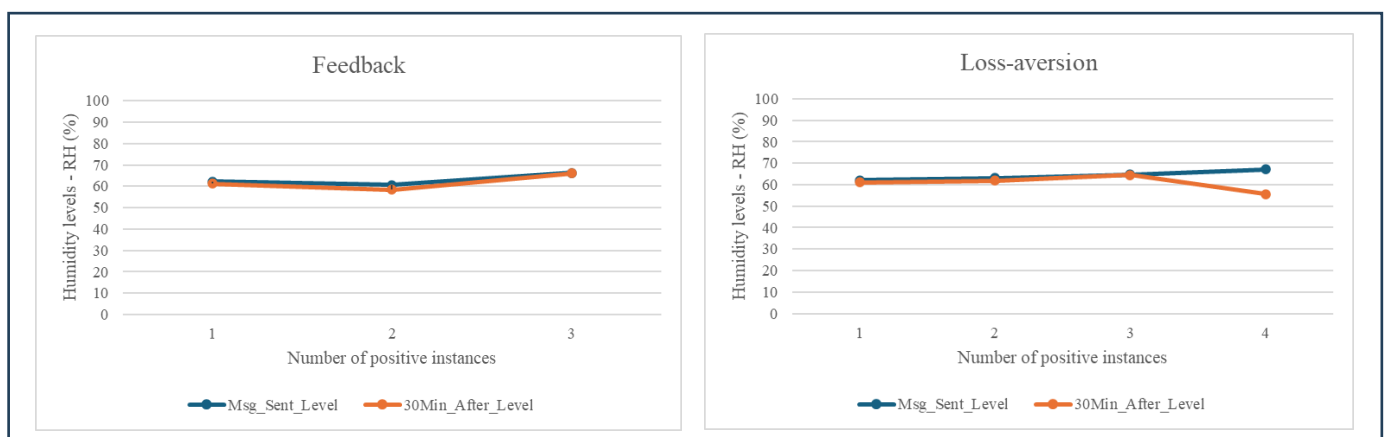


Figure 33: Plot 10 - Verification of the positive instances – monthly

5.2.2.4.3 Plot 12

Figure 34 shows that only one positive instance of feedback showed a significant reduction of high humidity levels, as it indicated a humidity reduction from 87.80% to 66.40% on a weekly

basis, suggesting that the home occupant had acted. Another positive instance of feedback showed a humidity reduction from 61% to 59%. However, this reduction is not a significant reduction. Those 2 humidity reductions had contributed for the appearance of the negative mean difference of feedback. Social comparison did not show any significant reduction. Loss-aversion showed that one instance out of the two positive instances showed a significant humidity reduction from 63.80% to 57.90%. However, no smart nudging intervention could maintain a consistent and reliable positive impact.

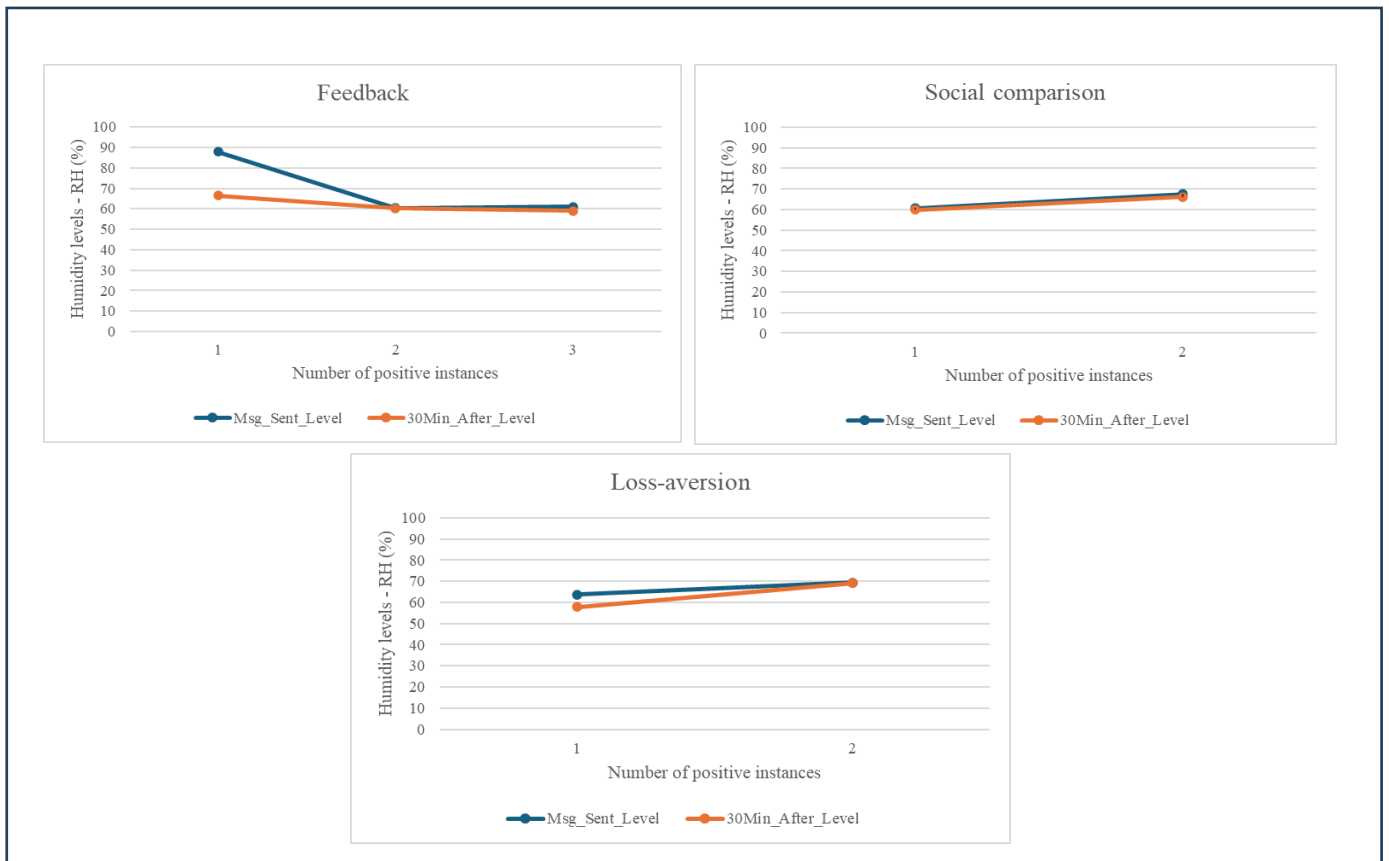


Figure 34: Plot 12 - Verification of the positive instances - weekly

Figure 35 shows that two instances out of 7 positive instances of feedback showed significant humidity reductions over the month. The 1st instance showed a humidity reduction from 87.80% to 66.40%, while the 4th instance showed a humidity reduction from 92.80% to 65.30%. Social comparison showed no significant humidity reductions. Therefore, the ‘uncertain impact’ of social comparison identified in Table 17 can be changed to a ‘no/negative impact’. Loss-aversion showed a significant humidity reduction from 63.80% to 57.90% in the 1st instance. Therefore, in comparison, feedback showed a higher number of real positive instances than social comparison and loss-aversion over the month.

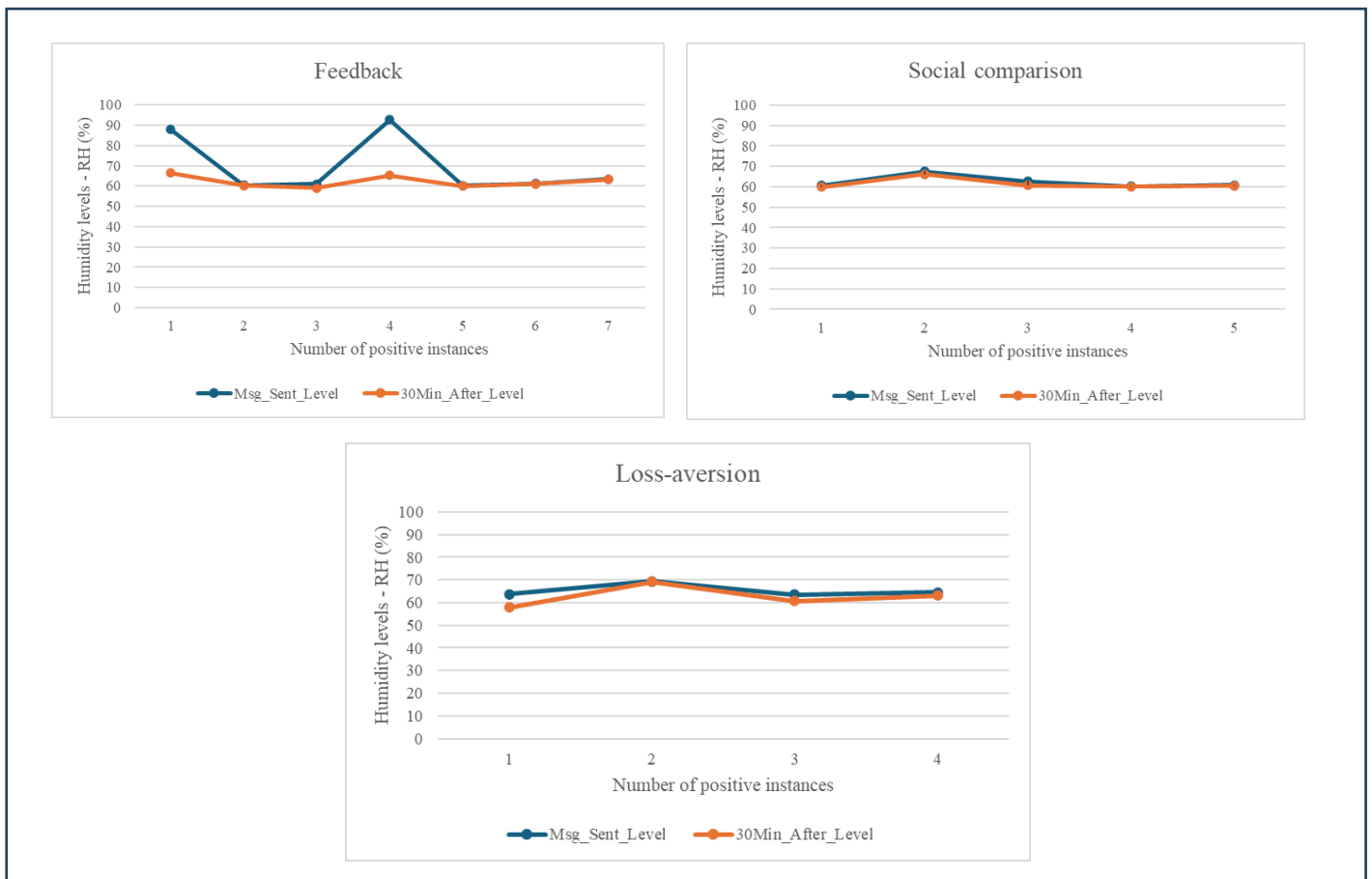


Figure 35: Plot 12 - Verification of the positive instances - monthly

5.2.2.5 Assessment of the most effective smart nudging intervention – Relative humidity

Table 18 shows the most effective smart nudging intervention in each plot on a weekly and a monthly basis. No reliable result related to the most effective intervention across each plot over the first week of the intervention period could be found. Social comparison was identified as the most effective intervention in plot 5 over the intervention period of one month. No smart nudging intervention was highlighted as the most effective intervention in plot 10 on a monthly basis. Feedback emerged as the most effective intervention in plot 12 on a monthly basis. In comparing the significant positive impact rate, feedback emerged as the most effective intervention in reducing the high humidity levels.

	Time period	The most effective smart nudging intervention	Significant Positive impact rate
Plot 5	One week	-	-
	One month	Social comparison	21%
Plot 10	One week	-	-
	One month	-	-
Plot 12	One week	-	-
	One month	Feedback	29%

Table 18: Most effective intervention - Relative humidity

5.2.2.6 Inferential statistics

Table 19 shows the inferential statistics related to relative humidity in plots 5 and 12. Social comparison and feedback were identified as the effective smart nudging interventions in plots 5 and 12, respectively (see Table 18). Therefore, inferential statistics is conducted to assess whether social comparison and feedback significantly outperform the other two interventions in each plot.

		Test name	Type of Smart nudging interventions	Test statistic	df	P-value	Effect size	Interpretation
Plot 5	Humidity reduction – one month	Friedman test	All interventions	0.58 (Chi-Square)	2	0.75	0.01 (Kendall's W)	Not statistically significant
Plot 12	Humidity reduction – one month	Friedman test	All interventions	2.33 (Chi-Square)	2	0.31	0.19 (Kendall's W)	Not statistically significant

Table 19: Inferential statistics - Humidity

The Friedman test is conducted to identify whether social comparison and feedback significantly outperforms the other two smart nudging interventions in reducing high humidity levels (>60%rh) in both plot 5 and plot 12 separately. The Friedman test results of plot 5 show a p-value of 0.75 ($\chi^2(2) = 0.58$, $W = 0.01$), showing no statistically significant difference between the three smart nudging interventions and a very low effect in reducing the high humidity levels. Similarly, the Friedman test results of plot 12 show a p-value of 0.31 ($\chi^2(2) = 2.33$, $W = 0.19$), showing no statistically significant difference between the three smart nudging interventions and a low effect in reducing the high humidity levels.

These results reveal that social comparison and feedback were effective in their context, but any intervention could not outperform the other two smart nudging interventions in a meaningful way. This may have occurred due to the lack of positive instances showing a significant reduction in high humidity levels, as highlighted in Figures 30 and 34. In addition, the absence of statistical significance is likely influenced by the high variability of data around the mean differences of smart nudging interventions. The observed positive impacts may not likely be due to random variations but because of the home occupant's actions, as identified in Figures 30 and 34. However, a further assessment through triangulation is needed to better understand the impacts of social comparison and feedback.

5.2.3 TVOC

5.2.3.1 Descriptive statistics

Table 20 shows the descriptive statistics related to the TVOC in the three plots. The descriptive statistics of the three smart nudging interventions are analysed on a weekly and monthly basis and are presented across the 15-minute and 30-minute windows in each plot. However, if any type of the smart nudging interventions was not delivered during any period in any plot, that row is left blank. The potential effectiveness of each smart nudging intervention is shown using three different colours: green for a positive impact/reduction, red for a no/negative impact/increase, and grey for a not conclusive outcome (or the availability of only a single instance) based on the mean differences. The standard deviations of smart nudging interventions in each plot show a high variability of TVOC data around their mean differences based on limited number of instances.

	Time period	Type of smart nudging interventions	Mean differences of the smart nudging interventions	Number of times (instances) the intervention was sent	Standard deviations	Overall TVOC reduction (potential effectiveness)		Remarks	
						Yes	No		
Plot 5	15-minutes window	One week	Feedback	-79	1	-			Not conclusive impact
			Social comparison	+8.50	2	67.18		✓	Negative impact/ Increase
			Loss-aversion	-	-	-	-	-	-
		One month	Feedback	+144	5	570.26		✓	Negative impact/ Increase
			Social comparison	+31.56	9	267.68		✓	Negative impact/ Increase
			Loss-aversion	-29	2	49.49	✓		Positive impact/ Reduction
	30-minutes window	One week	Feedback	-170	1	-			Not conclusive impact
			Social comparison	+1.50	2	41.72		✓	Negative impact/ Increase
			Loss-aversion	-	-	-	-	-	-
One month		Feedback	+190.20	5	824.84		✓	Negative impact/ Increase	
		Social comparison	-17.78	9	198.40	✓		Positive impact/ Reduction	
		Loss-aversion	-74.50	2	71.42	✓		Positive impact/ Reduction	
Plot 10	15-minutes window	One week	Feedback	-	-	-	-	-	-
			Social comparison	-2563	1	-			Not conclusive impact
			Loss-aversion	-	-	-	-	-	-
		One month	Feedback	-91.67	6	124.05	✓		Positive impact/ Reduction
			Social comparison	-317.22	9	852.78	✓		Positive impact/ Reduction
			Loss-aversion	+9.86	7	131.82		✓	Negative impact/ Increase
	One week	Feedback	-	-	-	-	-	-	-

	30-minutes window		Social comparison	-2538	1	-		Not conclusive impact	
			Loss-aversion	-	-	-	-	-	-
		One month	Feedback	-94.17	6	194.53	✓		Positive impact/Reduction
			Social comparison	-294.33	9	874.81	✓		Positive impact/Reduction
			Loss-aversion	+47.71	7	227.35		✓	Negative impact/Increase
Plot 12	15-minutes window	One week	Feedback	-	-	-	-	-	-
			Social comparison	-	-	-	-	-	-
			Loss-aversion	-181	1	-			Not conclusive impact
		One month	Feedback	-13	1	-			Not conclusive impact
			Social comparison	-4.50	2	26.16	✓		Positive impact/Reduction
			Loss-aversion	-20.17	6	95.62	✓		Positive impact/Reduction
	30-minutes window	One week	Feedback	-	-	-	-	-	-
			Social comparison	-	-	-	-	-	-
			Loss-aversion	-210	1	-			Not conclusive impact
		One month	Feedback	-16	1	-			Not conclusive impact
			Social comparison	+27.50	2	19.09		✓	Negative impact/Increase
			Loss-aversion	+47.67	6	183.63		✓	Negative impact/Increase
Legend									
	Positive impact / Reduction - Potential effectiveness		No or Negative impact / Increase - Potential effectiveness				Not conclusive impact		

Table 20: Descriptive statistics – TVOC

5.2.3.1.1 Plot 5

As per Table 20, the descriptive statistics related to plot 5 show that the mean differences of feedback within the 15-minute and 30-minute windows on a weekly basis are -79 and -170, respectively, based on single instances each. However, the potential effectiveness of feedback is not conclusive in both time windows, as feedback has single instances in each time window. In addition, no standard deviation is calculated, as it is not possible to calculate the variability of TVOC data around the mean difference with a single instance. Social comparison shows positive mean differences of 8.50 and 1.50 in the 15-minute window and 30-minute window, respectively, over the week. Social comparison shows a standard deviation of 67.18 based on 2 instances in the 15-minute window. Moreover, social comparison shows a standard deviation of 41.72 based on 2 instances in the 30-minute window. Loss-aversion was not delivered during the first week of the intervention period. Therefore, these data suggest that smart nudging interventions were delivered only three times during the first week of the intervention period. This might have been caused by the limited number of instances that showed an increase in high TVOC levels above the safe threshold of 400ppb.

In reviewing the 15-minutes window on a monthly basis, feedback and social comparison show positive mean differences of 144 and 31.56, respectively, indicating no potential effectiveness in reducing high TVOC levels. Feedback and social comparison show standard deviations of 570.26 based on 5 instances and 267.68 based on 9 instances, respectively. Loss-aversion indicates potential effectiveness, as it indicates a negative mean difference of 29. Loss-aversion shows a standard deviation of 49.49 based on 2 instances. In considering the 30-minutes window over the month, feedback shows a positive mean difference of 190.20, indicating no potential effectiveness. Feedback shows a standard deviation of 824.84 based on 5 instances. Social comparison and loss-aversion show negative mean differences of 17.78 and 74.50, respectively, indicating potential effectiveness. Social comparison and loss-aversion show standard deviations of 198.40 based on 9 instances and 71.42 based on 2 instances, respectively. In comparison, social comparison does not show potential effectiveness over the month in the 15-minute window, but it shows a potential effectiveness over the month in the 30-minute window.

5.2.3.1.2 Plot 10

According to Table 20, only social comparison was delivered over the first week of the intervention period. Social comparison shows negative mean differences of 2563 and 2538 within the 15-minute and 30-minute windows, respectively, based on single instances each. Therefore, the potential effectiveness is not conclusive. This may be attributed to a single instance in which increases in TVOC levels above the safe threshold of 400ppb were observed. In addition, this may have been caused by the random selection of other indoor air quality parameters in the plot, which could have affected the outcome. In reviewing the 15-minute window, feedback and social comparison show negative mean differences of 91.67 and 317.22, respectively, on a monthly basis. Therefore, both feedback and social comparison show potential effectiveness. Feedback and social comparison show standard deviations of 124.05 based on 6 instances and 852.78 based on 9 instances, respectively. Loss-aversion did not show potential effectiveness, as it showed a positive mean difference of 9.86 with a standard deviation of 131.82 based on 7 instances.

In considering the 30-minutes window of plot 10, feedback and social comparison show negative mean differences of 94.17 and 294.33, respectively, over the month. Therefore, both feedback and social comparison show potential effectiveness in reducing high TVOC levels. Feedback and social comparison show standard deviations of 194.53 based on 6 instances and 874.81 based on 9 instances, respectively. Loss-aversion did not show potential effectiveness,

as it indicated a positive mean difference of 47.71. Loss-aversion indicates a standard deviation of 227.35 based on 7 instances.

5.2.3.1.3 Plot 12

As per Table 20, only loss-aversion was delivered over the first week of the intervention period. Loss-aversion shows negative mean differences of 181 and 210 within the 15-minute and 30-minute windows, respectively, based on single instances each. As a result, the potential effectiveness of loss-aversion is not conclusive. The data suggests that this may have occurred due to a single instance in which increases in TVOC levels above the safe threshold of 400ppb were observed. In addition, this may have been caused by the random selection of other indoor air quality parameters in the plot, which could have influenced the result. In considering the 15-minute window, feedback, social comparison, and loss-aversion show negative mean differences of 13, 4.50, and 20.17, respectively, on a monthly basis. Feedback has only one instance. Thus, the impact is not conclusive. Social comparison shows a standard deviation of 26.16 based on 2 instances. Loss-aversion shows a standard deviation of 95.62 based on 6 instances.

In reviewing the 30-minutes window, feedback shows a negative mean difference of 16 based on a single instance, leading to an inconclusive impact. Social comparison and loss-aversion show positive mean differences of 27.50 and 47.67, indicating no potential effectiveness. Social comparison and loss-aversion show standard deviations of 19.09 based on 2 instances and 183.63 based on 6 instances, respectively. In comparison, both social comparison and loss-aversion showed potential effectiveness in the 15-minute window, while they did not show any potential effectiveness in the 30-minute window over the month.

5.2.3.2 Assessing the optimal time window for TVOC reduction evaluation

5.2.3.3 Discussion of the findings

According to the Table 20, the absence of consistent empirical findings among the 15-minute and 30-minute windows in plots may have been caused due to the: 1) lack of adequate time given in the 15-minute window to show real improvements in high TVOC levels or real impact of the smart nudging interventions after their delivery and nudging the home occupant to reduce high TVOC levels, 2) the delayed actions that performed during the last few minutes in the 15-minute window, and 3) real impact of interventions and real improvements in high TVOC levels above 400ppb likely takes time to reduce and manifest. For example:

- 1) In plot 5, social comparison did not show potential effectiveness over the 15-minute window on a monthly basis, but it showed a potential effectiveness over the month in the 30-minute window.
- 2) In plot 12, both social comparison and loss-aversion showed potential effectiveness over the 15-minute window on a monthly basis, but they did not show potential effectiveness over the month in the 30-minute window.

To further assess the optimal time window for TVOC reduction evaluation, the TVOC level at the time the smart nudging intervention was delivered, TVOC levels at the 15-minute and 30-minute post-delivery, were obtained for each instance. Figures 36, 37, and 38 show the comparison of those three TVOC levels in each instance across the three plots.

Figure 36 shows a comparison of three TVOC levels in plot 5. The high TVOC levels were reduced in 11 instances in the 15-minute window, while high TVOC levels were reduced in 12 instances in the 30-minute window. In comparison, high TVOC levels show significant reductions below 400ppb in 10 instances in a 30-minute window compared to the 15-minute window. This can be seen in the 2nd, 3rd, 4th, 10th, 11th, 12th, 13th, 14th, 15th, and 16th instances. Among these 10 instances, few examples of reductions are: 1) the 2nd instance shows a high TVOC reduction from 474ppb to 395ppb in the 15-minute window, while it further reduced to 304ppb in the 30-minute window, 2) the 10th instance shows that the high TVOC levels were reduced from 587ppb to 458ppb in the 15-minute window, while it further reduced to 392ppb in the 30-minute window, 3) the 12th instance shows a high TVOC reduction from 503ppb to 300ppb in the 15-minute window, while it further reduced to 170ppb in the 30-minute window, 4) the 14th instance shows a high TVOC reduction from 452ppb to 400ppb in the 15-minute window, while it further reduced to 392ppb in the 30-minute window, and 5) the 16th instance shows a high TVOC reduction from 494ppb to 350ppb in the 15-minute window, while it further reduced to 294ppb in the 30-minute window. The 4th instance shows an increase in high TVOC levels after 15-minutes window, as the TVOC level increased from 517ppb to 523ppb in the 15-minute window, but it reduced to 392ppb in the 30-minute window. This suggests a delayed action taken by the home occupant. The 5th, 8th, and 9th instances show no action taken by the home occupant.

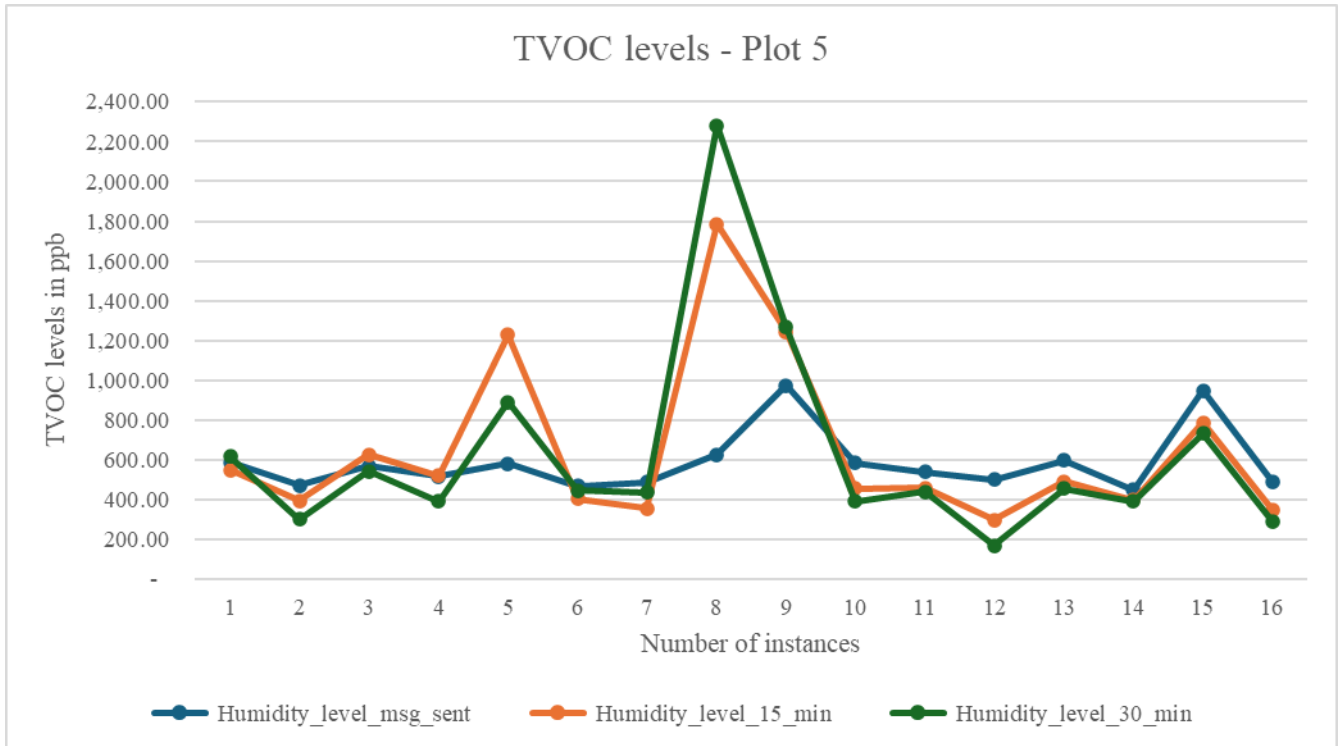


Figure 36: Comparison of TVOC levels in plot 5

Figure 37 shows the comparison of three levels of TVOC in plot 10. The high TVOC levels above 400ppb were reduced in 14 instances over the 15-minute window, while the 30-minute window showed reductions in 15 instances. Some instances showed that higher TVOC reductions were visible in the 30-minute window compared to the 15-minute window. Few examples are: 1) the 5th instance showed that the high TVOC levels were reduced from 1238ppb to 954ppb in the 15-minute window and it was further reduced to 903ppb in the 30-minute window, 2) the 6th instance showed high TVOC reductions from 940ppb to 741ppb in the 15-minute window and it was further decreased to 679ppb in the 30-minute window, 3) the 12th instance showed that the high TVOC levels were reduced from 608ppb to 247ppb in the 15-minute window and it was further reduced to 237ppb in the 30-minute window, 4) the 17th instance showed that the high TVOC levels were reduced from 1105ppb to 895ppb in the 15-minute window and it was further reduced to 817ppb in the 30-minute window. Most of the instances could not achieve the safe threshold of TVOC, which is 400ppb even though the high TVOC levels were decreased significantly. On the other hand, the 1st instance showed that the high TVOC levels were decreased from 2677ppb to 114ppb in the 15-minute window and showed a TVOC level of 139 ppb in the 30-minute window. This slight difference of 25 ppb between the 15-minute and 30-minute windows might have occurred due to a random fluctuation or sensor error or the amount of natural ventilation. Some instances such as the 15th instance and 16th instance showed a delayed action taken by the home occupant because the

TVOC levels were not reduced in the 15-minute window but reduced in the 30-minute window. In addition, some instances such as the 2nd, 7th, 9th, 10th, and 22nd instances show that the home occupant has not taken any action to reduce the high TVOC levels, suggesting no behavioural change after the delivery of the interventions.

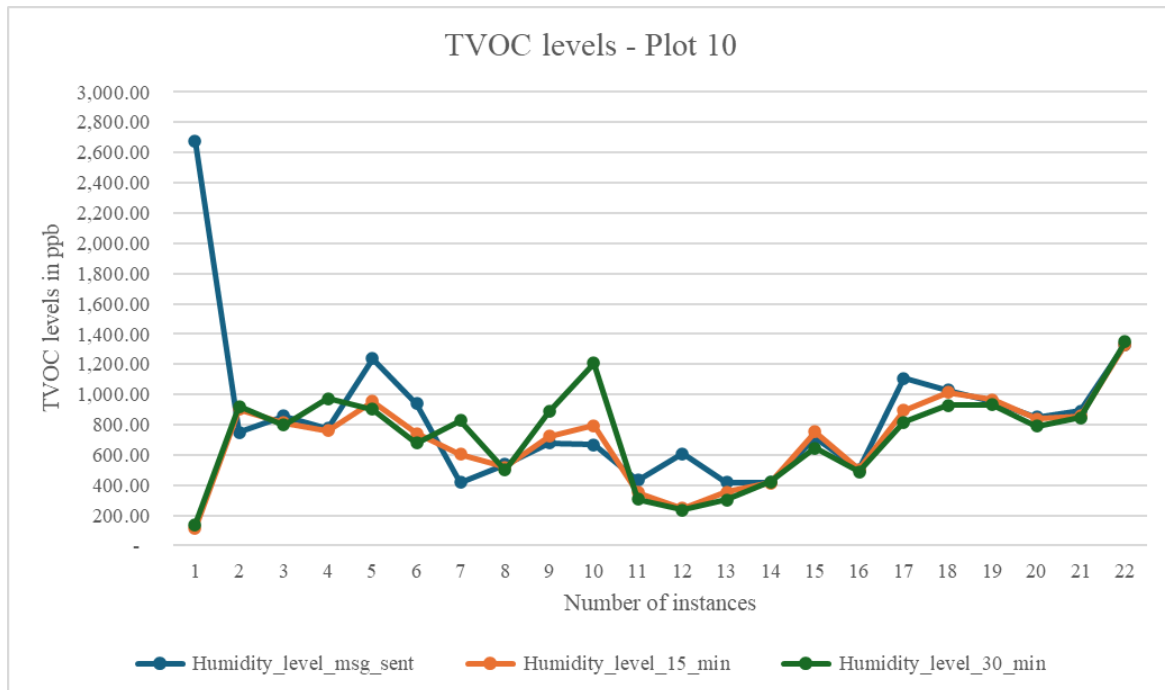


Figure 37: Comparison of TVOC levels in plot 10

Figure 38 shows the comparison of three TVOC levels in plot 12. The high TVOC levels above 400ppb were reduced in 6 instances within the 15-minutes window. Four instances showed reductions in high TVOC levels within the 30-minutes window. Only the 1st instances showed a high TVOC reduction from 436ppb to 255ppb in the 15-minutes window, while it was further dropped to 226ppb in the 30-minutes window, suggesting that a higher reduction can be observed in the 30-minutes window compared to the 15-minutes window. However, most of the instances out of the 9 instances showed that the home occupant had not taken any action to reduce the high TVOC levels. For examples, the 4th, 5th, 9th instances etc. The 2nd instance and 3rd instance showed that TVOC levels were slightly reduced in the first 15-minutes but increased in the next 15 minutes. This might be caused by the closing of windows after a few minutes.

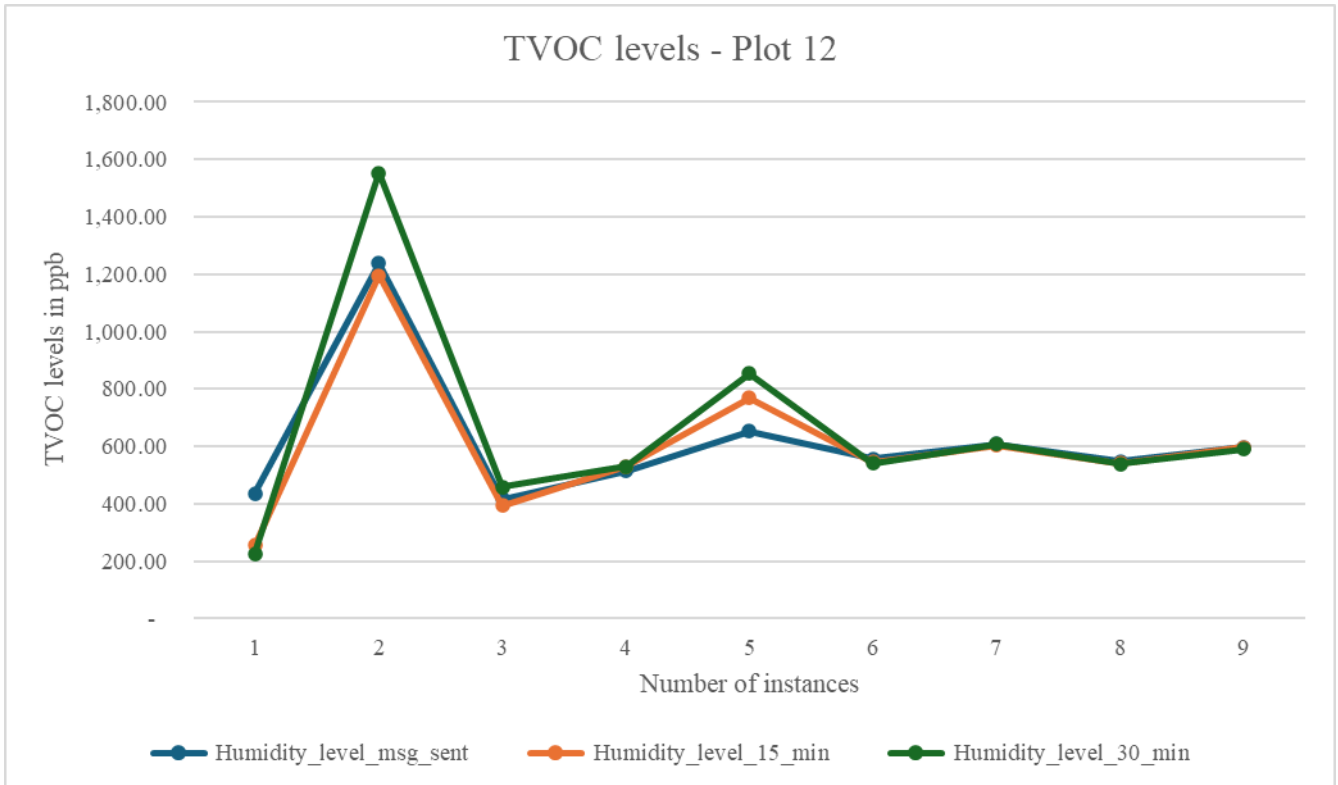


Figure 38: Comparison of TVOC levels in plot 12

In overall comparison, the empirical findings of this research showed that the 30-minute window is more appropriate to identify the significant reductions, as it provides more accurate results by providing 1) sufficient time for smart nudging interventions to reveal their true impact by reducing high TVOC levels, 2) adequate time for the TVOC levels to reduce and manifest, 3) sufficient time for the home occupant to act, 4) sufficient time to account for delays in actions, and 5) the opportunity to isolate the behavioural change by avoiding random fluctuations. Therefore, 30-minutes window is more appropriate for evaluation. In addition, the observed reductions in high TVOC levels may have been influenced by the duration of window opening, cooking patterns, and etc. Therefore, such factors may have caused delays in achieving the safe threshold of TVOC, which is 400ppb after the actions of the occupants.

5.2.3.4 Assessment of the impact of the smart nudging interventions

Table 21 shows the impact (positive impact or neutral impact or no/negative impact or uncertain impact) of each smart nudging intervention across the three plots on a weekly and a monthly basis in the 30-minute window.





	Time period	Smart nudging interventions	Mean difference	Number of instances/times the intervention was sent	Positive instances	No/Negative instances	Actual Impact comparison
Plot 5	One week	Feedback	-170	1	1	0	Grey
		Social comparison	+1.50	2	1	1	Yellow
	One month	Feedback	+190.20	5	4	1	Grey
		Social comparison	-17.78	9	6	3	Green
		Loss-aversion	-74.50	2	2	0	Green
Plot 10	One week	Social comparison	-2538	1	1	0	Grey
	One month	Feedback	-94.17	6	5	1	Green
		Social comparison	-294.33	9	6	3	Green
		Loss-aversion	+47.71	7	4	3	Grey
Plot 12	One week	Loss-aversion	-210	1	1	0	Grey
	One month	Feedback	-16	1	1	0	Grey
		Social comparison	+27.50	2	0	2	Red
		Loss-aversion	+47.67	6	3	3	Yellow
Legend							
	Positive impact		Neutral impact		No/Negative impact		Not conclusive/Uncertain impact

Table 21: Assessment of the impact of the smart nudging interventions - TVOC

According to Table 21, in plot 5, the impact of feedback is uncertain or not conclusive over the week, as the mean difference is based on a single instance. Social comparison showed a neutral impact over the week. Feedback showed an uncertain impact over the month, as the mean difference was positive, but the number of positive impact instances was higher than the no/negative impact instances. Few extreme no/negative values might be affected to the appearance of the positive mean difference of feedback. Therefore, a verification of the positive impact instances is needed to identify the true impact of feedback. Social comparison and loss-aversion showed positive impacts, as they indicated negative mean differences, and their number of positive impact instances are higher than the number of no/negative impact instances over the month.

In plot 10, the impact of social comparison is not conclusive because it has only a single instance. Both feedback and social comparison showed positive impacts on a monthly basis, as they showed negative mean differences, and their number of positive impact instances are higher than the number of no/negative impact instances on a monthly basis. Loss-aversion showed an uncertain impact, as it indicated a positive mean difference or an increase in high TVOC levels after the delivery, but the number of positive impact instances is higher than the number of no/negative impact instances. More specifically, the number of positive instances is

4 and number of no/negative impact instances is 3. Therefore, a verification of the positive instances is required to determine the true impact of loss aversion.

In plot 12, the impact of loss-aversion is uncertain or not conclusive over the first week of the intervention period because it has only one instance. Similarly, the impact of feedback is not conclusive, as it has only a single instance over the month. Social comparison showed a no/negative impact based on the positive mean difference and the two no/negative impact instances. Loss-aversion showed a neutral impact. Therefore, no smart nudging intervention succeeded in reducing high TVOC levels above 400ppb in plot 12.

5.2.3.5 Verification of the positive instances of the smart nudging interventions

5.2.3.5.1 Plot 5

Figure 39 shows the positive impact instances of feedback, social comparison, and loss-aversion in plot 5 on a monthly basis. Feedback showed significant TVOC reductions in all the positive instances. Feedback showed significant TVOC reductions from 474ppb to 304ppb, 503ppb to 170 ppb, 598ppb to 457ppb, and 452ppb to 392ppb in the 1st, 2nd, 3rd, and 4th positive instances, respectively. The 1st, 2nd, and 4th positive instances showed that high TVOC levels were reduced to reach safe thresholds. Only one instance, namely, the 3rd positive instance, showed a TVOC reduction from 598ppb to 457ppb but could not reach safe threshold. However, feedback showed a positive mean difference, as the only negative instance had a high value that extremely influenced the results compared to the four positive instances. However, all the four positive instances showed reductions, indicating that feedback is effective. Therefore, the ‘uncertain impact’ of feedback identified in Table 21 should be changed to a ‘positive impact’.

Social comparison showed high TVOC reductions in every positive instance. However, out of those 6 positive instances, only 2 instances showed significant reductions below the safe threshold of 400ppb. In addition, the 3rd, 5th, and 6th positive instances showed noteworthy reductions from 587ppb to 392 ppb, 951ppb to 735ppb, and 494ppb to 294ppb, respectively. Therefore, social comparison showed an overall positive impact. Loss-aversion showed positive impact, as both of the positive instances showed high TVOC reductions. In addition, out of those two positive instances, only one instance showed significant TVOC reductions from 517ppb to 392ppb. In conclusion, all three smart nudging interventions showed a positive impact. In comparison, feedback showed the highest positive impact, as the number of positive

instances that reached below the safe threshold of 400ppb is higher compared to social comparison and loss-aversion.



Figure 39: Plot 5 – Verification of the positive instances of TVOC – monthly

5.2.3.5.2 Plot 10

Figure 40 shows the positive impact instances of each smart nudging intervention in plot 10 over the month. Feedback showed high TVOC reductions in plot 10. However, any positive instance could not achieve a safe threshold below 400ppb. In contrast, social comparison showed significant high TVOC reductions below 400ppb. For examples, the 1st positive instance showed a reduction from 2677ppb to 139ppb, the 2nd positive instance showed a reduction from 433ppb to 308ppb, and the 3rd positive instance showed a reduction from 608ppb to 237ppb. Loss-aversion showed TVOC reductions in every positive instance. However, only one positive instance, namely, the 3rd positive instance, achieved a TVOC reduction below the safe threshold of 400ppb. Loss-aversion showed a positive mean difference, as shown in Table 21. The reason is that the extent of TVOC reductions were not substantial enough to highlight. In conclusion, the ‘uncertain impact’ of loss-aversion identified in Table 21 should be changed to a ‘positive impact’, as clear TVOC reductions were observed within the intervention period. In comparison, social comparison was highlighted as the most effective intervention in plot 10.

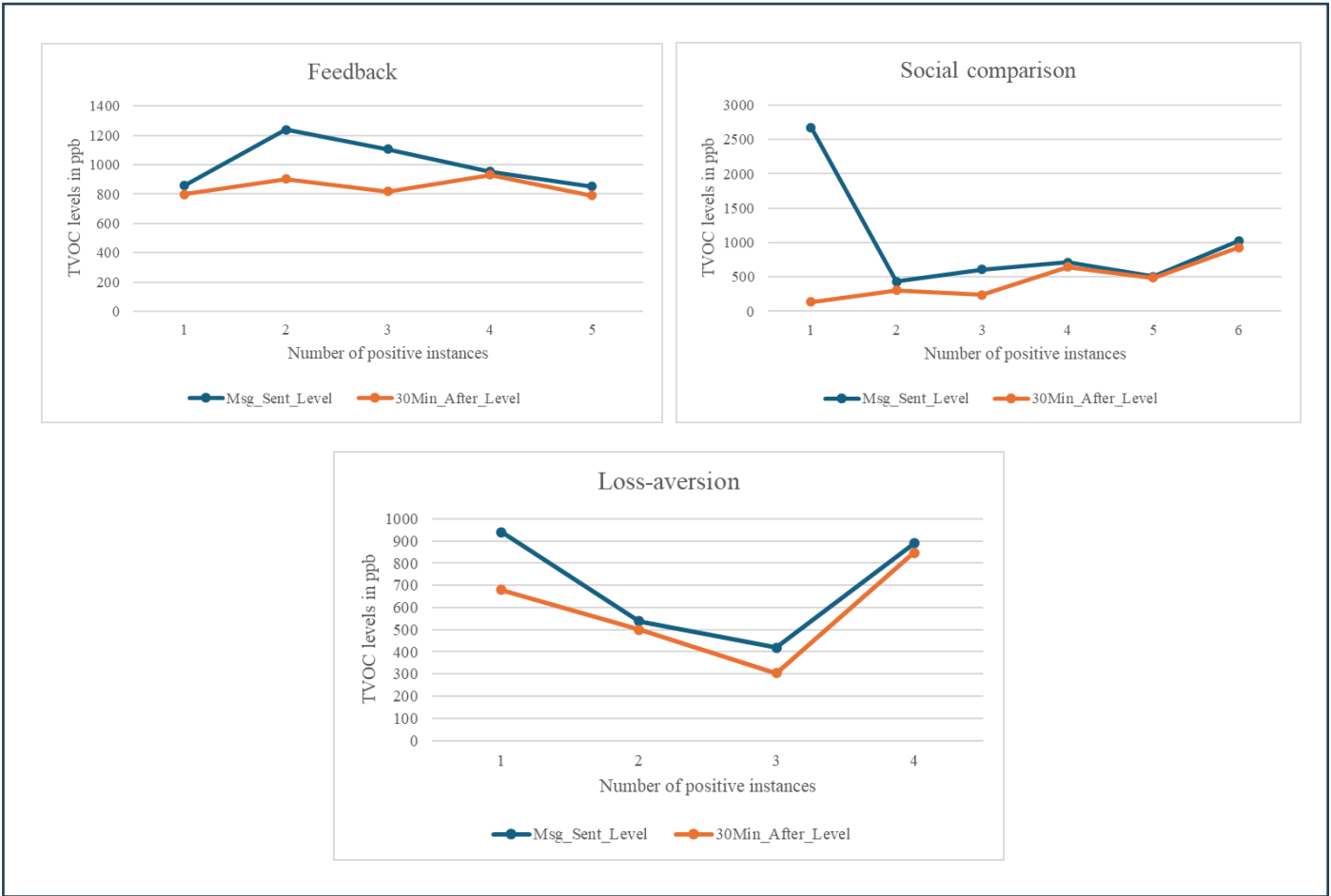


Figure 40: Plot 10 - Verification of the positive instances of TVOC – monthly

5.2.3.5.3 Plot 12

Figure 41 showed the positive impact instances in plot 12 over the intervention period. As per Table 21, loss-aversion showed a positive mean difference with a neutral impact. However, the Figure 41 shows that only one instance out of the positive instances showed a significant TVOC reduction. Therefore, loss-aversion cannot be considered as effective, as it could not show consistent significant reductions over the month and most of the instances were not effective.

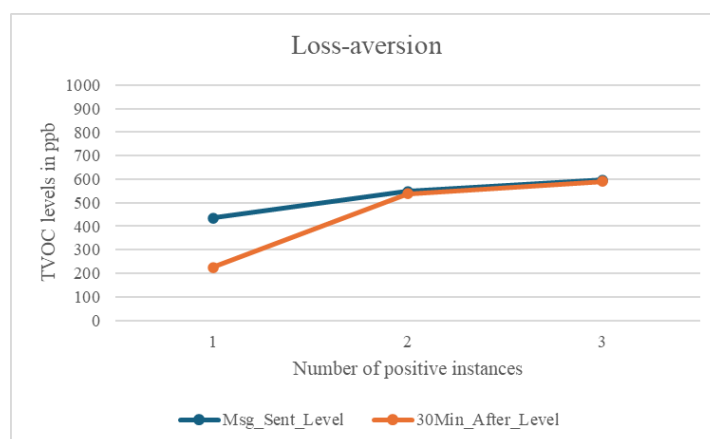


Figure 41: Plot 12 - Verification of the positive instances of TVOC – monthly

5.2.3.6 Assessment of the most effective smart nudging intervention – TVOC

Table 22 shows the summary of the most effective intervention in reducing high TVOC levels in each plot. Feedback emerged as the most effective intervention in plot 5 with a significant positive impact rate of 75%. Social comparison highlighted as the most effective intervention in plot 10 with a significant positive impact rate of 50%. No intervention was highlighted as the most effective intervention in plot 12. In overall comparison, feedback emerged as the most effective smart nudging intervention in achieving the safe threshold of TVOC with the highest significant positive impact rate.

	Time period	The most effective smart nudging intervention	Significant positive impact rate
Plot 5	One week	-	
	One month	Feedback	75%
Plot 10	One week	-	
	One month	Social comparison	50%
Plot 12	One week	-	
	One month	-	

Table 22: Most effective intervention – TVOC

5.2.3.7 Inferential statistics

Table 23 shows the inferential statistics related to TVOC in plot 10. Social comparison was identified as the most effective smart nudging intervention in plot 10 (see Table 22). Therefore, inferential statistics is performed to evaluate whether social comparison significantly outperform the other two interventions. On the other hand, feedback emerged as the most effective intervention in plot 5, as shown in Table 22. However, inferential statistics cannot be performed to assess the statistically significant difference between the interventions in plot 5, as the number of instances of loss-aversion is 2 (over the month), which may lead to unreliable results by reducing the statistical power. Therefore, inferential statistics is only conducted to assess the statistically significant difference in plot 10.

		Test name	Type of Smart nudging interventions	Test statistic	df	P-value	Effect size	Interpretation
Plot 10	TVOC reduction – one month	Friedman test	All interventions	1.00 (Chi-Square)	2	0.61	0.08 (Kendall's W)	Not statistically significant

Table 23: Inferential statistics – TVOC

The Friedman test results show a p-value of 0.61 ($\chi^2(2) = 1.00$, $W = 0.08$), showing no statistically significant difference between the three smart nudging interventions and a very low effect in reducing the high TVOC levels. More specifically, social comparison could not outperform the other two smart nudging interventions. High variability of data around their mean differences may have led to the absence of statistical significance. The observed positive instances of social comparison may not likely due to random variations but because of the home occupant's actions, as identified in Figure 40. However, a further assessment through triangulation with qualitative data from post-intervention interviews might be helpful to identify the impact of social comparison.

5.2.4 Temperature

5.2.4.1 Descriptive statistics

Table 24 shows the descriptive statistics of the three smart nudging interventions related to temperature in each plot within the 15-minute and 30-minute windows on a weekly and a monthly basis. If any smart nudging intervention was not delivered during any period in any plot, that row is left blank. In addition, the potential effectiveness of each smart nudging intervention in reducing high temperatures above 21⁰C is shown using three colours: green for a positive impact/reduction, red for a no/negative impact/increase, and grey for a not conclusive outcome or the availability of only a single instance based on their mean differences. On the other hand, the potential effectiveness of each smart nudging intervention in increasing low temperatures below 18⁰C is presented using three colours: green for a positive impact/increase in low temperatures up to a safe threshold, red for a no/negative impact/further reduction of low temperatures, and grey for a not conclusive outcome (or the availability of only a single instance) based on their mean differences.

	Time period	Type of smart nudging interventions	Mean difference of the smart nudging interventions	Number of times (instances) the intervention was sent	Standard deviations	Overall temperature improvement (potential effectiveness)		Remarks		
						Yes	No			
Plot 5	15-minutes window	One week below 18°C	Feedback	+0.06	7	0.09	✓		Positive impact	
			Social comparison	-	-	-	-	-	-	-
			Loss-aversion	0	10	0.07				Not conclusive/ uncertain impact
		One month above 21°C	Feedback	-0.11	16	0.24	✓			Positive impact/ Reduction
			Social comparison	+0.06	18	0.27		✓		Negative impact/ Increase
			Loss-aversion	+0.02	15	0.29		✓		Negative impact/ Increase
		One month below 18°C	Feedback	+0.03	19	0.08	✓			Positive impact
			Social comparison	-	-	-	-	-	-	-
			Loss-aversion	-0.02	19	0.15		✓		Negative impact
	30-minutes window	One week below 18°C	Feedback	+0.16	7	0.26	✓			Positive impact
			Social comparison	-	-	-	-	-	-	-
			Loss-aversion	+0.01	10	0.11	✓			Positive impact
		One month above 21°C	Feedback	-0.22	16	0.33	✓			Positive impact/ Reduction
			Social comparison	+0.01	18	0.33		✓		Negative impact/ Increase
			Loss-aversion	-0.03	15	0.32	✓			Positive impact/ Reduction
		One month below 18°C	Feedback	+0.06	19	0.18	✓			Positive impact
			Social comparison	-	-	-	-	-	-	-
			Loss-aversion	+0.02	19	0.09	✓			Positive impact
Plot 10	15-minutes window	One week above 21°C	Feedback	-0.03	12	0.14	✓		Positive impact/ Reduction	
			Social comparison	-0.05	11	0.16	✓		Positive impact/ Reduction	
			Loss-aversion	-0.26	8	0.53	✓		Positive impact/ Reduction	
		One month above 21°C	Feedback	-0.03	59	0.17	✓			Positive impact/ Reduction
			Social comparison	-0.02	63	0.19	✓			Positive impact/ Reduction

Plot 12		One month below 18°C	Loss-aversion	-0.08	52	0.26	✓		Positive impact/ Reduction		
			Feedback	+0.70	3	1.57	✓		Positive impact		
			Social comparison	-	-	-					
			Loss-aversion	-	-	-					
	30-minutes window	One week above 21°C	Feedback	-0.08	12	0.22	✓		Positive impact/ Reduction		
			Social comparison	-0.44	11	1.10	✓		Positive impact/ Reduction		
			Loss aversion	-0.26	8	0.48	✓		Positive impact/ Reduction		
		One month above 21°C	Feedback	-0.10	59	0.38	✓		Positive impact/ Reduction		
			Social comparison	-0.16	63	0.53	✓		Positive impact/ Reduction		
			Loss-aversion	-0.10	52	0.35	✓		Positive impact/ Reduction		
		One month below 18°C	Feedback	+1.00	3	2.44	✓		Positive impact		
			Social comparison	-	-	-	-	-	-		
			Loss-aversion	-	-	-	-	-	-		
		Plot 12	15-minutes window	One week above 21°C	Feedback	+0.06	8	0.16		✓	Negative impact/ Increase
					Social comparison	-0.03	3	0.06	✓		Positive impact/ Reduction
Loss-aversion	+0.03				3	0.12		✓	Negative impact/ Increase		
One month above 21°C	Feedback			+0.009	34	0.24		✓	Negative impact/ Increase		
	Social comparison			-0.004	26	0.27	✓		Positive impact/ Reduction		
	Loss-aversion			-0.06	26	0.53	✓		Positive impact/ Reduction		
One month below 18°C	Feedback			-0.03	3	0.15		✓	Negative impact		
	Social comparison			-	-	-	-	-	-		
	Loss-aversion			+0.13	4	0.13	✓		Positive impact		
30-minutes window	One week above 21°C		Feedback	+0.26	8	0.47		✓	Negative impact/ Increase		
			Social comparison	+0.07	3	0.21		✓	Negative impact/ Increase		
			Loss-aversion	-0.03	3	0.23	✓		Positive impact/ Reduction		
	One month		Feedback	+0.05	34	0.43		✓	Negative impact/ Increase		

	above 21°C	Social comparison	-0.01	26	0.37	✓		Positive impact/ Reduction
		Loss-aversion	-0.01	26	0.77	✓		Positive impact/ Reduction
	One month below 18°C	Feedback	-0.03	3	0.23		✓	Negative impact
		Social comparison	-	-	-	-	-	-
		Loss-aversion	+0.20	4	0.27	✓		Positive impact
	Legend							
Positive impact / Reduction - Potential effectiveness			No or Negative impact / Increase - Potential effectiveness			Not conclusive impact		

Table 24: Descriptive statistics - Temperature

5.2.4.1.1 Plot 5

As per Table 24, the descriptive statistics related to each smart nudging intervention within the 15-minute window suggest that only feedback shows the potential effectiveness in increasing the low indoor temperatures below 18°C on a weekly and a monthly basis. Feedback shows a positive mean difference of 0.06 and 0.03 on a weekly and a monthly basis, respectively. Feedback shows a standard deviation of 0.09 based on seven instances and a standard deviation of 0.08 based on 19 instances on a weekly and a monthly basis, respectively. Social comparison was not sent during the entire intervention period to increase the low temperatures below 18°C. This might have happened due to the random selection of the smart nudging interventions. The results suggest that the mean temperature increase of loss-aversion is zero on a weekly basis, showing no overall change in temperature after the delivery of the interventions, leading to a not conclusive/uncertain impact that requires a further assessment. Loss-aversion shows a mean difference of -0.02 over the month with a standard deviation of 0.15 based on 19 instances, indicating no potential effectiveness.

In reviewing the 15-minute window on a monthly basis, feedback shows a mean difference of -0.11 with a standard deviation of 0.24 based on 16 instances. Social comparison shows a mean difference of +0.06 with a standard deviation of 0.27, and this result is based on 18 instances. Loss-aversion shows a mean difference of +0.02 with a standard deviation of 0.29, based on 15 instances. These results suggest that feedback shows a small reduction (potential effectiveness) in high temperatures above 21°C in plot 5 after the delivery of the interventions. Social comparison and loss-aversion show a small increase in high temperatures after the delivery of the interventions, showing no potential effectiveness.

In reviewing the 30-minute window of plot 5, both feedback and loss-aversion show the potential effectiveness in increasing the low indoor temperatures below 18°C on a weekly and

a monthly basis. Feedback shows positive mean differences of 0.16 and 0.06 on a weekly and a monthly basis, respectively. Feedback shows a standard deviation of 0.26 based on seven instances and a standard deviation of 0.18 based on 19 instances on a weekly and a monthly basis, respectively. Loss-aversion shows a mean difference of +0.01 and a mean difference of +0.02 on a weekly and a monthly basis, respectively. Loss-aversion shows a standard deviation of 0.11 based on 10 instances over the week. In addition, loss-aversion shows a standard deviation of 0.09 based on 19 instances over the month. Social comparison was not sent during the entire intervention period to increase the low temperatures below 18⁰C.

In reviewing the 30-minute window of plot 5 on a monthly basis, both feedback and loss-aversion indicate negative mean differences, suggesting potential effectiveness in reducing high temperatures above 21⁰C. Feedback shows a mean difference of -0.22 with a standard deviation of 0.33 based on 16 instances. Loss-aversion shows a mean difference of -0.03 with a standard deviation of 0.32 based on 15 instances. Social comparison shows a mean difference of +0.01 with a standard deviation of 0.33 based on 18 instances. Therefore, only social comparison shows a small increase in high temperatures after the delivery of the interventions, showing no potential effectiveness.

In comparison, loss-aversion showed a positive mean difference, denoting a no/negative impact after the intervention delivery within the 15-minute window over the month. However, loss-aversion showed a negative mean difference, suggesting potential effectiveness in the 30-minute window over the month. Similarly, loss-aversion showed no potential effectiveness in increasing low temperatures below 18⁰C in the 15-minute window over the month. In contrast, loss-aversion showed potential effectiveness in increasing low temperatures below 18⁰C in the 30-minute window over the month. However, the data suggest that all the mean differences of all the smart nudging interventions are close to zero, denoting no considerable improvements in temperatures.

5.2.4.1.2 Plot 10

According to Table 24, the descriptive statistics of the smart nudging interventions in the 15-minute window in plot 10 show that the mean differences of feedback are -0.03 with a standard deviation of 0.14 based on 12 instances and -0.03 with a standard deviation of 0.17 based on 59 instances on a weekly and a monthly basis, respectively. Social comparison shows a mean difference of -0.05 with a standard deviation of 0.16 based on 11 instances and a mean difference of -0.02 with a standard deviation of 0.19 based on 63 instances on a weekly and a

monthly basis, respectively. Loss-aversion shows a mean difference of -0.26 with a standard deviation of 0.53 based on 8 instances and a mean difference of -0.08 with a standard deviation of 0.26 based on 52 instances on a weekly and a monthly basis, respectively. These results suggest that all three smart nudging interventions show reductions in high temperatures (above 21⁰C) after the delivery of the interventions and thereby, showing potential effectiveness in both weekly and monthly. Only feedback was delivered during the intervention period of one month to increase the low temperatures below 18⁰C. Feedback shows a mean difference of +0.70 with a standard deviation of 1.57 based on 3 instances, showing potential effectiveness.

In reviewing the 30-minute window of plot 10, feedback shows a small mean difference of -0.08 with a standard deviation of 0.22 based on 12 instances and a mean difference of -0.10 with a standard deviation of 0.38 based on 59 instances on a weekly and a monthly basis, respectively. Social comparison shows a mean difference of -0.44 with a standard deviation of 1.10 based on 11 instances and a mean difference of -0.16 with a standard deviation of 0.53 based on 63 instances on a weekly and a monthly basis, respectively. Loss-aversion shows a mean difference of -0.26 with a standard deviation of 0.48 based on 8 instances and a mean difference of -0.10 with a standard deviation of 0.35 based on 52 instances on a weekly and a monthly basis, respectively. These results reveal that all three smart nudging interventions indicate reductions in high temperatures (above 21⁰C) after the delivery of the interventions in both weekly and monthly. Therefore, all the three smart nudging interventions show potential effectiveness. Only feedback was delivered during the intervention period to increase the low temperatures below 18⁰C. Feedback shows a mean difference of +1.00 with a standard deviation of 2.44 based on 3 instances, showing potential effectiveness.

5.2.4.1.3 Plot 12

In analysing the 15-minute window of plot 12 shown in Table 24, feedback shows a positive mean difference of 0.06 with a standard deviation of 0.16 based on 8 instances and a very small positive mean difference of 0.009 with a standard deviation of 0.24 based on 34 instances on a weekly and a monthly basis, respectively. Social comparison shows a negative mean difference of 0.03 with a standard deviation of 0.06 based on 3 instances and a very small negative mean difference of 0.004 with a standard deviation of 0.27 based on 26 instances on a weekly and a monthly basis, respectively. Loss-aversion shows a positive mean difference of 0.03 with a standard deviation of 0.12 based on 3 instances and a negative mean difference of 0.06 with a standard deviation of 0.53 based on 26 instances on a weekly and a monthly basis, respectively. These results suggest that only social comparison shows reductions in high temperatures

(above 21⁰C) after the delivery of the interventions over the week and thereby, showing potential effectiveness. However, both social comparison and loss-aversion show potential effectiveness in reducing high temperature levels above 21⁰C over the month. Nevertheless, social comparison shows no considerable difference, as the mean difference almost equals to zero. Feedback and loss-aversion were delivered over the month to increase the low temperatures below 18⁰C. Feedback shows a negative mean difference of 0.03 with a standard deviation of 0.15 based on 3 instances, showing no potential effectiveness. Loss-aversion shows a positive mean difference of 0.13 with a standard deviation of 0.13 based on 4 instances, showing potential effectiveness.

In investigating the 30-minute window in plot 12, only loss-aversion shows potential effectiveness in reducing high temperatures above 21⁰C on a weekly basis. Loss-aversion shows a negative mean difference of 0.03 with a standard deviation of 0.23 based on 3 instances. Both feedback and social comparison show no potential effectiveness in reducing high temperatures above 21⁰C on a weekly basis. Feedback shows a positive mean difference of 0.26 with a standard deviation of 0.47 based on 8 instances. Social comparison shows a positive mean difference of 0.07 with a standard deviation of 0.21 based on 3 instances. Both social comparison and loss-aversion show potential effectiveness in reducing high temperatures above 21⁰C over the month. Social comparison shows a negative mean difference of 0.01 with a standard deviation of 0.37 based on 26 instances. Loss-aversion shows a negative mean difference of 0.01 with a standard deviation of 0.77 based on 26 instances. Feedback shows a positive mean difference of 0.05 with a standard deviation of 0.43 based on 34 instances, indicating no potential effectiveness. Similarly, feedback shows no potential effectiveness in increasing low temperatures below 18⁰C over the month. Feedback shows a negative mean difference of 0.03 with a standard deviation of 0.23 based on 3 instances. Social comparison was not delivered over the intervention period to increase low temperatures. Loss-aversion shows a positive mean difference of 0.20 with a standard deviation of 0.27 based on 4 instances, showing potential effectiveness.

In comparison, social comparison showed a negative mean difference, representing potential effectiveness in reducing high temperatures above 21⁰C within the 15-minute window over the week. However, social comparison showed a positive mean difference, suggesting no potential effectiveness in the 30-minute window over the week. Similarly, loss-aversion showed no potential effectiveness in reducing high temperatures above 21⁰C in the 15-minute window over the week. In contrast, loss-aversion showed potential effectiveness in reducing high

temperatures above 21⁰C in the 30-minute window over the week. However, the data indicate that all the mean differences of all the smart nudging interventions are close to zero, implying no considerable improvements in temperatures.

5.2.4.2 Assessment of the most effective intervention – temperature

Table 24 shows that most of the mean temperature differences of the smart nudging interventions are close to zero in both 15-minute and 30-minute windows. Therefore, it is important to assess the real effectiveness of all the interventions individually through visualisation over the intervention period. The real effectiveness of smart nudging interventions is assessed by comparing the three levels of temperature: 1) temperature at the message sent time, 2) temperature at the 15 minutes post-delivery, and 3) temperature at the 30-minutes post-delivery.

5.2.4.2.1 Plot 5

Figure 42 shows the three levels of temperature related to each smart nudging intervention within the 15-minute and 30-minute windows in plot 5. Feedback showed high temperature reductions by 1⁰C in a single instance but did not achieve the safe threshold in that single instance. For example: the 2nd instance showed a 1⁰C temperature reduction from 24.2⁰C to 23.1⁰C in the 30-minute window. The other instances of feedback did not show significant reductions. Therefore, feedback could not maintain consistent effectiveness. However, a further assessment is needed to identify whether this reduction was caused by a random fluctuation or by an occupant's action. Social comparison showed no significant reductions in high temperatures above 21⁰C, suggesting no real effectiveness. This agrees with the descriptive statistics shown in Table 24, as social comparison showed a positive mean difference, indicating no effectiveness in both 15-minute and 30-minute windows. In contrast, the loss-aversion showed a small negative mean difference within the 30-minute window as shown in Table 24, indicating potential effectiveness. However, loss-aversion showed no real effectiveness, as it did not show any temperature reductions in Figure 42.

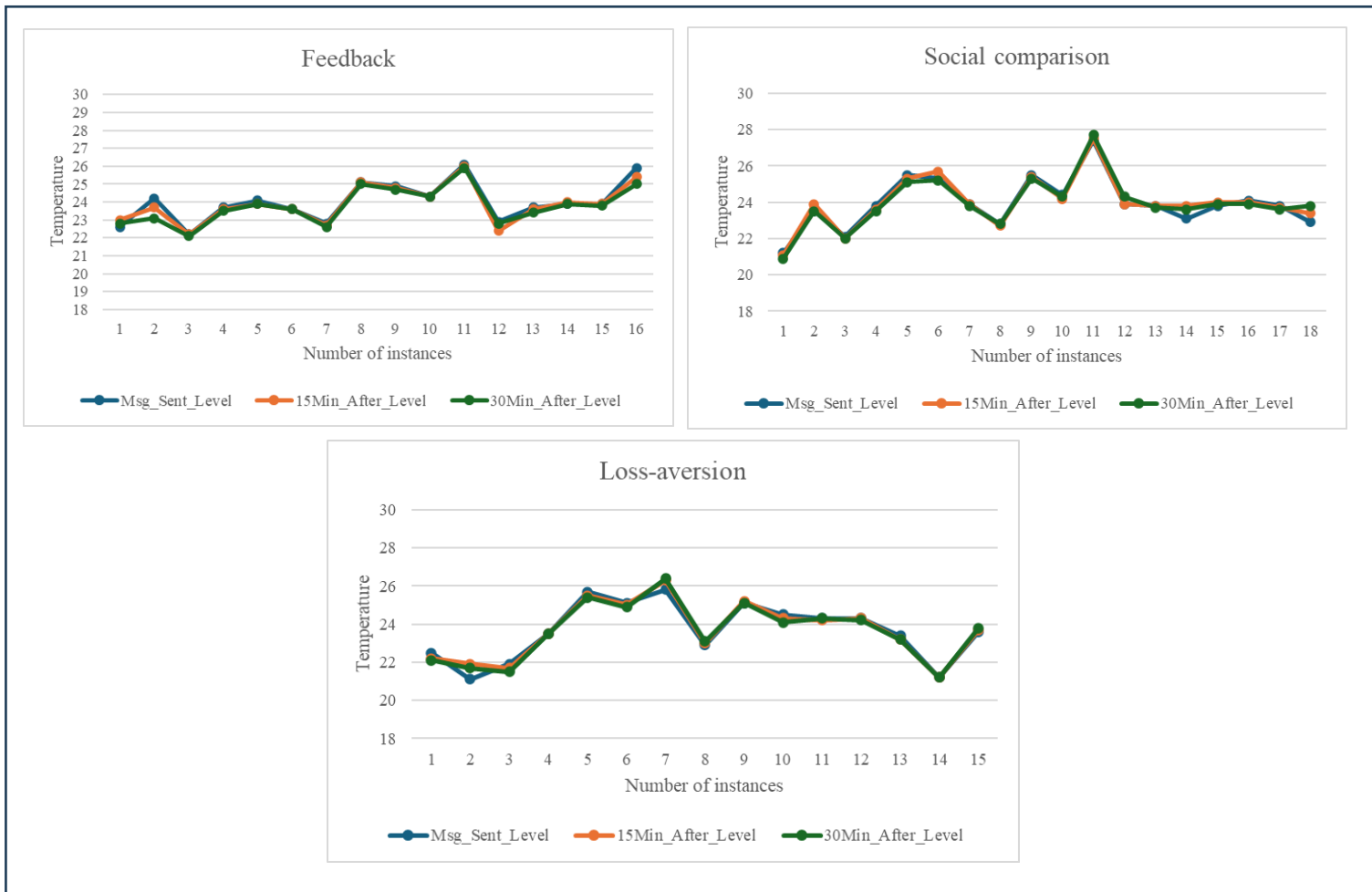


Figure 42: Temperatures above 21⁰C - Plot 5

Figure 43 shows the three levels of temperature (below 18⁰C) related to feedback and loss-aversion within the 15-minute and 30-minute windows in plot 5. Feedback showed an improvement in low temperatures below 18⁰C by 1⁰C in a single instance and achieved the safe threshold in that single instance. For example: the 1st instance showed a 1⁰C temperature increase from 17.4⁰C to 18.1⁰C in the 30-minute window. The other instances of feedback did not show significant improvements. Therefore, feedback could not maintain consistent effectiveness in increasing low temperatures. As a result, a further evaluation is needed to identify whether this improvement is caused by the impact of feedback or due to a random fluctuation. Moreover, loss-aversion did not show any significant improvements in low temperatures. In contrast, the descriptive statistics shown in Table 24 showed that loss-aversion was potentially effective, as it indicated a positive mean difference in the 30-minute window. However, Figure 43 shows that loss-aversion shows no real effectiveness.

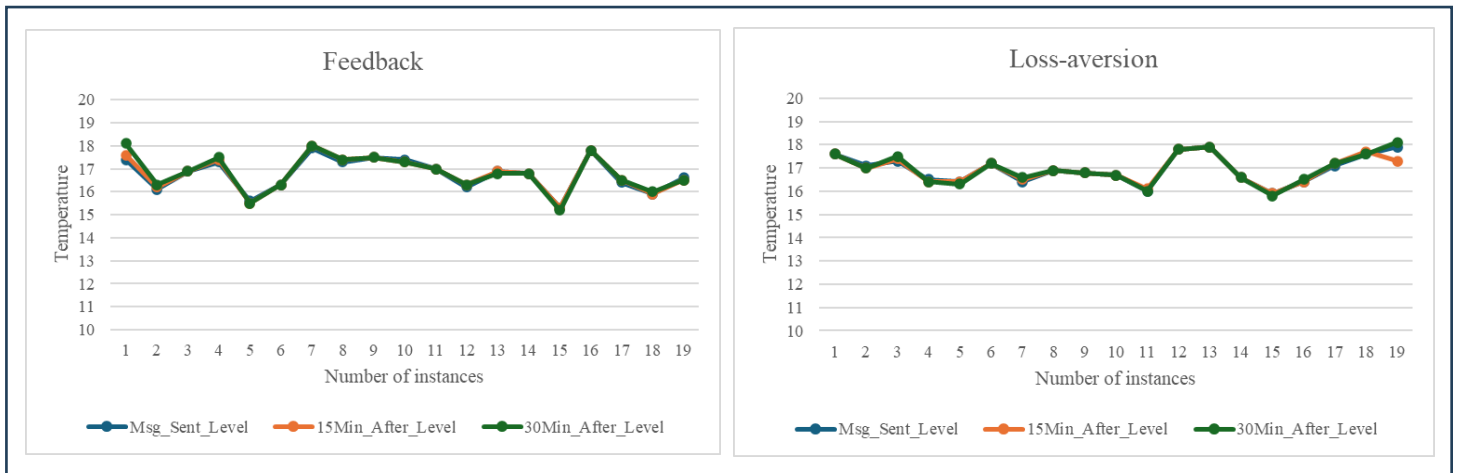


Figure 43: Temperatures below 18°C - Plot 5

5.2.4.2.2 Plot 10

Figure 44 shows the three levels of temperature reductions related to the three smart nudging interventions within the 15-minute and 30-minute windows in plot 10. Feedback and social comparison showed reductions in high temperatures above 21°C in single instances within the 30-minute windows. The 45th instance of feedback showed a temperature reduction from 25.6°C to 23.5°C in the 30-minute window. The 3rd instance of social comparison showed a temperature reduction from 22.7°C to 19°C in the 30-minute window. However, both feedback and social comparison could not maintain positive impact in multiple instances consistently. Therefore, it is necessary to assess whether these observed reductions were caused by the behavioural changes or due to random fluctuations. In addition, both feedback and social comparison showed negative mean differences in Table 24, indicating potential effectiveness. On the other hand, loss-aversion was not effective in nudging the home occupant towards reducing high temperatures, as it did not show reductions in Figure 44. In contrast, loss-aversion showed negative mean differences, indicating potential effectiveness in Table 24. However, Figure 44 reveals that loss-aversion shows no real effectiveness in reducing high temperatures above 21°C within the 15-minute and 30-minute windows in plot 10.

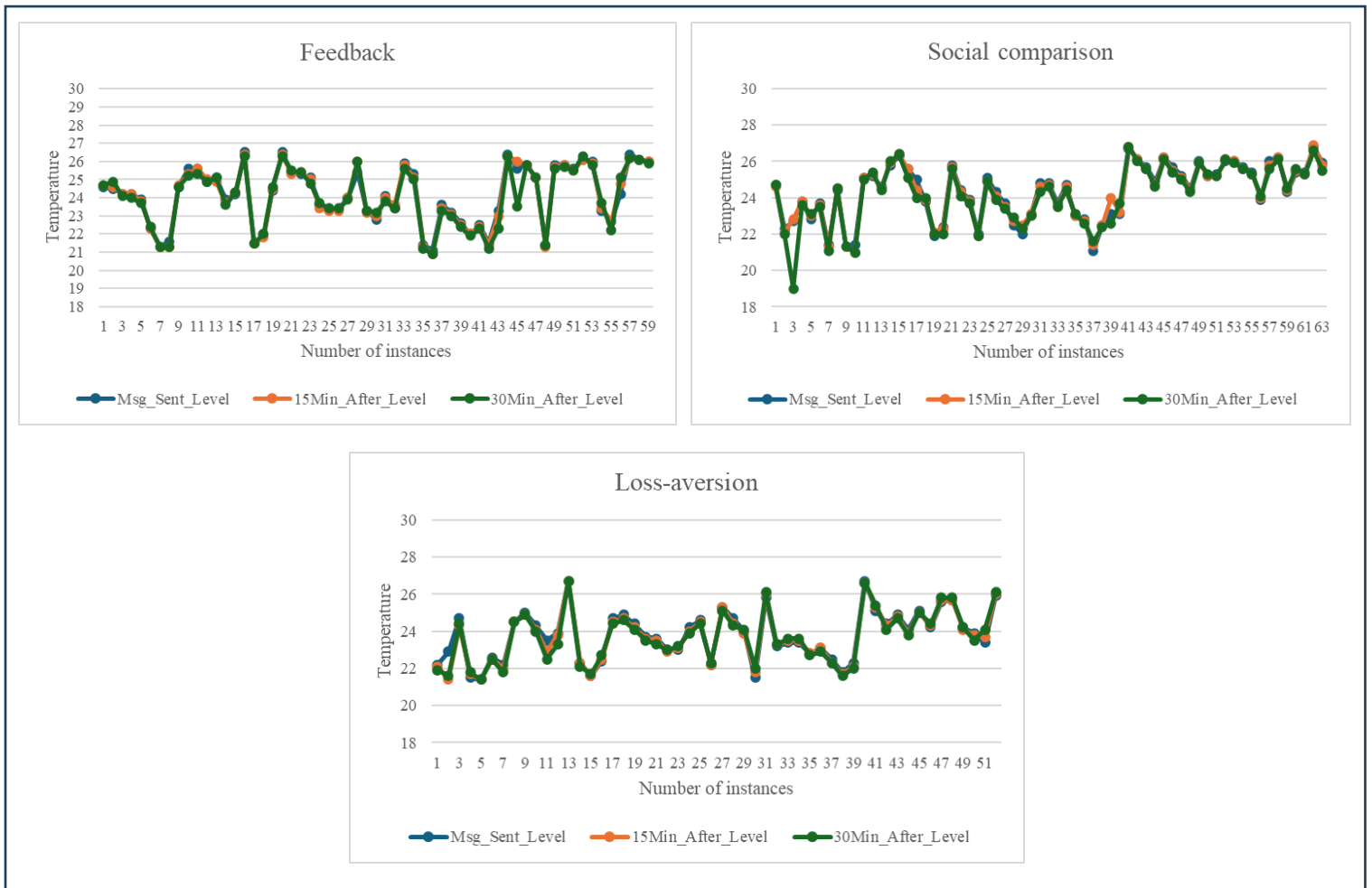


Figure 44: Temperatures above 21°C - Plot 10

Figure 45 shows the three levels of temperature related to feedback within the 15-minute and 30-minute windows in plot 10. Feedback showed an improvement in low temperatures below 18°C in a single instance but could not achieve the safe threshold in that single instance. For example: the 1st instance showed a temperature increase from 11.9°C to 15.7°C in the 30-minute window. In addition, Table 24 showed that feedback was potentially effective in increasing low temperatures, as it displayed a positive mean difference in the 30-minute window. However, feedback could not maintain a consistent positive impact in the other two instances. Therefore, a further assessment is needed to identify whether this improvement was caused because of the occupant's action or due to a random fluctuation.

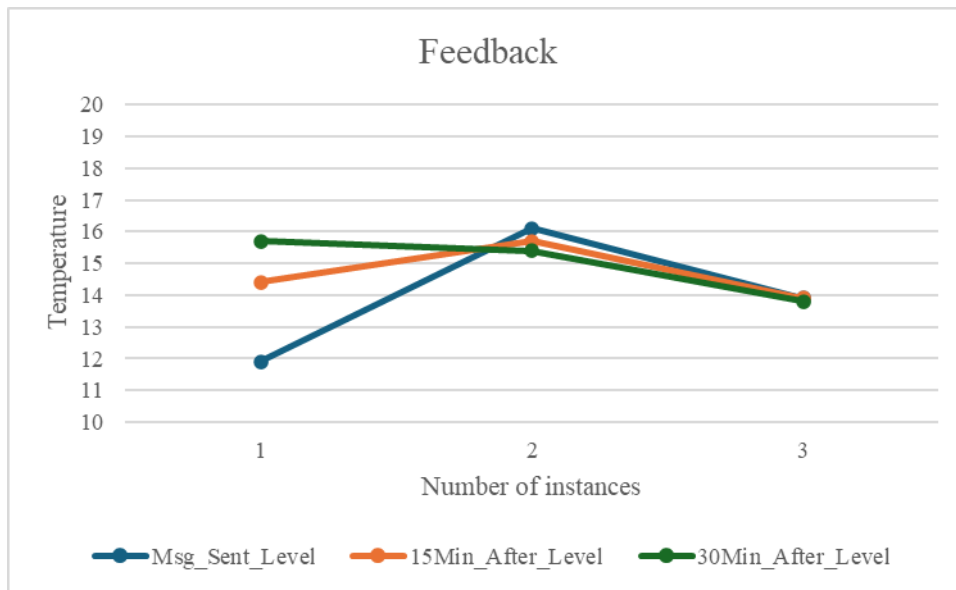


Figure 45: Temperatures below 18°C - Plot 10

5.2.4.2.3 Plot 12

Figure 46 shows the three levels of temperature related to the three smart nudging interventions within the 15-minute and 30-minute windows in plot 12. Feedback showed no significant reductions in high temperatures above 21°C. Therefore, feedback showed no effectiveness in plot 12. In addition, Table 24 showed that feedback was potentially not effective, as it showed positive mean differences in both 15-minute and 30-minute windows. In contrast, social comparison showed potential effectiveness, as it showed negative mean differences in both 15-minute and 30-minute windows on a monthly basis in Table 24. However, Figure 46 reveals that social comparison is not effective in both 15-minute and 30-minute windows, indicating no real effectiveness. Only loss-aversion showed high temperature reduction by 1°C in a single instance. For example: the 16th instance showed a temperature reduction from 24.8°C to 21.6°C in the 30-minute window. The other instances of loss-aversion did not show significant reductions. Therefore, loss-aversion could not maintain consistent effectiveness. As a result, a further assessment is needed to identify whether this reduction was caused as a result of the home occupant's action or due to a random fluctuation.

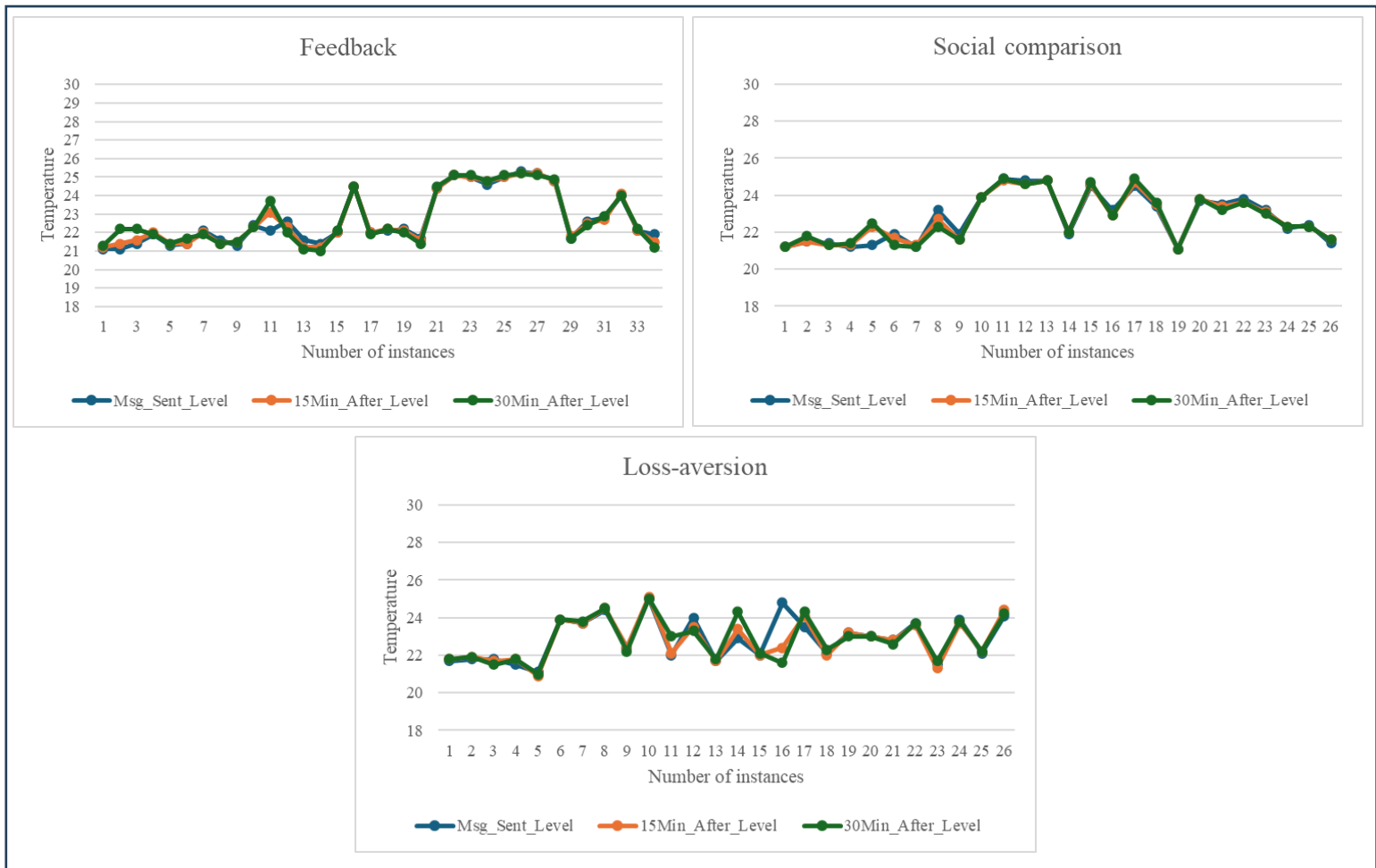


Figure 46: Temperatures above 21°C - Plot 12

Figure 47 shows the three levels of temperature (below 18°C) related to feedback and loss-aversion within the 15-minute and 30-minutes windows in plot 12. Both feedback and loss-aversion showed no improvements in low temperatures below 18°C. Therefore, feedback and loss-aversion show no real effectiveness in increasing low temperatures in plot 12.

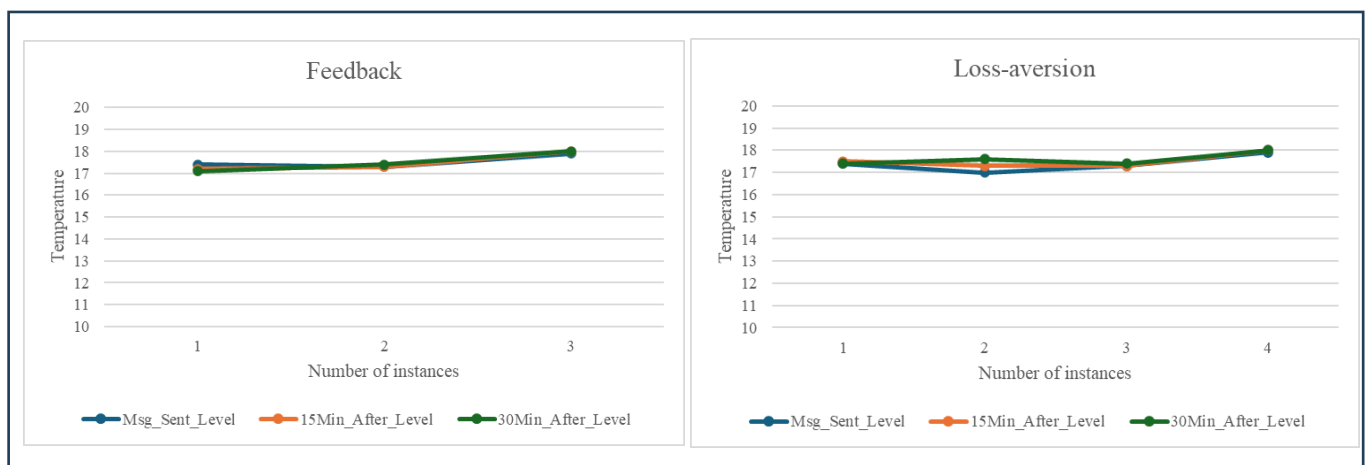


Figure 47: Temperatures below 18°C - Plot 12

5.2.4.3 Inferential statistics

Table 25 shows the inferential statistics related to temperature in plots 5, 10, and 12. The Friedman test is conducted to identify whether there is any statistically significant difference between the three smart nudging interventions in reducing high temperatures above 21°C. The Wilcoxon Signed-Rank test is performed to assess the statistical significance of the interventions in improving the low temperatures below 18°C.

		Test name	Type of Smart nudging interventions	Test statistic	df	P-value	Effect size	Interpretation
Plot 5	Temperature above 21°C	Friedman test	All interventions	1.00 (Chi-Square)	2	0.61	0.03 (Kendall's W)	Not statistically significant
	Temperature below 18°C	Wilcoxon Signed-Rank Test	Feedback	1.33 (z-value)	19	0.19	r = 0.31	Not statistically significant
			Loss-aversion	1.04 (z-value)	19	0.29	r = 0.24	Not statistically significant
Plot 10	Temperature above 21°C	Friedman test	All interventions	0.85 (Chi-Square)	2	0.65	0.008 (Kendall's W)	Not statistically significant
Plot 12	Temperature above 21°C	Friedman test	All interventions	0.33 (Chi-Square)	2	0.85	0.006 (Kendall's W)	Not statistically significant

Table 25: Inferential statistics – Temperature

In plot 5, the Friedman test results of the parameter, which is the temperature above 21°C, show a p-value of 0.61 ($\chi^2(2) = 1.00$, $W = 0.03$), showing no statistically significant difference between the three smart nudging interventions and a very low effect in reducing the high temperatures. The Wilcoxon Signed-Rank Test results of the parameter, which is the temperature below 18°C, show a p-value of 0.19 ($z(19) = 1.33$, effect size = 0.31), showing no statistically significant difference between the pre- and post-delivery of feedback and a small effect in improving the low temperatures. Similarly, the Wilcoxon Signed-Rank Test results of the parameter, which is the temperature below 18°C, show a p-value of 0.29 ($z(19) = 1.04$, effect size = 0.24), showing no statistically significant difference between the pre- and post-delivery of loss-aversion and a small effect in improving the low temperatures. Therefore, feedback and loss-aversion do not have strong impacts on increasing the low temperatures.

The Friedman test results of the parameter, which is the temperature above 21°C in plot 10, show a p-value of 0.65 ($\chi^2(2) = 0.85$, $W = 0.008$), showing no statistically significant difference among the three smart nudging interventions and a very low effect in reducing the high temperatures. Similarly, the Friedman test results of the parameter, namely, the temperature

above 21⁰C in plot 12, show a p-value of 0.85 ($\chi^2(2) = 0.33$, $W = 0.006$), showing no statistically significant difference between the three smart nudging interventions and a very low effect in reducing the high temperatures. These results reveal that any intervention could not outperform the other two interventions in a meaningful way. Moreover, these inferential statistics reveal that the single positive impact instances that showed temperature reductions or temperature improvements in plots 5, 10 and 12 were likely be due to random variations but not because of the home occupant's actions.

In conclusion, no smart nudging intervention showed real effectiveness in reducing the high temperatures or improving the low temperatures. These results agree with the study of Myers and Souza (2020), as no significant positive impact was observed after delivering the smart nudging interventions. In contrast, the existing studies, such as 1) Kim et al. (2022) showed that feedback delivered through a mobile application indicated a positive impact on occupant behaviours and improving thermostat settings; however, specific percentages of thermostat changes or the positive impact percentage was not provided in the study and 2) the study of Mogles et al. (2017) showed that the feedback delivered through an application reduced the mean household temperature from 22.4⁰C to 21.7⁰C and the temperature reduction was statistically significant, and 3) Canale et al. (2021) showed that social comparison reduced the heating consumption by 17%.

5.2.5 Summary of the quantitative findings

Table 26 shows the summary of the quantitative findings related to the most effective smart nudging intervention in improving each indoor air quality parameter separately. This shows that smart nudging interventions can improve indoor air quality parameters by changing behaviours of the home occupants.

Indoor air quality parameter	Most effective intervention	Significant positive impact rate
CO ₂	Loss-aversion	100%
Relative humidity	Feedback	29%
TVOC	Feedback	75%
Temperature	-	-

Table 26: Summary of the quantitative findings

The most effective smart nudging interventions for improving CO₂, relative humidity, and TVOC are loss-aversion with a significant positive impact rate of 100%, feedback with a significant positive impact rate of 29%, and feedback with a significant positive impact rate of 75%, respectively. No smart nudging intervention was effective in improving temperature. In overall comparison, loss-aversion emerge as the most effective smart nudging intervention for

improving overall indoor air quality because it achieved a 100% significant positive impact rate. These findings answer the first and second research questions, which is ‘Can smart nudging interventions induce behavioural changes that improve indoor air quality parameters to reach the recommended thresholds in house?’ and 2) ‘What is the most effective smart nudging intervention in reducing indoor air emissions related to household energy consumption and improving indoor air quality holistically in the residential settings?’, from a quantitative perspective. However, these quantitative findings should be triangulated with the qualitative findings to answer the research questions in a robust way.

5.3 Qualitative findings

The results and discussion of the pre-intervention and post-intervention interviews are presented below. The pre-intervention interviews were conducted to understand the existing behaviours of the home occupants, their daily routines including occupancy periods, perceptions, choices, and beliefs to formulate the smart nudging interventions. The post-intervention interviews were conducted to triangulate the quantitative research findings.

5.3.1 Pre-intervention interviews - findings

The results obtained from the pre-intervention interviews are analysed to understand the occupants’ existing behaviours, perceptions, daily routines, and beliefs and contribute towards the formulation of the extended smart nudge design and logics of the smart nudging interventions. The results are analysed under four main themes: 1) understanding existing behaviours, 2) occupancy period, 3) knowledge about air emissions associated with household energy use, and 4) interventions for sustainable behavioural change. Table 27 shows the results of the pre-intervention interviews conducted across the three plots.

Themes	Codes	Sub-codes	Plot 5		Plot 10		Plot 12	
			Summary of the findings	Quotes	Summary of the findings	Quotes	Summary of the findings	Quotes
Understanding existing behaviours	Reducing stuffiness	Regular cooking	The householder cooks regularly. The householder opens the kitchen window and uses the extractor fan while cooking. However, the householder does not close the kitchen door.	<i>“I definitely open kitchen windows and put the extractor on when cooking regularly. I do not close the kitchen door because I need to check on my kids”</i>	The householder cooks regularly. The householder closes the kitchen door, uses the extractor fan less frequently, and does not open the kitchen windows normally.	<i>“We cook nearly every day. We sometimes turn on the extractor fan without the windows open sometimes. You know the kitchen door, because my oldest son has special needs. So, he always runs into the kitchen. So, it's not very safe. We closed the kitchen door”</i>	The householder shows irregular cooking. The householder uses the extractor fan. However, the householder does not close the kitchen door and does not open kitchen windows while cooking.	<i>“I've been fortunate enough that my sister cooks for me most of the time. So, I cook twice or three times in the week. But I cook definitely on weekends. I do put the extractor on in the kitchen. I do not open windows in the winter. My kitchen door is always open.”</i>
		Irregular cooking						
Opening kitchen windows								
Closing kitchen door								
Using extractors								
		Drying clothes	The householder has a tumble dryer. Therefore, it is clear that the householder does not dry clothes on radiators.	<i>“I have a tumble dryer”</i>	The householder has an air rack. Therefore, the householder does not dry clothes on radiators.	<i>“I leave my clothes on an air rack”</i>	The householder has an air rack. Hence, the householder does not dry clothes on radiators.	<i>“I don't have a tumble dryer. I have an air rack.”</i>

		Opening non-kitchen doors	The householder opens windows and doors to reduce high humidity and improve ventilation. Moreover, the householder opens the bathroom window to ventilate the bathroom whenever steam is generated.	<i>"I open windows and doors to get fresh air. At night I open these two doors if I feel bit stuffy because heating comes on in the morning".</i> <i>"I open the bathroom window to reduce the steam"</i>	The householder opens doors to reduce high humidity and improve ventilation. Moreover, the householder opens the bathroom window to improve ventilation in the bathroom.	<i>"I do not find my house stuffy in winter. But, if I feel stuffy, and if it is really bad, I open the doors"</i> <i>"I open the bathroom windows if lot of steam was generated"</i>	The householder opens windows to improve ventilation and reduce high humidity. In addition, the householder opens bathroom windows to ventilate the bathroom.	<i>"I open the windows in the kitchen and in the hallways if I feel stuffy. Windows in the bathrooms are always open"</i>
	Heating	Thermostat temperature	The householder maintains the thermostat temperature at 30°C, which substantially exceeds the threshold.	<i>"I keep it at 30 degrees to make my home warmer"</i>	The householder maintains the temperature at 30°C, which significantly exceeds the threshold.	<i>"I keep it at 30 degrees Celsius"</i>	The householder maintains the temperature at 23°C, which is higher than the threshold.	<i>"I keep it at 23 degrees Celsius"</i>
Occupancy period	All-day occupancy	-	Majority of the occupancy period of the householder is from 4:00 PM to 8:00 AM the following day.	<i>"Majority I am at home. During weekdays from Monday to Friday, I will be off from 8.00-4.00pm. Saturday and Sunday varies".</i>	Majority of the occupancy period is from 4.00PM to 9.00AM the following day.	<i>"I'll probably leave about 9.00 o'clock in the morning and come back around 4:00 o'clock"</i>	Majority of the occupancy period is from 4.00PM to 8.30AM the following day.	<i>"We leave the house by around 8:30. I finished work and I'm home by 4:00."</i>
	Morning occupancy	-						
	Evening occupancy	-						
Knowledge about air emissions associated with household energy use	Air emissions awareness	-	The householder shows lack of awareness or knowledge about air emissions.	<i>"Not much about carbon emissions".</i>	The householder shows lack of knowledge about air emissions.	<i>"Don't know much"</i>	The householder lacks sufficient knowledge about air emissions.	<i>"Not much"</i>

Interventions for sustainable behavioural change	Previous app experience	-	The householder has no prior experience using a mobile application that provides personalised feedback on air emissions related to household energy use.	<i>"I haven't used a mobile app".</i>	The householder has used a browser that provided information about air emissions. The householder showed less engagement with the browser. However, the householder has not used a mobile application.	<i>"I wouldn't say it is an app. It was a browser. I didn't constantly monitor it, but I used to look at it before. And it was good. It gave information about carbon emissions"</i>	The householder has used a mobile application for a shorter period.	<i>"I did at one point with my old phone and then somehow the app disappeared, and I never got it back. So, I don't I even remember the name. I wanted to download it again. So, I did have experience for few periods".</i>
	Perceptions about personalised messages	-	The householder is open to receiving personalised messages.	<i>"Definitely it will improve my behaviour"</i>	The householder is prepared to receive personalised messages.	<i>"Possibly. Yeah. It will be good"</i>	The householder is open to receiving the personalised messages. However, the householder feels somewhat stressed when receiving daily notifications.	<i>"I think it would be. It would make me more aware if I am using a bit more than usual. I like to learn but at the same time, every day knowing how much I have used will stress me out a little bit as well."</i>

Table 27: Pre-intervention interviews - findings

As per Table 27, the pre-intervention interviews reveal that the home occupant in plot 5 cooks regularly, opens the kitchen window, and uses the extractor fan while cooking. However, the occupant does not close the kitchen door. This can allow the steam, smoke, and indoor air pollutants such as TVOCs, PM_{2.5}, etc. to escape and reduce the indoor air quality in the house. Therefore, closing the kitchen door while cooking can be beneficial for improving the air quality in the whole house. The home occupant in plot 10 cooks regularly, closes the kitchen door while cooking, but uses the extractor fan or opens the kitchen window less frequently. This can lead to the build-up of pollutants such as TVOCs. Therefore, using the extractor fans more frequently or opening the kitchen window for few minutes while cooking can help to improve the indoor air quality. The plot 12 householder shows irregular cooking patterns. The home occupant in plot 12 uses the extractor fans while cooking. However, the home occupant does not open the kitchen window and close the kitchen door. In this case, closing the kitchen door while cooking and opening the kitchen window if the indoor air pollutants have exceeded their safe thresholds could be beneficial for improving Indoor Air Quality.

In addition, all the home occupants interviewed open non-kitchen windows and doors to ventilate the house, which might be an indicator of good whole house ventilation. On the other hand, the occupant in plot 5 only uses a tumble dryer, whilst the home occupants in plots 10 and 12 use air racks to dry their clothes. The usage of air racks in indoors can lead to increase the moisture levels inside the house, reducing indoor air quality. Good ventilation rates are key to prevent any risk of condensation and mould growth.

From the pre-intervention interviews conducted and analysis of occupant behaviours, it can be inferred that the smart nudging interventions nudging the occupants towards closing kitchen doors, using extractor fans, and opening kitchen windows while cooking can have a positive impact on the indoor air quality. Also, nudging people into opening windows when CO₂ levels are high can help to reduce moisture levels and improve air quality. However, opening windows and doors for longer time than needed for replacing the stale indoor air with fresh air can lead to higher energy consumption and costs. This implies that it is necessary to make the home occupants aware about the energy efficiency and heat loss, especially in the colder months, as opening windows or doors for a longer time can lead to higher energy consumption and costs.

Regarding heating practices, home occupants in plots 5 and 10 maintain the thermostat at 30⁰C, which is significantly higher than the safe threshold, leading to high energy consumption,

increased costs, reduced comfort, and reduced indoor air quality. The home occupant in plot 12 maintains the thermostat at 23⁰C, which is higher than the recommended threshold. Nudging the home occupants towards setting the thermostat within recommended thresholds (between 18⁰C-21⁰C) can have a positive impact in terms of reducing energy consumption and, thereby, energy bills.

The interviews showed that home occupants lacked awareness or knowledge about indoor air emissions and indoor air quality, underscoring the need. Therefore, it is necessary to educate the home occupant about how occupant behaviours contribute to indoor air emissions, poor indoor air quality, their negative consequences, and what measures or best practices they can adopt to achieve a sustainable living environment.

The home occupants in plots 5 and 10 did not have prior experience in using a mobile application that provides personalised push notifications on reducing indoor air emissions related to household energy use and improving indoor air quality, whilst the home occupant in plot 12 had some experience for a short period of time. Despite not having enough previous experience with similar mobile applications, they all seemed positive about the experience, as they felt it could help them be more aware of their behaviours influencing indoor emissions related to energy consumption and indoor air quality, although there were some concerns about the potential stress of receiving daily notifications (Plot 12). In addition, the home occupants are open to receive the push notifications. The occupant periods of the home occupants in plots 5, 10, and 12 are from 4.00pm to 8.00am, 4.00pm to 9.00am, and from 4.00pm to 8.30am in the weekdays, respectively.

5.3.2 Post-intervention interviews – findings

The results obtained from the post-intervention interviews are analysed to: 1) assess and understand the effectiveness of the smart nudging interventions deployed across the plots, 2) their suitability in making a behavioural change and the intended aim of the research, 3) gain insights on which smart nudging intervention was deemed more impactful by the participant, 4) gain feedback on whether the smart nudging interventions were successfully educating the home occupants, 5) understand whether the home occupants developed a better awareness about indoor air emissions and indoor air quality, and 6) internally validate and triangulate the quantitative findings and to ensure the depth and consistency in the research findings. The interviews are analysed under four main themes: 1) assessing behavioural change, 2) learning about air emissions associated with household energy use, 3) experience with smart nudging

interventions, and 4) identifying the most effective smart nudging intervention. Table 28 shows the results of the post-intervention interviews conducted across the three plots.

Themes	Codes	Sub-codes	Plot 5		Plot 10		Plot 12	
			Summary of the findings	Quotes	Summary of the findings	Quotes	Summary of the findings	Quotes
Assessing behavioural change	Reducing stuffiness	Opening kitchen windows	The householder has made changes to the cooking behaviours by opening kitchen windows and using extractor fans more frequently than before. The householder was unable to close the kitchen door based on a reasonable and understandable reason (due to childcare and security concerns).	<i>"I opened windows and used extractors while cooking. Now I am using extractors more. But I couldn't close the kitchen doors. I couldn't do that with the kids. I have to keep an eye on them."</i>	The householder has changed the cooking behaviours by opening the kitchen window and using the extractor fans more frequently than before. The householder has experienced less stuffiness in the kitchen.	<i>"I open windows a lot more because I'm seeing now the notifications and I'm using the extractors a lot more now. I never used to open the kitchen window so much and I feel like kitchen is less stuffy now. I mean, so yeah, it made a good impact, to be honest."</i>	The householder has opened the kitchen windows more frequently than before. However, the householder did not mention about the kitchen door.	<i>"I have been opening kitchen windows more than usual because I get these reminders."</i>
		Closing kitchen door						
		Using extractors						
		Opening non-kitchen doors and windows	The householder has opened windows more frequently than before and therefore, the householder has felt less stuffy.	<i>"I opened windows. But I have not seen mould issues. I never had those. I felt less stuffy."</i>	The householder has opened windows in the bathroom to reduce the steam generated in the bathroom and experienced fewer mouldy issues or condensation.	<i>"I open windows. I don't get any hot water vapours now. I can see mouldy issues are less in the bathroom. Everything goes in line."</i>	The householder has opened bathroom windows more frequently than before.	<i>"I open bathroom windows constantly now."</i>
	Heating	Changing thermostat temperature	The householder has changed the thermostat temperature to 21°C.	<i>"I did changes. I didn't understand that first, but the messages told me, like, you could do better. I reduced the temperature for 21 degrees"</i> .	Firstly, the householder has changed the temperature to 20°C. However, later, the householder has identified that 21°C is	<i>"I made changes. But if I put it to 20 now, it doesn't get really warm, but if I put it on 21 then it starts getting warmer."</i>	The householder has set the thermostat to 21°C.	<i>"I did set it low. I think I had it for like on 21."</i>

					the ideal temperature to stay warm.			
Learning about air emissions associated with household energy use	Indoor Air Quality Awareness	-	The householder learnt that it is valuable to adopt sustainable behaviours constantly for reducing air emissions and improving indoor air quality, even if the person could not directly sense issues such as poor air quality.	<i>"I've learned that when I'm cooking, it becomes very humid, even if sometimes I can't sense it, messages allowed me to act. Even though I can't sense it, the sensors told me that in a simple way."</i>	The householder learnt that maintaining a high temperature is not appropriate. Moreover, the householder learnt the correct threshold for maintaining the best indoor temperature.	<i>"When it was saying that the temperature is quite high, and it just made me a lot more alert of what I'm doing day to day in my house. I would have known this ages ago. So, I could change my habits. Yeah, I'm learning now. It's good."</i>	The householder learnt about air emissions. Moreover, the householder makes efforts to ensure good air quality is maintained in the house.	<i>"I learned few things. So, I have been doing extra to make sure that there's enough air circulating around the house."</i>
	Reading user guides	-	The householder has not read the user guides.	<i>"I am busy. I still did not have chance to dig into it."</i>	The householder has read the user guides.	<i>"I did go through it previously. I think I've done the reading. But now I was looking at notifications."</i>	The householder has read the digital user guides. However, the householder found the digital user guides are broad and less user-friendly even though the user guides contain information about the house-specific low-carbon technologies, how those systems should be maintained, the general energy-saving tips, etc.	<i>"I try to read on it, but I don't think it is user friendly to be honest. The information it gives you is kind of broad, I didn't find it to be very specific to my home. There is information on there, but it's more of a general user guide for plots. And even when you look at it, it just tells you the design of the house. Well, yeah, I guess it's helpful, but I didn't think much."</i>
Experience with smart nudging interventions	Personalised messages	-	The householder found that the personalised messages were good and beneficial.	<i>"I think it's really good. It just messaged me to let me know the status of the house. So it's really handy."</i>	The householder mentioned that the personalised messages were good, and those messages pushed the	<i>"Messages were good. I'm noticing when getting the messages, it's saying that the air quality is not good. It</i>	The householder found that the personalised messages were helpful in making	<i>Notifications that tell me 'Your humid level or the something level at your house is that</i>

					householder to adopt sustainable behaviours. However, the householder found that messages were repetitive in some instances.	<i>made me to act. I find them quite helpful. But sometimes they are quite repetitive."</i>	sustainable behavioural changes.	<i>percent'. So yeah, it's been a constant reminder of like how much air is in the house, what my heating is like, how high my temperature is set, and also like what the neighbours is like. So, I think those are reminders kind of helped me to close the door, open the window and set my temperature low.</i>
Identifying the most effective smart nudging intervention	Type of personalised message	-	The householder identified that 'social comparison' was the most effective intervention.	<i>"I think the messages that included my neighbour's details. Yeah, I'm thinking, they're doing right and what I'm doing wrong. So yeah, definitely that one."</i>	The householder found that the most effective smart nudging intervention is 'social comparison'.	<i>"I think that the best one was that gave me about neighbour's information. It made me think what am I doing really wrong then?"</i>	The householder found that 'feedback' is the most effective intervention.	<i>I like the one that says, you know, which means less indoor air quality, improve it by using extractors while cooking and save on the health costs. Yeah, that one is a good reminder, and it gives me a push. I'm not very fussed about what my neighbour is doing, to be honest. So, I like the message that gives me general information.</i>

Table 28: Post-intervention interviews - findings

Table 28 reveals that the plot 5 householder has made changes to the cooking behaviours by opening kitchen windows and using the extractor fans more frequently than before, although there had not been changes in closing the kitchen door due to childcare. Although having the kitchen door open might contribute to air pollutants travelling to other parts of the house, the use of an extractor fan, and the opening of windows in the kitchen have the potential to mitigate this risk substantially. Both occupants in Plots 10 and 12 have made changes to their cooking behaviours by opening the kitchen window and using the extractor fan more frequently than before. More specifically, the home occupant in plot 10 admitted that the stuffiness of the house was reduced as a result of adopting these sustainable behaviours. All the home occupants have opened non-kitchen windows, especially in living rooms and bathrooms to reduce the stuffiness and condensation.

The home occupants in each plot claimed to have changed their thermostat settings to 21⁰C, which is a significant behavioural change. All the home occupants admitted that they learnt about optimal temperature thresholds and actions leading to poor indoor air quality by reading the smart nudging interventions or push notifications. Moreover, all the home occupants found that the personalised push notifications were helpful and nudged them to act as well as making them more aware of the effects of daily activities to improve the air quality of their house, contributing to achieving sustainable behaviours. Overall, they felt that the personalised push notifications were good and beneficial, although sometimes these could be a bit repetitive. On the other hand, they felt that the digital homes user guide that came with the app was not as helpful as the push notifications or smart nudging interventions. In this line, home occupant in plot 5 had not read the digital user guides, while the home occupants in plots 10 and 12 had read the user guides but felt they were quite general and not very user friendly.

With regards their perception on which type of push notification or smart nudging intervention was more effective, the home occupants of plots 5 and 10 felt that social comparison was the most effective smart nudging intervention, while the home occupant in plot 12 believed that feedback was the most effective smart nudging intervention.

5.4 Triangulation of the research findings

To strengthen the validity of the research findings, a triangulation approach was used in this study. The decision to use the triangulation approach to triangulate quantitative and qualitative data was driven by the small sample size, which posed limitations in terms of statistical power and generalisability. By integrating insights from multiple data sources, including engagement

analytics or quantitative data and interviews, this study aimed to offset the limitations, provide an understanding of the behavioural change, and ensure the results are grounded in both empirical evidence and real-life experiences. Moreover, qualitative data from interviews is compared against quantitative findings to assess if perceptions from occupants about which type of smart nudging intervention they believe is more effective align with quantitative data obtained from sensors after the different smart nudging interventions were sent.

5.4.1 CO₂

In considering plot 5, the qualitative findings showed that the householder had opened windows more frequently than before to ventilate the house and to reduce the stuffiness. In addition, the householder mentioned that the smart nudging interventions were helpful to reduce the stuffiness and had learnt that it is valuable to adopt the best practices, such as opening windows to reduce stuffiness and improve CO₂ levels in the house. As a result, it seems that the best practices suggested in the smart nudging interventions have nudged the householder to act and improve CO₂ levels in plot 5. Therefore, it can be inferred that the observed reductions in high CO₂ levels were not due to random fluctuations, and these are in line with the occupant's perceptions.

In considering plot 10, the householder believed that the stuffiness was reduced, as the smart nudging interventions nudged the householder to open windows more frequently than before. Moreover, the householder had read the digital user guides and learnt how to reduce stuffiness from the best practices that were included in the smart nudging interventions. Therefore, the observed reductions of high CO₂ levels were not due to random chances but were a direct result of the householder's actions. Therefore, the qualitative findings align with the quantitative findings. Similarly, in plot 12, the qualitative findings align with the quantitative findings, as qualitative results indicated that the householder opened windows more frequently than before after reading and learning from the smart nudging interventions. Therefore, the observed reductions in high CO₂ levels above 1000ppm were due to the householder's actions.

5.4.2 Relative humidity

In plot 5, the observed reductions of high relative humidity levels above 60%rh (as shown in the quantitative analysis) align with the qualitative findings. The householder admitted that the recommended best practices, such as opening windows (both kitchen and non-kitchen windows) and using extractor fans, were adopted more frequently than before and those best practices helped the householder to reduce the moisture levels in the house. Moreover, in terms

of learning, the householder mentioned that the smart nudging interventions were useful, and the householder had learnt about the best practices to reduce high humidity levels. The householder does regular cooking and could not close the kitchen door, and thereby, it may have hindered the reduction of high humidity levels in the house at some points. It seems that the smart nudging interventions have educated and nudged the householder to act and improve the indoor air quality in the house. Therefore, this validates that the significant reductions of high humidity levels shown in quantitative analysis are not due to random variations but because of the occupant's actions.

In plot 10, the qualitative findings showed that the smart nudging interventions nudged the householder to act, and thereby, the householder opened kitchen windows and used extractor fans more frequently than before to reduce the high humidity levels. Moreover, qualitative findings showed that the householder opened the bathroom windows to reduce the steam in the bathroom, and as a result, the householder experienced less condensation in the bathroom. In contrast, the quantitative findings showed that most of the instances of all the three smart nudging interventions did not show significant reductions. The contradiction in results might be related to the air quality sensor being installed in the kitchen and living room but not in the bathroom.

In plot 12, the quantitative findings are consistent with qualitative findings. Qualitative findings showed that the householder had opened windows to ventilate the house, more specifically the kitchen windows to reduce the moisture levels while cooking. The qualitative findings showed that previously the householder had not opened kitchen windows. Therefore, after reading the smart nudging interventions and learning about the negative impacts, the householder had adopted the best practices, indicating a sustainable behavioural change. Therefore, the observed reductions in high humidity levels were not due to the random fluctuations but due to the actions of the householder.

5.4.3 TVOC

In plot 5, the observed reductions of high TVOC levels above 400ppb (as shown in quantitative findings) align with the qualitative findings, as the householder admitted that she opened windows to ventilate the house more frequently than before. This demonstrates the effectiveness of the interventions in improving TVOC levels by nudging the home occupant towards achieving a sustainable behavioural change. In addition, these results show that the

reductions of high TVOC levels are not due to random fluctuations but due to the actions of the home occupant.

In plot 10, the qualitative findings align with the quantitative findings, as the qualitative findings indicated that the householder opened windows more frequently than before after reading the smart nudging interventions. Therefore, it can be concluded that the reductions in high TVOC levels were caused by not random chances. In plot 12, the qualitative findings do not align with quantitative findings because the qualitative findings revealed that the householder had opened windows to improve ventilation and indoor air quality. In contrast, the quantitative findings showed no significant TVOC reductions in most of the instances, indicating that all the three smart nudging interventions were not effective. Therefore, the quantitative and qualitative findings show contradictions. This contradiction might have occurred due to the research limitation of not specifying the house location to open the windows for a few minutes. As a result, the occupant may not have known where to take the action and could have opened the window in a different house location.

5.4.4 Temperature

In plot 5, the householder mentioned that the thermostat temperature was changed to 21⁰C after reading and learning from the smart nudging interventions. However, quantitative findings showed no reductions in high temperatures. In addition, quantitative findings showed that all the three smart nudging interventions were not effective in nudging the home occupant towards achieving the safe threshold of temperature. Therefore, this demonstrates contradictory findings between the qualitative and quantitative data. In addition, based on the findings related to the pre-intervention interviews, the householder mentioned that typically the householder set the thermostat temperature at 30⁰C. However, this was not reflected in the pre-intervention levels or intervention sent levels shown in above Figure 41. This discrepancy suggests that the householder's perception of maintaining the thermostat to 30⁰C does not align with the actual thermostat behaviour.

In plot 10, the quantitative findings show contradictions with qualitative findings. The qualitative findings showed that the householder adjusted the thermostat temperature to 20⁰C and found that 20⁰C was not ideal and later identified that 21⁰C is the ideal temperature to stay warm. In addition, the qualitative findings revealed that the householder had learnt both the negative consequences of maintaining the thermostat temperature above 21⁰C and the correct threshold for maintaining indoor temperature through the smart nudging interventions. This

learning effect is aligned with the study of Lynham et al. (2016), which found that feedback had nudged the occupants to reduce the electricity consumption up to 11%, and this reduction was mainly driven by the ‘learning’ effect’. However, the householder’s behavioural change through learning effect was not reflected in the quantitative data analysis of plot 10. Therefore, this study did not achieve a real positive impact or real effectiveness in improving temperature through any of the smart nudging interventions.

In plot 12, the quantitative findings indicate contradictions with qualitative findings. The qualitative findings showed that the householder changed the thermostat temperature to 21°C after reading and learning from the interventions. Previously, before the interventions were delivered, the householder had maintained the thermostat temperature to 23°C. In addition, the qualitative findings revealed that the smart nudging interventions were helpful in reminding her to set the thermostat between 18-21°C. Therefore, while the qualitative findings revealed the householder’s behavioural change, this behavioural change was not shown in the quantitative data analysis. Moreover, the householder could not achieve the safe threshold between 18-21°C.

5.4.5 Smart nudging effectiveness

Table 29 shows the triangulation of the research findings related to the most effective smart nudging interventions in improving indoor air quality parameters in each plot separately. In addition, this Table 29 provides the qualitative findings for the most effective smart nudging intervention in each plot to triangulate the quantitative findings.

Plot	Type of indoor air quality parameter improved	Type of smart nudging intervention	Significant positive impact rate	Qualitative findings – most effective intervention
Plot 5	CO ₂	Loss-aversion	100%	Social comparison
	Relative humidity	Social comparison	21%	
	TVOC	Feedback	75%	
	Temperature	-		
Plot 10	CO ₂	Feedback	50%	Social comparison
	Relative humidity	-		
	TVOC	Social comparison	50%	
	Temperature	-		
Plot 12	CO ₂	Feedback	67%	Feedback
	Relative humidity	Feedback	29%	
	TVOC	-		
	Temperature	-		

Table 29: Triangulation of the research findings

According to Table 29, while quantitative data showed that different smart nudging interventions were most effective for specific indoor air quality parameters in plot 5 (CO₂ was

improved by loss-aversion, relative humidity was improved by social comparison, and TVOC was improved by feedback), the qualitative findings showed that social comparison was identified overall as the most effective intervention. Social comparison showed a comparatively less significant positive impact rate of 21% based on the quantitative findings. In contrast, loss-aversion was identified as the most effective intervention in comparing the significant positive impact rates, as it showed a significant positive impact rate of 100% in plot 5. However, in triangulating the two data sets of quantitative and qualitative findings, social comparison can be considered as the most effective smart nudging intervention in plot 5.

The quantitative findings showed that both feedback and social comparison were effective in plot 10, showing significant positive impact rates of 50% each. Qualitative findings showed that social comparison is the overall most effective smart nudging intervention in plot 10. Therefore, considering both datasets, social comparison can be identified as the most effective smart nudging intervention in plot 10. In plot 12, feedback was found to be effective in both quantitative and qualitative data, confirming its overall effectiveness.

While loss-aversion showed the highest overall effectiveness with a significant positive impact rate of 100% based on the quantitative data analysis, triangulated findings across the plots indicated that social comparison was most consistently perceived as the most effective smart nudging intervention overall. Therefore, when considering both quantitative data and home occupants' perceptions, social comparison appeared as the most effective smart nudging intervention for overall indoor air quality improvement and reduction of indoor air emissions related to household energy use. This finding aligns with the literature review findings related to the most effective smart nudging intervention across the empirical studies (as shown in Table 8 – Chapter 2: Literature Review), as social comparison was identified as the most effective smart nudging intervention despite the research designs and digital platforms. Furthermore, the two studies of Dominicis, et al. (2019) and Kazukauskas, et al. (2021), which compared social comparison and feedback, revealed that social comparison is the most effective intervention compared to feedback in the same research.

Additionally, the original null hypothesis (as described in Chapter 3: Action Research Methodology), which assumed that there is no significant difference in the effectiveness of the three smart nudging interventions is rejected. Instead, the triangulated analysis supports the alternative hypothesis by using both qualitative and quantitative insights of this research. Furthermore, these findings answer the research questions of this study.

5.4.5.1 Research limitations

One of the key research limitations of this study is the unequal number of instances across the smart nudging interventions, which may have influenced the identification of the real impact of interventions, as some interventions were delivered only once in many instances, leading to a not conclusive/uncertain impact. For example: feedback, social comparison, and loss-aversion were delivered 1, 2, and 6 times, respectively, to reduce high TVOC reductions in plot 12 over the month. In addition, this might have been affected by the absence of confirmation of whether all the three smart nudging interventions were delivered more than once in each plot, as smart nudging interventions were delivered randomly. In addition, all the types of smart nudging interventions were not delivered over the weeks. For example: no smart nudging intervention was delivered to reduce the high CO₂ levels in plot 12 over the week. Therefore, this lack of control over intervention delivery is a critical limitation that needed to be rectified in the proposed smart nudge design.

During the data cleaning and analysis stage, it was found that some indoor air quality parameters showed slight deviations from the defined thresholds. For example, 1) loss-aversion was delivered to reduce the relative humidity level from 60.5% rh to below 60% rh in plot 5, 2) social comparison was delivered to reduce the CO₂ levels from 1005ppm to below 1000ppm in plot 10, and 3) loss-aversion was sent to improve the temperature from 21.1⁰C to below 21⁰C. These slight variations may have occurred due to random fluctuations captured by the sensors, potential sensor errors, or other measurement-related uncertainties. This limitation can affect the overall impact of the interventions. Therefore, specifying the most critical indoor air quality parameter that shows the highest deviation from the defined threshold during the process can mitigate this issue by sending interventions to assess the impact in a robust way.

No sensor was installed in the bathroom to capture the indoor air quality data, which was highlighted as research limitation. This might affect the accuracy of the intervention's impact assessment, as capturing the less condensation in bathrooms, especially in plot 10 was not possible. The smart nudging interventions did not clearly specify the duration for which windows should be opened and the location of window openings to improve indoor air quality, which may have influenced the impact of the interventions. Therefore, this limitation highlights the need for more structured logics for smart nudging interventions to nudge the home occupants towards achieving sustainable behaviours.

As social comparison required similar demographics and household characteristics across the selected plots, the findings are limited to a specific context of these three low-carbon houses, limiting the generalisability of the research findings. Therefore, the limited sample size of only three low-carbon homes or plots restricts the ability to draw widespread conclusions. In addition, the lack of diversity in housing type and occupant characteristics constrain wider generalisability to more heterogeneous housing stocks including older housing stocks, non-low-carbon houses, and more socio-demographically diverse households. Consequently, while this study provides robust evidence for behavioural interventions or smart nudging interventions in low-carbon homes, broader generalisability would require testing across a larger and more diverse sample.

5.5 Chapter summary

The research findings identified that 30-minute window is the most suitable window to 1) capture immediate behavioural changes and isolate the impact of behavioural changes by avoiding random fluctuations, 2) provide adequate time for the householder to act, 3) account for delays in actions, 4) provide adequate time to reveal the true impact of smart nudging interventions, and 5) allow adequate time for the indoor air quality parameters to reduce and manifest.

The quantitative findings related to the improvement of CO₂ levels revealed that loss-aversion is the most effective intervention in reducing high CO₂ levels, as it showed the significant positive impact rate of 100%. Feedback showed the highest effectiveness in reducing high relative humidity levels and TVOC levels by indicating significant positive impact rates of 29% and 75%, respectively. The observed reductions of high CO₂ levels aligned with the qualitative findings. The observed reductions of high relative humidity levels in plots 5 and 12 aligned with the qualitative findings, while plot 10 showed contradictions. In addition, the observed reductions of high TVOC levels in plots 5 and 10 aligned with the qualitative findings, while plot 12 showed contradictions. No smart nudging intervention was effective in reducing high temperatures above 21⁰C or improving low temperatures below 18⁰C and showed contradictions with the qualitative results. The triangulated findings revealed that social comparison is the most effective smart nudging intervention for overall reduction of indoor air emissions related to household energy use and improvement of indoor air quality in the residential sector.

6 Proposed smart nudge design

6.1 Introduction

In this chapter, the proposed smart nudge design is presented, building upon the smart nudge design introduced in “Chapter 4 – Smart nudge design”. While the initial smart nudge design was developed based on insights from the existing literature, this proposed smart nudge design integrates empirical findings of this study by assessing both quantitative and qualitative results. This proposed smart nudge design refines the understanding of the structured process used to create, implement, and evaluate the smart nudging interventions by reflecting real-world home occupant behaviours, engagement patterns, and occupants’ responses. In addition, this chapter outlines the evolution of the smart nudge design into a validated smart nudge design by describing key modifications based on the study’s empirical findings and feedback from the industry partner. The proposed smart nudge design provides a practical and an evidence-based contribution to the existing research, enhancing its application in reducing anthropogenic air emissions related to household energy consumption and improving indoor air quality by changing occupant behaviours. Moreover, the previous logic formulations of the three smart nudging interventions are modified using the empirical findings of this research and existing literature.

6.2 Formulation of the proposed smart nudge design

The smart nudge design (introduced in “Chapter 4 – Smart nudge design”) included 13 steps. The steps were: 1) define the goal, 2) understand the users, 3) understand the context, 4) identifying the indoor air quality parameters, 5) monitor real-time data, 6) trigger point identification, 7) decision-making process, 8) random selection of the smart nudging intervention, 9) design the logics, 10) select the time frame, 11) deliver the smart nudging intervention, 12) assess the indoor air quality parameter, and 13) evaluate the smart nudging intervention. These steps are modified by adding new steps based on the empirical findings of this study. Furthermore, the proposed smart nudge design is validated with the industry partner. The modifications and new steps are shown in below Table 30.

Steps	Smart nudge design	Proposed smart nudge design	Remarks
1	Define the goal	Define the goal	No modification
2	Understand the users	Understand the users	No modification
3	Understand the context	Understand the context	No modification
4	Identifying the indoor air quality parameters	Identifying the suitable indoor air quality parameters	No modification
5		Set the “cool off” period (59 minutes)	New step
6	Monitor real-time data	Monitor real-time data in different house locations	Modified
7	Trigger point identification	Trigger point identification	No modification
8	Decision-making process	Decision-making process	No modification
9		Identifying the most critical Indoor Air Quality parameter	New step
10		Fetch device sensor data related to the most critical Indoor Air Quality parameter via the API to the mobile application	New step
11	Random selection of the smart nudging intervention	Random selection of the smart nudging intervention	No modification
12	Design the logics	Design the logics	Modified the logic formulations
13	Select the time frame	Select the time frame	No modification
14		Confirm no interventions during the cool-off period	New step
15	Deliver the smart nudging intervention	Deliver the smart nudging intervention	No modification
16	Assess the indoor air quality parameter	Assess the most critical indoor air quality parameter	Modified
17		Verify if all the interventions have been applied at an equal number of instances	New step
18	Evaluate the smart nudging intervention	Evaluate the smart nudging intervention	No modification

Table 30: Comparison of steps between the smart nudge design and the proposed smart nudge design

Table 30 shows the comparison between the original steps of the smart nudge design (shown in Figure 14 in Section 4.2) and the modified steps and newly added steps in the proposed smart nudge design that build upon the empirical findings of this study.

- Step 1 – Define the goal – no modifications to the original step.
- Step 2 – Understand the users – no modifications to the original step.
- Step 3 – Understand the context – no modifications to the original step.
- Step 4 - Identify the indoor air quality parameters - no modifications to the original step. However, the wording has changed from ‘Identifying the indoor air quality parameters’ to ‘Identifying the suitable indoor air quality parameters’.

- Step 5 – Monitor real-time data – this step is modified as ‘Monitor real-time data in different house locations’.
- Step 6 - Trigger point identification – no modifications to the original step.
- Step 7 - Decision-making process – no modifications to the original step.
- Step 8 - Random selection of the smart nudging intervention – no modifications to the original step.
- Step 9 - Design the logics – the logics of the smart nudging interventions are modified and refined.
- Step 10 - Select the time frame – no modifications to the original step.
- Step 11 - Deliver the smart nudging intervention – no modifications to the original step.
- Step 12 - Assess the indoor air quality parameter – the step is modified as ‘assessing whether the most critical indoor air quality parameter has reached its safe levels’.
- Step 13 - Evaluate the smart nudging intervention - no modifications to the original step.
- New steps added to the smart nudge design – ‘Set the “cool-off” period of 59 minutes’, ‘Identifying the most critical indoor air quality parameter’, and ‘Fetch device sensor data related to the most critical IAQ parameter via the API to the mobile application’, ‘Confirm no interventions during the cool-off period’, and ‘Verify if all the interventions have been applied at an equal number of instances’.

The below sections 6.2.1 and 6.2.2 presents a discussion of all the steps in the proposed smart nudge design along with how the research findings of this study informed the improvement of steps in the proposed smart nudge design.

6.2.1 Discussion of the steps

The proposed smart nudge design provides a structured process to achieve the nudging goal and provide a clear pathway for the design and implementation of the smart nudging in the household energy sector. This proposed smart nudge design intends to support home occupants to make informed decisions by learning through their actions, real-time insights, and smart nudging interventions. The steps of the proposed smart nudge design are explained below.

- 1) Define the goal – this step is similar to the first step introduced in the smart nudge design. This step identifies the nudging goal. The nudging goal is reducing anthropogenic indoor

air emissions related to the household energy consumption and improving indoor air quality by achieving a sustainable behavioural change among home occupants.

- 2) Understand the users – this step is similar to the original step in the smart nudge design. This step focuses on personalisation. Personalisation serves as the first step of extending digital nudging to qualify as smart nudging to make the nudging interventions more effective and user centric. This step involves gaining demographic information such as number of adults and children, age range, income range, homeownership status, and education level about each household separately. In addition, this step involves identifying the existing energy consumption behaviours related to different household activities such as cooking and heating, perceptions, occupancy periods, and preferences of the home occupants. Moreover, this step identifies the knowledge and awareness of the home occupants regarding air emissions and their capacity to interact with digital technologies or a mobile application. This can be achieved through pre-intervention interviews with the home occupants.
- 3) Understand the context – this step is similar to the original step and focuses on context-awareness. This step serves as the second step of extending digital nudging to qualify as smart nudging and highlights as a crucial and a mandatory step in designing smart nudging interventions. This step identifies the context of the households by gathering information related to the house characteristics such as EPC rating of the house, type of the house, design of the house including building airtightness, low-carbon technologies, etc., number of rooms, location, and local weather conditions specific to a house location.
- 4) Identifying the suitable indoor air quality parameters – this step is similar to the original step in the smart nudge design. However, this step should ensure that the study selects the most suitable and manageable indoor air quality parameters out of the indoor air quality parameters shown in the sensor data to avoid overloading householders with excessive information and smart nudging interventions. It is necessary to identify the indoor air quality parameters that can be easily linked to the occupant activities to facilitate the design and creation of more targeted and personalised smart nudging interventions. For example, opening a window for few minutes can reduce the higher levels of CO₂ above 1000ppm. Therefore, CO₂ can be selected as a parameter.

- 5) Set the "cool off" period (59 minutes) – this step is newly added to the proposed smart nudge design. Even though this step was implemented in the process, it was not shown as one of the steps in the design. Therefore, this step is included in the proposed smart nudge design. The ‘cool-off’ period is the time gap that must pass between consecutive smart nudging interventions before another one can be delivered to the same householder. This prevents excessive interventions delivered to the same home occupant within a very short period of time. Therefore, the indoor air quality parameters are monitored for 59 minutes before sending the smart nudging intervention in the next minute. Smart nudging interventions are set up to send every hour if the indoor air quality parameters exceed their safe thresholds. The rationale for selecting ‘59 minutes’ is that the last-minute data of the previous hour related to an indoor air quality parameter is considered as a reference point for sending the smart nudging intervention in the next minute to avoid unnecessary fluctuations, to ensure that the intervention is timely and accurate, and to facilitate the implementation of the design in the mobile application.
- 6) Monitor real-time data in different house locations - this is a modified step in the proposed smart nudge design to enhance precision. Previously, home occupants were nudged based on house-specific data, as the smart nudging interventions did not specify the location where the indoor air quality parameter exceeded the defined threshold. However, in this proposed smart nudge design, room-specific monitoring is used to identify the indoor air quality parameters that exceed the defined thresholds as an effective measure of nudging home occupants towards achieving the nudging goal by specifying the location in the push notifications.
- 7) Trigger point identification – this step is similar to the original step in the smart nudge design. This step identifies whether the indoor air quality parameters have exceeded their defined thresholds.
- 8) Decision-making process – this step matches the original step in the smart nudge design. The diamond boxes represent the decision-making process. This step identifies whether the last-minute sensor data of the previous hour related to the indoor air quality parameter has been exceeded the threshold. If the last-minute sensor data has not exceeded the specified threshold, no smart nudging intervention is required and will be subjected to continuous

monitoring. However, if the last-minute sensor data has exceeded the threshold, a smart nudging intervention will be applied.

- 9) Identifying the most critical IAQ parameter – this is a newly added step. This step identifies the most critical indoor air quality parameter with the highest deviation from the threshold. This step ensures the designing of a targeted and effective smart nudging intervention by prioritising the most critical parameter based on the real-time data.
- 10) Fetch device sensor data related to the most critical indoor air quality parameter via the API to the mobile application – Even though this step was executed in the process, it was not shown as one of the steps in the smart nudge design and was not executed for the most critical indoor air quality parameter. Therefore, this step is added to the proposed smart nudge design and this new step ensures that the mobile application fetch the sensor data related to the most critical indoor air quality parameter via the API to create the smart nudging intervention.
- 11) Random selection of the smart nudging intervention – this step is similar to the smart nudge design. The three smart nudging interventions, namely, feedback, social comparison, and loss-aversion are selecting randomly to avoid the ‘order bias’. This step helps to conduct a more accurate and a balanced assessment of the effectiveness of each intervention separately, as the home occupant is not accustomed or resistant to a single type of smart nudging intervention. This can increase the positive impact of smart nudging interventions.
- 12) Design the logics – the logics of each smart nudging intervention is modified and are described in the below section 6.2.4.
- 13) Select the time frame – this step matches the original step, as an hourly time frame is selected for delivering the smart nudging intervention by monitoring the last-minute sensor data of the previous hour. Smart nudging interventions are scheduled to deliver hourly if the last-minute sensor data of the previous hour relates to an indoor air quality parameter has exceeded the threshold.
- 14) Confirm no interventions during the cool-off period - This step was executed in the process. However, it was not shown as one of the steps in the smart nudge design. Therefore, this step is added to the proposed smart nudge design to avoid overloading the home occupant with excessive smart nudging interventions.

- 15) Deliver the smart nudging intervention – this step matches the original step in the smart nudge design and highlights the delivery of smart nudging interventions as push notifications based on the timeframe scheduled in step 13.
- 16) Assess the most critical indoor air quality parameter – the original step is modified, as this step ensures that the most critical indoor air quality parameter with a highest deviation from the threshold has reached its safe threshold. If the indoor air quality parameter has not reached its safe threshold, then it will proceed to step 11, and again a smart nudging intervention will be applied to nudge the home occupant in the next hour. This will run in a cycle during the occupancy period until all interventions are applied and until the most critical indoor air quality parameter reaches its safe threshold. If it has reached the safe threshold, then it will proceed to the step 9 to identify the most critical indoor air quality parameter and to the step 18 for the evaluation.
- 17) Verify if all the interventions have been applied– this step ensures that all the types of smart nudging interventions are applied more than once or at least once if the parameter did not reach the safe threshold. If the safe threshold is still not achieved after applying all the types of smart nudging interventions during the occupancy period, the process moves directly to step 18.
- 18) Evaluate the smart nudging intervention – this step evaluates the impact of the smart nudging intervention within the 30-minute window (30-minute post-delivery) in achieving the safe threshold of the most critical indoor air quality parameter.

The proposed smart nudge design is shown in Figure 48.

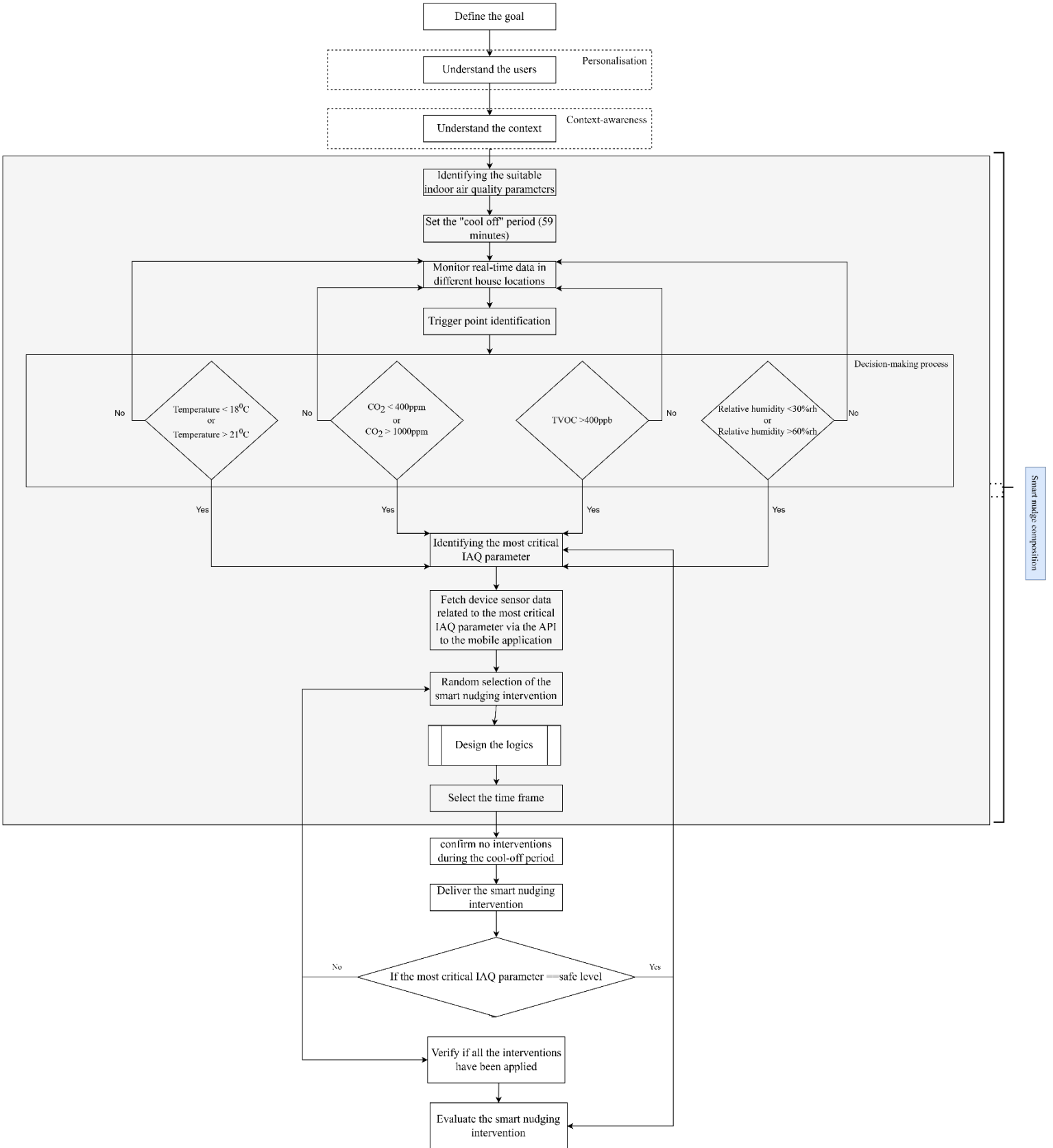


Figure 48: The proposed smart nudge design

6.2.2 Empirical findings informing design development

The 5th step of the smart nudge design was modified as “Monitor real-time data in different house locations” in the proposed smart nudge design and included it as the 6th step to create more informative and structured smart nudging interventions to help occupants know exactly where to act (e.g. kitchen, living room, bathrooms, bedrooms) and which window should be opened for a few minutes to improve the indoor air quality. This can provide the clearer actions and might increase the likelihood of the correct and effective responses. In addition, this step can mitigate the research limitations found in this study. Based on the research findings of this study, the qualitative findings revealed that the occupant in plot 10 opened bathroom windows to reduce the steam generated in the bathroom after reading the push notifications, and as a result, the occupant experienced less condensation. Moreover, the home occupant in plot 10 opened kitchen windows and used the extractor fan in the kitchen more frequently than before to reduce high relative humidity levels (as shown in Table 28 in Section 5.3.2). However, this was not reflected in the quantitative research findings (as shown in Table 18 in Section 5.2.2.5). This contradiction between the quantitative and qualitative data might be related to not installing the sensors in the bathrooms and not specifying the location where the occupant needs to act to reduce high humidity. Therefore, this limitation can be mitigated by specifying the location to act in formulating the logics of the smart nudging interventions. In addition, specifying the window opening duration in the smart nudging interventions can improve the indoor air quality by minimising the heat loss and energy bills.

The 9th step, which is “Identifying the most critical Indoor Air Quality parameter”, was newly added in the proposed smart nudge design to target the indoor air quality parameter that showed the highest deviation from the recommended threshold, prioritise actions, and maintain greater control over intervention delivery rather than delivering interventions across parameters that showed low deviations randomly. For example, when evaluating the quantitative data in this research, it was observed that social comparison was delivered to reduce CO₂ levels in plot 10 from 1005ppm to below 1000ppm, indicating only a slight increase in the level from the specified threshold of 1000ppm. In such cases, it might be more effective to focus on a parameter that shows the highest deviation from its specified threshold because this could better show the impact of the smart nudging intervention in reducing the most critical parameter.

The 17th step in the proposed smart nudge design, which is “Verify if all the interventions have been applied”, was added to avoid the limitation of unequal number of instances and avoid the lack of control over intervention delivery to ensure that each smart nudging intervention was applied to compare and assess the effectiveness. In considering the research findings, it was observed that smart nudging interventions were not delivered even once in some plots to improve the indoor air quality. For example, 1) feedback and loss-aversion were not delivered over the first week of the intervention period in plot 10 to reduce high TVOC levels (as shown in Table 20 in Section 5.2.3.1) and 2) no smart nudging interventions were delivered to reduce high CO₂ levels over the first week in plot 12 (as shown in Table 13 in Section 5.2.1.1) . In addition, some smart nudging interventions were delivered only once, while others were delivered multiple times, making it difficult to assess the impact through a comparative analysis due to an imbalance of data. For example, feedback, social comparison, and loss-aversion were delivered 1, 2, and 6 times, respectively in plot 12 to reduce high TVOC levels over the month (as shown in Table 20 in Section 5.2.3.1), indicating lack of control over intervention delivery. Therefore, these limitations can be mitigated through the proposed smart nudge design.

6.2.3 Industry inputs into the proposed smart nudge design

The design process involved industry inputs from Covatic to ensure the practical relevance and real-world application of the proposed design. The industry inputs are presented in Table 31.

Industry input	How it informed the proposed smart nudge design
5 th step – Set the “cool off” period (59 minutes)	The 59 minutes cooling-off period informed the proposed design by highlighting the need to avoid overloading the occupants with repeated prompts and to reduce the intervention fatigue. In addition, this step was included to inform future designers about the importance of sufficient spacing between the smart nudging interventions to maintain occupant engagement and effectiveness.
10 th step - Fetch device sensor data related to the most critical IAQ parameter via the API to the mobile application	Inclusion of this step informed the design by enabling a personalised, timely, and context-aware interventions that are based on actual and critical air quality conditions rather than static schedules and providing a scalable solution for the future designers or researchers to apply the interventions in the most needed time.
14 th step - Confirm no interventions during the cool-off period	This step informed the design by validating that no smart nudging intervention is sent unless 59 minutes have passed since the last one to prevent user overload.

Table 31: Industry inputs to formulate the proposed smart nudge design

6.2.4 The logic formation

The logic formation is the 12th step in the proposed smart nudge design (as shown in Figure 48 in section 6.2.1). This step includes the three logics of the three smart nudging interventions, namely, feedback, social comparison, and loss-aversion. Table 32 presents the steps of the logic formation of each smart nudging intervention, indicating whether each step was modified or not.

Steps	Feedback	Modifications	Social comparison	Modifications	Loss-aversion	Modifications
1	Urgency	No	Urgency	No	Urgency	No
2	Personalisation	No	Personalisation	No	Personalisation	No
3	Personal performance information	Yes	Peer behaviour information	Yes	Potential loss information + best practice	Yes
4	Emoji	No	Emoji	No	Incentives	No
5	Emotions	No	Emotions	No	Emoji	No
6	Best practices	Yes	Best practices	Yes	Emotions	No
7	Incentives	No	Incentives	No	Value	No
8	Value	No	Exclusivity	No		
9			Value	No		

Table 32: Logic Modifications

According to the Table 32, the 1st, 2nd, 4th, 5th, 7th, and 8th steps of feedback logic are similar to the previous logic formulation of feedback (shown in Figure 16 in Section 4.2.2.4) and those steps are not modified. Similarly, the 1st, 2nd, 4th, 5th, 7th, 8th, and 9th steps of social comparison logic are similar to the original logic formulation of social comparison (shown in Figure 17 in Section 4.2.2.4), and those steps are not modified. In addition, the 1st, 2nd, 4th, 5th, 6th, and 7th steps of loss-aversion logic are not modified and are similar to the original logic formulation (shown in Figure 18 in Section 4.2.2.4). The 3rd step, which includes the three types of personalised information is modified in the three proposed logic formulations. The 6th step which is ‘best practices’, is modified in both feedback and social comparison logic formulations. The modifications are described in detail below.

6.2.4.1 The type of personalised information - modifications

The 3rd step, which includes the three types of personalised information, namely, the personal performance information in feedback, peer behaviour information in social comparison, and potential loss information including best practices in loss-aversion, is modified in the three proposed logic formulations by specifying the location. Specifying the house location (example: kitchen window) makes the smart nudging intervention clearer, more actionable, and contextually

relevant. This increases the likelihood of occupant engagement. This modification is shown in the below Figure 49.

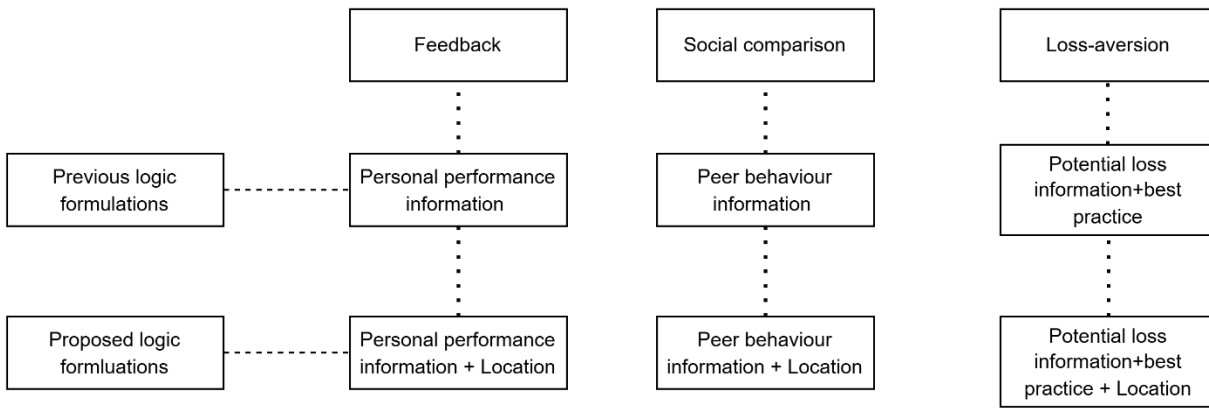


Figure 49: Type of personalised information - Modifications

6.2.4.2 Best practices – modifications

Table 33 shows the best practices for each indoor air quality parameter, namely, temperature, CO₂, relative humidity, and TVOC are shown by highlighting which have been modified and which remain unchanged. These modifications are proposed based on the empirical findings of this research and existing literature.

Indoor air quality parameter	Previous best practice	Modified best practice
Temperature	Maintain thermostat at 18°C-21°C (Public Health England, 2013, cited in Public Health England, 2014, p.4).	<ul style="list-style-type: none"> No modification
CO ₂	Opening windows (Deng, et al., 2021; Elwell & Few, 2021; Park & Choi, 2019; Sharpe, et al., 2016, Gunes & Undar, 2024)	<ul style="list-style-type: none"> Opening the window for 5-15 minutes (Muelas, et al., 2022; Hsu, et al., 2024).
Relative humidity	Using extractors when cooking, opening windows, closing the kitchen door (Chen, et al., 2023; NHBC, 2023)	<ul style="list-style-type: none"> Keep the extractor fan on and/or the kitchen window open, and the kitchen door closed for about 20 minutes after cooking and washing (NHBC,2023). Opening the bathroom window for 20 minutes and closing the bathroom door after bathing (NHBC,2023).
TVOC	Reducing the use of diffusers, air fresheners, and scented candles, window opening (Kim, et al., 2024; Warburton, et al., 2023; Gunes & Undar, 2024).	<ul style="list-style-type: none"> Opening the windows for 5-15minutes. Reducing the use of diffusers, air fresheners, and scented candles.

Table 33: Best practices – modifications

According to the Table 33, the best practice for maintaining a safe room temperature is not modified. Therefore, a home occupant should maintain the thermostat between 18°C-21°C to maintain energy efficiency and to improve indoor air quality. The best practices for maintaining safe CO₂ levels and TVOC levels have been modified. This is modified to guide the home occupants in a structured and effective manner. The existing research and the empirical findings of this research have shown that opening windows for 5-15 minutes lower high indoor CO₂ levels and high TVOC levels. In addition, the best practice to improve humidity levels has been modified.

The proposed logic formulations are shown in Figure 50.

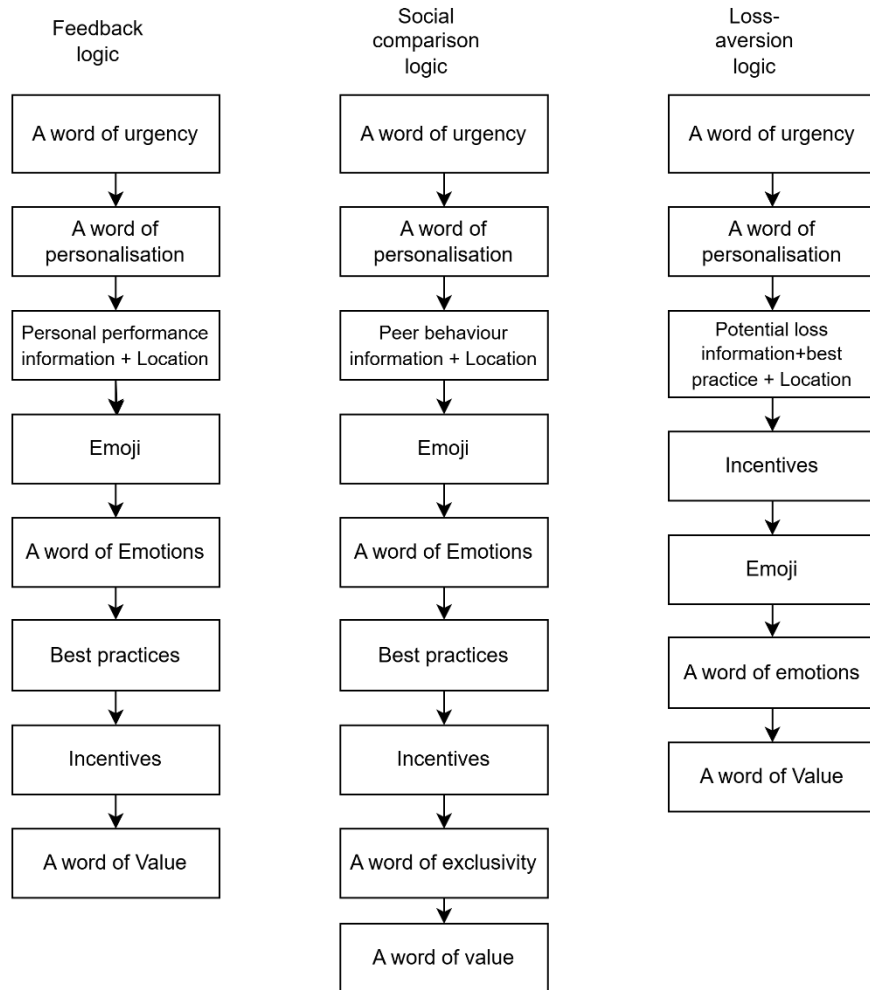


Figure 50: Proposed logic formulations

6.3 Chapter summary

In conclusion, this chapter has presented a proposed smart nudge design that builds upon the smart nudge design introduced in Chapter 4 – Smart nudge design, integrating insights from empirical findings of this research, existing literature, and practical validation from the industry partner. This proposed smart nudge design provides the clear pathway for designing and developing smart nudging interventions for home occupants. Moreover, the logics of the three smart nudging interventions are modified to increase the precision, contextual relevance, actionable, and clarity, paving the way for practical implementation of the smart nudging interventions.

7 Conclusion

7.1 Introduction

This research aimed to reduce anthropogenic indoor air emissions related to household energy consumption and improve indoor air quality in the residential sector through nudging the home occupants using digital technology. More importantly, this research proposed a smart nudge design that includes different logic formulations of different smart nudging interventions to nudge the home occupants, make informed decisions about their behaviours, and achieve a sustainable living environment. By using an action research methodology that included a multiple case-study design with a mixed method approach, this study investigated the interaction between the objective measures and subjective assessments of home occupants' behaviours related to the indoor air emissions and indoor air quality in the household energy sector. This provided a unique lens through which to identify the effectiveness of smart nudging interventions in achieving the safe thresholds of different indoor air quality parameters and the most effective smart nudging intervention overall in reducing indoor air emissions and improving indoor air quality in the household energy sector. Furthermore, the research findings were validated and triangulated to increase the credibility of the results and thereby, formulate a robust smart nudge design as one of the main research contributions.

In this concluding chapter, the key findings of the study are summarised with a restatement of research objectives and achievement, followed by a discussion on the contributions made to the field. In addition, the limitations of the research and future recommendations are presented in this chapter. Finally, a reflection on the broader significance of the study is presented.

7.2 Review of research objectives and summary of the key findings

The main findings of this research and the research objectives achieved are summarised in Table 34. This provides a clear mapping between the research objectives and the research findings achieved.

	Research objectives	Summary of the research findings
1.	To define and examine the existing body of knowledge on anthropogenic air emissions and behavioural economics, including strategies to effectively nudge individuals towards reducing anthropogenic air emissions in home energy consumption and improving indoor air quality through the application of digital technology.	<ul style="list-style-type: none"> • Building on the theoretical insights identified in the literature review, this research presented a smart nudge design to address and fill the knowledge gaps and research gaps in the existing empirical research. • This study identified and presented the smart nudge components to formulate different logics for the different smart nudging interventions that are tailored to achieve the research aim.
2	To develop a smart nudge design based on the literature review, complete with a process flow diagram and clearly articulate the steps involved in implementing the smart nudge design.	
3	To compose smart nudging interventions within the newly designed smart nudge design, ensuring they are tailored to influence user behaviour, make informed decisions, reduce anthropogenic air emissions related to household energy use, and improve indoor air quality.	
4	To conduct testing, analysis, and validation of the different smart nudging interventions by utilising the engagement analytics of the users and assessing user interviews through an action research methodology.	<ul style="list-style-type: none"> • This study identified that the 30-minute window is the most suitable window to evaluate the effectiveness of the smart nudging interventions in making a sustainable behavioural change among occupants. • <u>According to the quantitative findings:</u> <ul style="list-style-type: none"> ➤ Smart nudging interventions could reduce higher levels of CO₂ and achieve the safe threshold. The most effective smart nudging intervention to reduce the high CO₂ levels and achieve the safe threshold is loss-aversion and it indicated a significant positive impact rate of 100%. ➤ Smart nudging interventions could improve relative humidity levels. The most effective smart nudging intervention to reduce the high relative humidity levels and achieve the safe threshold is feedback and it indicated a significant positive impact rate of 29%. ➤ Smart nudging interventions could reduce higher TVOC levels and achieve the safe threshold. The most effective smart nudging intervention to reduce the high TVOC levels and achieve the safe threshold is feedback and it showed a significant positive impact rate of 75%. ➤ No smart nudging intervention was effective in improving the temperature. • <u>According to the qualitative findings:</u> <ul style="list-style-type: none"> ➤ The home occupants in all plots had taken measures to improve the indoor air quality parameters. ➤ Regarding perception of which type of smart nudging intervention was more effective, the home occupants of plots 5 and 10 felt that social comparison was the most effective smart nudging intervention, while the home occupant in plot 12 believed that feedback was the most effective smart nudging intervention.

		<ul style="list-style-type: none"> • Triangulated findings concluded that social comparison was identified as the most effective smart nudging intervention for overall reduction of indoor air emissions and improvement of indoor air quality related to the household energy sector holistically.
5	To propose an effective smart nudge design aimed at reducing anthropogenic air emissions related to household energy use and improving indoor air quality by changing human behaviours and consolidating findings from the literature review, design development, testing phases, and expert reviews to formulate an actionable design for behavioural change.	<ul style="list-style-type: none"> • A smart nudge design was proposed using empirical research findings and industry feedback to validate the design and formulations of the logics.

Table 34: Mapping of research objectives and research findings

As shown in Table 34, all research objectives were successfully achieved. The design of the smart nudge design and logic formulations of the smart nudging interventions were developed by a comprehensive and a systematic literature review. The testing, analysis, and validation phases led to the identification of the effectiveness of smart nudging interventions in achieving the safe thresholds of different indoor air quality parameters and the most effective smart nudging intervention that provided the overall contribution to achieve the research aim through validation and triangulation. The learnings from the empirical research and industry feedback contributed to formulate the proposed smart nudge design and confirm the design’s applicability in the real-world settings.

7.3 Research contributions

This study makes several key contributions to the field of built environment, particularly in the context of sustainability and behavioural change.

- **Theoretical contribution:** This study makes a theoretical contribution by applying smart nudging to the context of indoor air emissions related to household energy consumption and indoor air quality, as existing literature investigated the effectiveness of smart nudging using other metrics related to energy consumption, such as electricity, gas, room temperature, and hot water. Instead, this study used indoor air quality parameters such as CO₂, relative humidity, TVOC, and temperature to obtain a holistic understanding in this domain. In addition, this study makes a significant theoretical contribution by introducing a proposed smart nudge design applied to the household energy sector, where no such design was introduced in this domain.

- **Methodological contribution:** This research introduces a within-subject repeated measures design to deploy multiple smart nudging interventions within the same household to measure and compare the most effective smart nudging intervention in this context. Prior studies did not use within-subject repeated measures designs to assess the effectiveness of the smart nudging interventions, as the same user did not receive different types of interventions at different timestamps in those prior studies. This methodological contribution provides the opportunity for a more robust comparison of the effectiveness of the interventions.
- **Practical contribution:** This research presents a practical and evidence-based smart nudge design and new logic formulations for different smart nudging interventions that can be used in a real-life setting. The proposed smart nudge design can be implemented in any digital platform. Moreover, the proposed smart nudge design, including logics of smart nudging interventions, can be an effective tool for policymakers, developers, housing associations, and practitioners who are looking to develop and implement tools to change home occupants' behaviours, such as smart nudging, aimed at reducing indoor air emissions and improving indoor air quality in the household energy sector.

7.4 Implications of the study

The research findings of this study have several important implications:

- **Practical implications for home occupants:** This research highlighted the importance of tailoring smart nudging interventions to specific behaviours, perceptions, attitudes, specific household characteristics, and existing living conditions of home occupants. These tailored smart nudging interventions nudged the home occupants towards achieving the sustainable behaviours and reducing indoor air emissions related to household energy consumption and improving indoor air quality. The engagement analytics or the quantitative analysis showed the engagement of the occupants. In addition, the qualitative findings showed that the occupants were successfully engaged in achieving the sustainable behaviours through reading and learning from the smart nudging interventions. Therefore, this study showed that nudging interventions that focus solely on digital technology may be insufficient unless they also focus the demographics, contextual factors, and existing behaviours or habits or choices of the home occupants. Therefore, future smart nudging interventions

should continue to prioritise personalisation and context-awareness thoroughly to increase the positive impact of the interventions and maintain the sustained behavioural change.

- **Policy implications:** This study revealed that smart nudging interventions, more particularly social comparison, hold promise for reducing indoor air emissions related to household energy use and improving indoor air quality by achieving a sustainable behavioural change. This could inform policymakers to include smart nudging interventions or social comparison into broader strategies for managing indoor air pollution and indoor air quality, especially in high-risk areas such as urban environments.
- **Implications for future research:** This study shows the need for further research to investigate the effectiveness of smart nudging interventions in a wider range of residential contexts. It also highlights for more in-depth studies on the integration of mixed methods or both quantitative and qualitative research findings, as well as the long-term impacts of smart nudging interventions.

7.5 Limitations of the study

Although this research provides valuable insights, it is not free from limitations. The research limitations are highlighted as follows:

- **Limited sample size:** While social comparison was implemented across the three plots, it required similar demographics and household characteristics to ensure reliable results. As a result, three low-carbon houses with similar demographics and household characteristics were selected for this study. While the smart nudging interventions showed effectiveness in this low-carbon housing context, it may need to be adapted for a broader or different context to generalise and improve the applicability of the research findings. Therefore, this limitation highlighted that findings may not be generalisable to a broader or more diverse population. Moreover, a larger sample size would be needed to better understand the discrepancies between quantitative and qualitative results, exploring in more depth the impact of occupant perceptions in air quality improvement.
- **Lack of control over intervention delivery:** The smart nudging interventions had unequal number of instances in this study. This limitation influenced the identification of the real effectiveness of the smart nudging interventions, as some interventions had only one instance, leading to a non-conclusive or uncertain impact. This may have been affected

by the absence of confirmation of whether all the smart nudging interventions were delivered more than a single instance. In addition, some interventions were not delivered over the first week of the intervention period. Moreover, smart nudging interventions were delivered to improve the indoor air quality parameters that were slightly deviated from the recommended thresholds at some instances, affecting the overall impact of the interventions. These limitations highlight the lack of control over delivery of the interventions.

- **Limited sensor coverage:** The sensors were installed in living rooms and kitchens only. As a result, some occupant actions taken to reduce high relative humidity, such as opening windows in the bathrooms, were not captured, missing the impact of the performed actions.

7.6 Recommendations for future research

Building on the research findings and limitations of the study, the following recommendations are highlighted for future research:

- **Broader sample and context:** Future research should implement different smart nudging interventions in different contexts while maintaining similar demographics and household characteristics across the selected households. This would help assess the effectiveness of the smart nudging interventions in different contexts or real-life settings and improve the generalisability and the applicability of the research findings.
- **Long-term studies:** Future research should investigate the long-term effectiveness of smart nudging interventions on this domain. This could involve conducting research over several months or even years to assess the effectiveness of the interventions.
- **Control over intervention delivery:** Future research should include a step in the design to verify if all the smart nudging interventions were applied at an equal number of instances for the most critical parameter (the parameter that showed the highest deviation from the recommended threshold). The home occupants should receive the smart nudging interventions during their periods of occupancy.
- **Sufficient sensor coverage:** Future research should overcome the limitation of limited sensor coverage by installing sensors in multiple house locations such as kitchen, living

rooms, bedrooms, and bathrooms. This would enable more accurate monitoring and a better understanding of how occupant actions in different rooms affect indoor air quality.

7.7 Final reflections

This research has made important contributions to the field of built environment, especially in relation to the sustainability and behavioural change in the residential sector to reduce indoor air emissions related to household energy consumption and improve indoor air quality through smart nudging. The most effective smart nudging interventions in reducing high levels of CO₂, relative humidity, and TVOC were loss-aversion, feedback, and again feedback, respectively. Social comparison emerged as the most effective intervention in overall reduction of indoor air emissions and improvement of indoor air quality holistically. This study proposed a practical and evidence-based smart nudge design and new logic formulations for the smart nudging interventions based on a real-life context. Future research should build upon the research findings of this study, focusing on refining the proposed smart nudge design and logic formulations and exploring the long-term impacts of the interventions with a diverse sample size and different contexts with similar demographics and household characteristics. Ultimately, this research contributes to a growing body of knowledge aimed at reducing anthropogenic indoor air emissions and improving indoor air quality in the household energy sector.

References

- Afifa, et al., 2024. Air pollution and climate change as grand challenges to sustainability. *Science of the Total Environment*, Volume 928, pp. 1-16.
- Alam, S. M. I., 2022. *Behavioral Economics: Concepts, History, and Evolution*, Dhaka: Jahangirnagar University, Bangladesh.
- Al-Hafith, O., BK, S. & de Wilde, P., 2024. Impact of the energy crisis on indoor temperatures and thermal comfort in UK houses during winter 2023. *Energy & Buildings*, Volume 323, pp. 1-13.
- Amaratunga, D., Baldry, D., Sarshar, M. & Newton, R., 2002. Quantitative and qualitative research in the built environment: application of “mixed” research approach. *Emerald*, 51(1), pp. 17-31.
- Asensio, O. I. & Delmas, M. A., 2016. The dynamics of behavior change: Evidence from energy conservation. *Journal of Economic Behavior & Organization*, 126(1), pp. 196-212.
- ASHRAE, 2016. *ASHRAE Handbook—HVAC Systems and Equipment*. s.l.:ASHRAE.
- ASHRAE, 2022. *ASHRAE Position Document on Indoor Carbon Dioxide*, s.l.: ASHRAE.
- Avineri, E., 2012. On the use and potential of behavioural economics from the perspective of transport and climate change. *Journal of Transport Geography*, 24(1), p. 512–521.
- Aydin, E., Brounen, D. & Kok, N., 2018. Information provision and energy consumption: Evidence from a field experiment. *Energy Economics*, 71(1), pp. 403-410.
- Ayeni, A. W., 2014. *Empirics of Standard Deviation*. s.l., Landmark university.
- Bager, S. & Mundaca, L., 2017. Making ‘Smart Meters’ smarter? Insights from a behavioural economics pilot field experiment in Copenhagen, Denmark. *Energy Research & Social Science*, 28(1), pp. 68-76.
- Berger, M., Lange, T. & Stahl, B., 2022. A digital push with real impact – Mapping effective digital nudging elements to contexts to promote environmentally sustainable behavior. *Journal of Cleaner Production*, 380(1), pp. 1-18.

- Bolton, P., 2025. *Research Briefing - Energy efficiency of UK homes*, s.l.: House of Commons Library Research Briefing.
- Brülisauer, M. et al., 2020. Appliance-specific feedback and social comparisons: Evidence from a field experiment on energy conservation. *Energy Policy*, 145(1), pp. 1-9.
- Bugayong, C., 2022. *Featured home - Understanding VOC's and its effects on health*. [Online] Available at: <https://getuhoo.com/blog/home/understanding-vocs-and-its-effects-on-health/> [Accessed 08 05 2023].
- Buha, A., 2011. *The Greenhouse Effect*, s.l.: Toxipedia.
- Buheji, M., 2018. Understanding the Potential of Behavioural Economics on Establishing 'Quality of Life' Constructs. *American Journal of Economics* , 8(6), pp. 279-288.
- Burchell, K., Rettie, R. & Roberts, T. C., 2016. Householder engagement with energy consumption feedback: the role of community action and communications. *Energy Policy*, 88(1), p. 178–186.
- Camara, N., Xu, D. & Binyet, E., 2017. Understanding household energy use, decision making and behaviour in Guinea-Conakry by applying behavioural economics. *Renewable and Sustainable Energy Reviews*, 79(1), pp. 1380 - 1391.
- Canale, L. et al., 2021. Do in-home displays affect end-user consumptions? A mixed method analysis of electricity, heating and water use in Danish apartments. *Energy & Buildings*, 246(1), pp. 1-20.
- Cappa, F., Rosso, F., Giustiniano, L. & Porfiri, M., 2020. Nudging and citizen science: The effectiveness of feedback in energy-demand management. *Journal of Environmental Management*, 269(1), pp. 1-13.
- Caraban, A., Karapanos, E., Gonçalves, D. & Campos, P., 2019. 23 Ways to Nudge: A Review of Technology-Mediated Nudging in Human-Computer Interaction. CHI, pp. 1-15.
- Castmo, M. & Persson, R., 2018. *The alliance between Digital Nudging & Persuasive Design*, Lund: Lund University.
- Charness, G., Gneezy, U. & Kuhn, M. A., 2012. Experimental methods: Between-subject and within-subject design. *Journal of Economic Behavior & Organization*, 81(1), pp. 1-8.

- Chenari, B., Carrilho, J. D. & da Silva, M. G., 2016. Towards sustainable, energy-efficient and healthy ventilation strategies in buildings: A review. *Renewable and Sustainable Energy Reviews*, Volume 59, p. 1426–1447.
- Chen, X. et al., 2023. An Experimental Study on Temperature, Relative Humidity, and Concentrations of CO and CO₂ during Different Cooking Procedures. *Processes*, Volume 11, pp. 1-14.
- Chin, J.-Y. et al., 2014. Levels and sources of volatile organic compounds in homes of children with asthma. *Indoor Air*, Volume 24, p. 403–415.
- Chugh, R., 2017. *The Magic Of Power Words In Push Notifications*. [Online] Available at: <https://www.linkedin.com/pulse/magic-power-words-push-notifications-radhika-chugh/> [Accessed 25 June 2023].
- Coghlan, D. & Shani, A. B., 2021. Abductive Reasoning as the Integrating Mechanism between First- Second- and Third-Person Practice in Action Research. *Systemic Practice and Action Research*, Volume 34, p. 463–474.
- Committee on Climate Change, 2016. *The Fifth Carbon Budget: The next step towards a low-carbon economy*, s.l.: Committee on Climate Change.
- Committee on Climate Change, 2020. *The Sixth Carbon Budget- Methodology Report*, s.l.: Committee on Climate Change.
- Conaty, F., 2021. Abduction as a Methodological Approach to Case Study Research in Management Accounting — An Illustrative Case. *Accounting, Finance & Governance Review*, 27(1), pp. 1-26.
- Costello, G. J., Conboy, K. & Donnellan, B., 2015. *Reflections on 'reflection' in Action Research*. Warsaw, s.n., pp. 1-29.
- Darnton, A., 2008. *An overview of behaviour change models and their uses*, Westminster: University of Westminster.
- DellaValle, N., 2019. People's decisions matter: understanding and addressing energy poverty with behavioral economics. *Energy & Buildings*, 204(1), pp. 1-8.

Deng, T., Shen, X., Cheng, X. & Liu, J., 2021. Investigation of window-opening behaviour and indoor air quality in dwellings situated in the temperate zone in China. *Indoor and Built Environment*, 30(7), pp. 938-956.

Dissanayake, E. V. A., 2023. *Research Onion: A Systematic Approach for Designing Research*. New York: s.n.

Dominicis, S. D., Sokoloski, R., Jaeger, C. M. & Schultz, P. W., 2019. Making the smart meter social promotes long-term energy conservation. *PALGRAVE COMMUNICATIONS*, 5(51), pp. 1-8.

Dubois, A. & Gadde, L.-E., 2002. Systematic combining: an abductive approach to case research. *Journal of Business Research*, 55(1), p. 553 – 560.

El-Gohary, H. O., 2021. *The impact of E-marketing practices on market performance of small business enterprises. An empirical investigation*, Bradford: University of Bradford.

Elwell, C. & Few, J., 2021. *Open or Closed? Use of Windows and Doors at Home: Ventilation Rates in Occupied Dwellings*. s.l., ASHRAE.

Energy Saving Trust, 2020. *On the path to net zero: low carbon heating*. [Online] Available at: <https://energysavingtrust.org.uk/path-net-zero-low-carbon-heating/> [Accessed 30 12 2024].

Environment and Climate Change Committee, 2022. *1st Report of Session 2022–23: In our hands: behaviour change for climate and environmental goals*, s.l.: The Authority of the House of Lords.

eurostat, 2015. *Manual for air emissions accounts*, s.l.: European Union.

Frederiks, E. R., Stenner, K. & Hobman, E. V., 2015. Household energy use: Applying behavioural economics to understand consumer decision-making and behaviour. *RenewableandSustainableEnergyReviews*, 41(1), pp. 1385 - 1394.

Gherasim, A., Lee, A. G. & Bernstein, J. A., 2024. Impact of Climate Change on Indoor Air Quality. *Immunology and Allergy Clinics of North America*, 44(1), pp. 55-73.

Ghesla, C., Grieder, M., Schmitz, J. & Stadelmann, M., 2020. Pro-environmental incentives and loss aversion: A field experiment on electricity saving behavior. *Energy Policy*, 137(1), pp. 1-9.

Gleerup, M., Larsen, A., Leth-Petersen, S. & Togeby, M., 2010. The Effect of Feedback by Text Message (SMS) and Email on Household Electricity Consumption: Experimental Evidence. *The Energy journal*, 31(3), pp. 113-132.

Golzar, J. & Tajik, O., 2022. Convenience Sampling. *IJELS*, 1(2), pp. 72-77.

Good, N., 2019. Using behavioural economic theory in modelling of demand response. *Applied Energy*, 239(1), pp. 107-116.

GOV.UK, 2011. *Behaviour change and energy use*, London: The Cabinet Office Behavioural Insights Team.

GOV.UK, 2021. Net Zero Strategy: Build Back Greener, s.l.: GOV.UK.

GOV.UK, 2022. *Air Pollution in the UK 2021*, s.l.: Department for Environment Food and Rural Affairs.

GOV.UK, 2022. *Indoor Air Quality*, s.l.: Air Quality Expert Group.

GOV.UK, 2023. *Health Effects of Climate Change (HECC) in the UK: 2023 report; Chapter 5. Impact of climate change policies on indoor environmental quality and health in UK housing*, s.l.: UK Health Security Agency.

GOV.UK, 2023. *Net Zero Government Initiative - UK Roadmap to Net Zero Government Emissions*, s.l.: Department for Energy Security & Net Zero.

GOV.UK, 2024. *2022 UK Greenhouse Gas Emissions, Final Figures*, s.l.: Department for Energy Security and Net-zero.

GOV.UK, 2025. English Housing Survey 2023 to 2024: headline findings on housing quality and energy efficiency, s.l.: GOV.UK.

Gunes, G. & Undar, O. T., 2024. Effect of natural ventilation on indoor air quality parameters in different microenvironments. *International Journal of Environmental Science and Technology*, pp. 1-16.

Gustafsson, J., 2017. *Single case studies vs. multiple case studies: A comparative study*, Halmstad: Halmstad University.

Halios, C. H. et al., 2022. Chemicals in European residences – Part I: A review of emissions, concentrations and health effects of volatile organic compounds (VOCs). *Science of the Total Environment*, Volume 839, pp. 1-21.

Heeley-Hill, A. C. et al., 2021. Frequency of use of household products containing VOCs and indoor atmospheric concentrations in homes. *Environmental Science Processes & Impacts*, Volume 23, p. 699–713.

Henry, M. L., Ferraro, P. J. & Kontoleon, A., 2019. The behavioural effect of electronic home energy reports: Evidence from a randomised field trial in the United States. *Energy Policy*, 132(1), pp. 1256-1261.

Hsu, H.-C., Chang, C.-W., Chen, C.-C. & Pan, . C.-Y., 2024. Natural Ventilation: Optimizing Window Opening Size for CO₂ Concentration Control and Thermal Comfort on Nonwindward Facades. *Indoor Air*, 2024(1), pp. 1-18.

Ibrahim, F., Samsudin, E. Z., Ishak, A. R. & Sathasivam, J., 2024. The relationship between occupant behaviour and indoor air quality in Malaysian hospital outpatient departments: A multistage cross-sectional study. *Heliyon*, Volume e34454, pp. 1-19.

IEA, 2025. *Net Zero by 2050 - A Roadmap for the Global Energy Sector*, s.l.: IEA.

Igwenagu, C., 2016. *Fundamentals of research methodology and data collection*. 1st ed. Nsukka: Enugu State University of Science and Technology.

Institute of Air Quality Management, 2021. *Indoor Air Quality Guidance: Assessment, Monitoring, Modelling and Mitigation*, s.l.: IAQM.

IPCC, 2018. *Global warming of 1.5°C*, s.l.: IPCC.

IPCC, 2021. *Climate Change 2021: The Physical Science Basis*, s.l.: Intergovernmental Panel on Climate Change.

Karlsen, R. & Andersen, A., 2019. Recommendations with a Nudge. *Technologies*, 7(45), pp. 1-16.

Karlsen, R. & Andersen, A., 2022. The Impossible, the Unlikely, and the Probable Nudges: A Classification for the Design of Your Next Nudge. *Technologies*, 10(110), pp. 1-17.

- Kazukauskas, A., Broberg, T. & Jaraite, J., 2021. Social Comparisons in Real Time: A Field Experiment of Residential Electricity and Water Use. *The Scandinavian Journal of Economics*, 123(2), pp. 558-592.
- Kim, H. B. et al., 2020. Field experiment of smartphone-based energy efficiency services for households: Impact of advice through push notifications. *Energy & Buildings*, 223(1), pp. 1-12.
- Kim, H. et al., 2022. MySmartE – An eco-feedback and gaming platform to promote energy conserving thermostat-adjustment behaviors in multi-unit residential buildings. *Building and Environment*, 221(1), pp. 1-18.
- Kim, P.-G. et al., 2024. Increase of the indoor concentration of volatile organic compounds after the use of incense and scented candle in studio apartments determined using passive sampling. *Chemosphere*, 359(1), pp. 1-8.
- Kotronoulas, G. et al., 2023. An Overview of the Fundamentals of Data Management, Analysis, and Interpretation in Quantitative Research. *Seminars in Oncology Nursing*, 39(2023), pp. 1-9.
- Kotter, J. P., 2008. *A sense of urgency*. U.S. edition ed. Boston: Harvard Business Press.
- Kumar, R., 2011. *Research Methodology - a step-by-step guide for beginners*. 3rd ed. London: SAGE.
- Kureshi, R. R., Thakker, D., Mishra, B. K. & Barnes, J., 2023. From Raising Awareness to a Behavioural Change: A Case Study of Indoor Air Quality Improvement Using IoT and COM-B Model. *Sensors*, Volume 23, pp. 1-29.
- Lewis, A. et al., 2022. *Indoor Air Quality*, s.l.: Department for the Environment, Food and Rural Affairs.
- Lin, B. et al., 2017. Analyzing the Relationship between Human Behavior and Indoor Air Quality. *Journal of Sensor and Actuator Networks*, 6(3), pp. 13-31.
- Liu, M. et al., 2022. The effect of normative-based feedback messaging on room air conditioner usage in university dormitory rooms in winter season. *Energy & Buildings*, 277(1), pp. 1-15.
- Lynham, J., Nitta, K., Saijo, T. & Tarui, N., 2016. Why does real-time information reduce energy consumption?. *Energy Economics*, 54(1), pp. 173-181.

- Makivierikko, A. et al., 2023. Reducing electricity peak loads through ‘pause hours’ - a community-based behavioural demand response approach. *Journal of Cleaner Production*, 408(1), pp. 1-18.
- Marć, M., Śmiełowska, M., Namieśnik, J. & Zabiegała, B., 2018. Indoor air quality of everyday use spaces dedicated to specific purposes—a review. *Environmental Science and Pollution Research*, Volume 25, p. 2065–2082.
- Mateo-Garcia, M. et al., 2023. *PROJECT 80 - Eco Drive Handsworth - Future homes standard case study*, Birmingham: Birmingham City University.
- Mele, C., Spena, T. R., Kaartemo, V. & Marzullo, M. L., 2021. Smart nudging: How cognitive technologies enable choice architectures for value co-creation. *Journal of Business Research*, 129(1), pp. 949-960.
- Melnikovas, A., 2018. Towards an Explicit Research Methodology: Adapting Research Onion Model for Futures Studies. *Journal of Futures Studies*, 23(2), p. 29–44.
- Meske, C. & Amojó, I., 2020. *Ethical Guidelines for the Construction of Digital Nudges*. Hawaii, 53rd Hawaii International Conference.
- Metcalf, R. & Roth, S., 2025. Making the invisible visible: the impact of revealing indoor air pollution on behaviour and welfare. Grantham Research Institute on Climate Change and the Environment Working Paper 422. London: London School of Economics and Political Science.
- Miller, J. . E., Amit, E. & Posten, A.-C., 2016. Behavioural economics. In: *Encyclopedia of Global Bioethics*. 1st ed. s.l.:Springer, pp. 1-7.
- Mishra, P. et al., 2019. Descriptive Statistics and Normality Tests for Statistical Data. *Annals of Cardiac Anaesthesia*, 22(1), p. 67–72.
- Mishra, P. et al., 2019. Application of Student's t-test, Analysis of Variance, and Covariance. *Annals of Cardiac Anaesthesia*, 22(4), pp. 407-411.
- Mogles, N. et al., 2017. How smart do smart meters need to be?. *Building and Environment*, 125(1), pp. 439-450.

- Muelas, A. et al., 2022. Analysis of different ventilation strategies and CO2 distribution in a naturally ventilated classroom. *Atmospheric Environment*, 283(1), pp. 1-10.
- Muhammad, L. N., 2023. Guidelines for repeated measures statistical analysis approaches with basic science research considerations. *The journal of clinical investigation*, 133(11), pp. 1-3.
- Myers, E. & Souza, M., 2020. Social comparison nudges without monetary incentives: Evidence from home energy reports. *Journal of Environmental Economics and Management*, 101(1), pp. 1-19.
- NHBC, 2019. *Moisture in new homes: A Guide for Occupants*, s.l.: UKCMB: UK Center for Moisture in Buildings.
- NHBC, 2023. *About condensation in your home*, s.l.: NHBC.
- O'Leary, C., Jones, B., Dimitroulopoulou, S. & Hall, . I. P., 2019. Setting the standard: The acceptability of kitchen ventilation for the English housing stock. *Building and Environment*, Volume 166, pp. 1-12.
- Orru, H., Ebi, K. L. & Forsberg, B., 2017. The Interplay of Climate Change and Air Pollution on Health. *Current Environmental Health Report*, Volume 4, p. 504–513.
- Oswald, D., Sherratt, F. & Smith, S., 2014. Handling the Hawthorne effect: The challenges surrounding a participant observer. *Review of Social Studies* , 1(1), pp. 53-73.
- Oyeka, I. C. A. & Ebu, G. U., 2012. Modified Wilcoxon Signed-Rank Test. *Open Journal of Statistics*, 2(1), pp. 172-176.
- Pablo-Romero, M. d. P., Pozo-Barajas, R. & Yñiguez, R., 2017. Global changes in residential energy consumption. *Energy policy*, 101(1), pp. 342-352.
- Page, M. J. et al., 2021. *The PRISMA 2020 statement: an updated guideline for reporting systematic reviews*, s.l.: BMJ.
- Parhizkar, H. et al., 2023. Objective indoor air quality parameters and their association to respiratory health and well-being among office workers. *Building and Environment* , Volume 246, pp. 1-7.

- Park, J. & Choi, C., 2019. Modeling occupant behavior of the manual control of windows in residential buildings. *Indoor Air*, 29(2), pp. 242-251.
- Parliamentary Office of Science and Technology (POST), 2023. *POSTbrief 54: Indoor Air Quality*, s.l.: UK Parliament.
- Peng, Z., Deng, W. & Tenorio, R., 2017. Investigation of Indoor Air Quality and the Identification of Influential Factors at Primary Schools in the North of China. *sustainability*, 9(1180), pp. 1-14.
- Petrou, G. et al., 2024. Placement of monitors for quantifying indoor air pollutant exposure in UK homes: issues for consideration. London, UCL.
- Petrov, M., Nikolaeva, Z. & Dimitrov, A., 2023. The impact of anthropogenic activity on the global environment. International scientific journal "Science. Business. Society", 8(2), pp. 59-64.
- Piao, X. & Managi, S., 2023. Household energy-saving behavior, its consumption, and life satisfaction in 37 countries. *Scientific Reports*, 13(1382), pp. 1-13.
- Pipal, A. S. & Taneja, A., 2023. Measurements of Indoor Air Quality: Science and Applications. In: D. K. Aswal, et al. eds. (eds.), *Handbook of Metrology and Applications*. Agra: Springer Nature Singapore Pte Ltd., pp. 1-35.
- Pollitt, M. G. & Shaorshadze, I., 2011. *The Role of Behavioural Economics in Energy and Climate Policy*, s.l.: University of Cambridge.
- Public Health England, 2014. *Minimum home temperature thresholds for health in winter – A systematic literature review*, London: PHE publications.
- Public Health England, 2019. *Indoor Air Quality Guidelines for selected Volatile Organic Compounds (VOCs) in the UK*, s.l.: Public Health England.
- Pūce, L., 2019. CRITICISM OF BEHAVIOURAL ECONOMICS: ATTACKS TOWARDS IDEOLOGY, EVIDENCE AND PRACTICAL APPLICATION. *Journal of WEI Business and Economics*, 8(1), pp. 32-46.
- Rajasekar, S., Philominathan, P. & Chinnathambi, V., 2013. *RESEARCH METHODOLOGY*, Tamilnadu: Bharathidasan University.

Rama, E. et al., 2025. Clinical Outcomes of Passive Sensors in Remote Monitoring: A Systematic Review. *Sensors*, 25(11), pp. 1-24.

RESET, 2019. *Air Standard for residential*, s.l.: RESET.

Roever, L., 2018. PICO: Model for Clinical Questions. *Evidence Based Medicine and Practice*, 3(2), pp. 1-2.

Rowe, G. & Rank, F., 2024. *Research Briefing: Housing and net zero*, s.l.: House of Commons Library.

Royal Society of Chemistry, 2022. *Indoor Air Quality: A workshop report on the contribution chemical sciences can make to improving indoor air quality in the UK*, s.l.: Royal Society of Chemistry.

Ruokamo, E. et al., 2022. The effect of information nudges on energy saving: Observations from a randomized field experiment in Finland. *Energy Policy*, 161(1), pp. 1-15.

Saunders, M. N., Lewis, P. & Thornhill, A., 2007. *Research Methods for Business Students*. 4th ed. Harlow: Pearson Education.

Shafqat, O., Rosberg, E., Bogdan, C. & Lundström, A., 2019. *Per-appliance energy feedback as a moving target*. s.l., Stockholm.

Shahzad, U. & Riphah, 2015. Global Warming: Causes, Effects and Solutions. *Durreesamin Journal*, 1(4), pp. 23-31.

Sharpe, T., McGill, G., Gupta, R. & Mawditt, I., 2016. *Characteristics and performance of MVHR systems - A meta study of MVHR systems used in the Innovate UK Building Performance Evaluation Programme*, s.l.: Innovate UK.

Skinner, B. F., 2014. *Science and human behaviour*. s.l.:The B. F. Skinner Foundation.

Stark, J. L., 2014. The potential of Deweyan inspired action research. *Education and Culture*, 30(2), pp. 87-101.

Stieglitz, S. et al., 2023. The potential of digital nudging to bridge the gap between environmental attitude and behavior in the usage of smart home applications. *International Journal of Information Management*, 72(1), pp. 1-19.

Strauss, G. P. & Allen, D. N., 2008. Emotional intensity and categorisation ratings for emotional and nonemotional words. *Cognition and emotion*, 22(1), pp. 114-133.

Su, W. et al., 2023. Maintaining an acceptable indoor air quality of spaces by intentional natural ventilation or intermittent mechanical ventilation with minimum energy use. *Applied Energy*, Volume 348, pp. 121504-121504.

Sundarakani, B., Ajaykumar, A. & Gunasekaran, A., 2021. Big data driven supply chain design and applications for blockchain: An action research using case study approach. *Omega*, Volume 102, pp. 1-19.

Taherdoost, H., 2016. Sampling Methods in Research Methodology; How to Choose a Sampling Technique for Research. *International Journal of Academic Research in Management*, 5(2), pp. 18-27.

Taneja, S. & Mandys, F., 2022. Drivers of UK household energy expenditure: Promoting efficiency and curbing emissions. *Energy Policy*, 167(1), pp. 1-9.

Thaler, R. & Sunstein, C., 2008. *Nudge: Improving decisions about health, wealth and happiness*, London: Penguin.

Tran, V. V., Park, D. & Lee, Y.-C., 2020. Indoor Air Pollution, Related Human Diseases, and Recent Trends in the Control and Improvement of Indoor Air Quality. *International Journal of Environmental Research and Public Health*, 17(8), pp. 2927-2954.

UNFCCC, 2016. *The Paris Agreement*, Paris: United Nations Framework Convention on Climate Change (UNFCCC).

USEPA, 2024. *Climate Change Indicators: Greenhouse Gases*. [Online] Available at: <https://www.epa.gov/climate-indicators/greenhouse-gases> [Accessed 30 12 2024].

USEPA, 2024. *Indoor Air Quality and Climate Change*. [Online] Available at: <https://www.epa.gov/indoor-air-quality-iaq/indoor-air-quality-and-climate-change> [Accessed 30 12 2024].

USEPA, 2024. *Indoor Pollutants and Sources*. [Online] Available at: <https://www.epa.gov/indoor-air-quality-iaq/indoor-pollutants-and-sources> [Accessed 15 11 2024].

USEPA, 2024. *Introduction to Indoor Air Quality*. [Online] Available at: [https://www.epa.gov/indoor-air-quality-iaq/introduction-indoor-air-quality#:~:text=Indoor%20Air%20Quality%20\(IAQ\)%20refers,up%2C%20be%20aggravated%20or%20worsened](https://www.epa.gov/indoor-air-quality-iaq/introduction-indoor-air-quality#:~:text=Indoor%20Air%20Quality%20(IAQ)%20refers,up%2C%20be%20aggravated%20or%20worsened). [Accessed 30 December 2024].

USEPA, 2024. *Sources and Solutions: Fossil Fuels*. [Online] Available at: <https://www.epa.gov/nutrientpollution/sources-and-solutions-fossil-fuels#:~:text=When%20fossil%20fuels%20are%20burned,referred%20to%20as%20nitrogen%20oxides>. [Accessed 30 12 2024].

USEPA, 2024. *Understanding the Issue: Household Energy and Clean Air*. [Online] Available at: <https://www.epa.gov/indoor-air-quality-iaq/understanding-issue-household-energy-and-clean-air#:~:text=Burning%20solid%20fuels%20indoors%20releases,Health%20Organization's%20air%20quality%20guidelines%20>. [Accessed 30 12 2024].

Uwamusi, C. B. & Ajisebiyawo, A., 2023. Participant Observation as Research Methodology: Assessing the Defects of Qualitative Observational Data as Research Tools. *Asian Journal of Social Science and Management Technology*, 5(3), pp. 19-32.

Warburton, T. et al., 2023. The impact of plug-in fragrance diffusers on residential indoor VOC concentrations. *Environmental Science Processes & Impacts*, 25(1), p. 805–817.

Warburton, T. et al., 2025. Yearlong study of indoor VOC variability: insights into spatial, temporal, and contextual dynamics of indoor VOC exposure. *Environmental Science: Processes & Impacts*, Volume 27, pp. 1025-1040.

Weinmann, M., Schneider, C. & Brocke, J. v., 2016. Digital Nudging. *Business and Information Systems Engineering*, 58(1), p. 433–436.

WHO, 2009. *WHO guidelines for indoor air quality : dampness and mould*, s.l.: World Health Organization.

WHO, 2019. *What is Air Pollution?*, s.l.: WHO.

Williamson, K., Satre-Meloy, A., Velasco, K. & Green, K., 2018. *Climate Change Needs Behavior Change - Making the Case for Behavioral Solutions to Reduce Global Warming*, Arlington: Rare.

Wojnowski, W. et al., 2024. Exposure to cooking emitted volatile organic compounds with recirculating and extracting ventilation solutions. *Building and Environment*, Volume 261, pp. 1-11.

Yahya, W. . K. & Marzuki, . S. Z. S., 2012. INVESTIGATING THE RELATIONSHIP BETWEEN CLIMATE CHANGE, GLOBAL WARMING AND SUSTAINABLE CONSUMPTION. *Business & Management Quarterly Review*, 3(1), pp. 53-59.

Yang, S. et al., 2020. Energy, indoor air quality, occupant behavior, self-reported symptoms and satisfaction in energy-efficient dwellings in Switzerland. *Building and Environment*, Volume 171, pp. 1-9.

Yu, G. et al., 2024. A study of quantifying the influence of kitchen human activity on indoor air quality dynamics. *Environmental Pollution*, Volume 362, pp. 1-11.

Zhao, D. et al., 2017. Interaction effects of building technology and resident behaviour on energy consumption in residential buildings. *Energy and Buildings*, Volume 134, pp. 223-233