Design for Sustainable behaviour: Exploring the Electricity-Related Feedback Interventions of Measurable Energy Smart Sockets at Park Eat Restaurant

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Undergraduate Research Opportunity Placement

School of Construction Management and
Engineering University of Reading

August 2024

Undergraduate Research Opportunities Programme

measurable•energy

University of Reading

Are measurable.energy sockets smart enough to reduce energy consumption and change energy consumption behaviour?

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Overview:

Measurable.energy's innovative sockets use LED indicators to show the carbon intensity of electricity from the National Grid, helping users make informed decisions about energy use. Our 6-week placement aimed to evaluate the effectiveness of measurable.energy sockets in reducing energy consumption and carbon emissions at Park Eat restaurant. We also assessed how their traffic light system influences staff behavior and identified best practices for their adaptation. The measurable.energy sockets lead to significant reductions in energy use and emissions, especially in bar areas with up to 56.2% less energy consumption and 41.5% lower CO_2 emissions. However, results varied for coffee machines and other appliances, suggesting differing effectiveness based on application. The study also explored how personal moral norms and motivation impact energy-saving intentions and behaviors.

Introduction:

In commercial buildings, over 20% of small power energy is wasted, often due to appliances left on or in standby. Measurable.energy addresses this by identifying the energy state of equipment and powering it off when not needed. Additionally, as appliances like fridges and freezers age, they become less efficient, consuming more energy over time. By using measurable.energy's technology to monitor energy consumption and emissions, we can detect inefficiencies and plan timely replacements. For example, the below figure identified that replacing five inefficient double bottle fridges led to an 89% reduction in energy use and a £12,000 annual savings, with projected five-year savings of £60,000 and a reduction of over 20 tonnes of carbon emissions.

Measurable.Energy Case Studies:

Organization	Savings Achieved
Kier Group	59% reduction in energy use, £3,031 savings/year, 4,566 kWh energy savings, 3.8 t CO2 reduction
Wernick Group	20% reduction in energy use, 23% reduction in CO2 emissions.
Royal Cornwall Hospitals NHS Trust	59% reduction in energy us
PKF Francis Clark's Bristol Office	38% reduction in energy consumption, over 20% savings on energy costs.
University of Reading	872 kWh energy savings, 148 kg CO2 reduction, 6-month payback.

Data and methods:

Measurable.energy platform provided longitudinal hourly electricity monitoring for 6 automated and 10 manually controlled sockets across Park Eat restaurant. An extended TPB-based survey gathered self-reported data from 22 catering staff on influence of the traffic light system on their energy-saving behaviors.

Findings:

- **The bar chiller electricity consumption showed a notable trend of increased usage, with significant savings from January to March, followed by smaller savings in April and May.**

- **Automating sockets in high-energy consumption areas results the best financial returns.**
- **Confusion about the meaning of the measurable.energy traffic light colour codes highlight the need for clearer guidance and training.**
- **Past energy-saving behavior influences attitudes and intentions but does not significantly predict actual energy-saving behavior.**

Conclusion:

- Measurable.energy sockets benefits vary by appliance and usage, automatisation reduced energy use and reduce environmental impact.
- Measurbale.energy sockets reveal significant gaps in energy-saving education and communication.

This project was supported by the UROP (Undergraduate Research Opportunities Programme) scheme at the University of Reading. UROP is managed by Careers.

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[1] This is an example of a UROP poster, not the final version. It serves as a preliminary draft to illustrate the key elements and layout we are considering. The final version will incorporate additional data, refined graphics and any feedback received during the review process to ensure it effectively communicates our research findings and conclusions.

Acknowledgements

We would like to thank all the staff members at the Park Eat restaurant for their support throughout this research project.

We are also grateful to the following individuals: Dan Williams, Chief Executive Officer of Measurable Energy, Josh Eadie, Chief Technical Officer of Measurable Energy, Mashal Sadiq, Head of Customer Success at Measurable Energy, Samantha Mudie, Director at Hospitality Energy Saving & Sustainability, Luke Canttelow, Energy Officer at University of Reading, Matt Tebitt, Director of Dining at University of Reading and Joseph Jacob, Regional Sales Manager at Solartron ISA.

If it were not for their contribution, this work would not have been completed.

A special thank you to the Undergraduate Research Opportunity Placement scheme, through which the two projects received funding.

Abstract

Measurable.energy's innovative sockets use LED indicators that reflect the carbon intensity of electricity sourced from the National Grid. The color-coded system provides real-time information about the energy source: green indicates predominantly renewable energy (e.g., wind, solar), amber represents a mix of renewable and non-renewable sources (including fossil fuels and nuclear) and red signifies energy primarily derived from non-renewable sources. This feature is designed to assist users in making informed decisions about when to use their devices, thereby reducing their carbon footprint.

This study aims to provide a comprehensive understanding of how Measurable.energy smart sockets impact user's energy consumption behaviour and to investigate their overall efficiency. The implementation of smart energy sockets in the Park Eat restaurant has led to a notable reduction in energy consumption. For example, bar sockets experienced significant reductions in energy use and emissions, with some achieving up to 56.2% decreases in energy consumption and up to 41.5% reductions in CO_2 emissions. In contrast, coffee machines showed varied results: while some sockets experienced higher energy consumption, they also achieved higher emissions reduction. This suggests that while automation can increase certain operational aspects, its effectiveness can differ depending on the specific application and context. The results indicate that high-energy appliances, such as those used in bar areas and for coffee machines, exhibit the most favorable payback periods. Conversely, kitchen appliances show varied payback periods while others (such as manually controlled sockets) have longer durations due to lower cost reductions. Incorporating Personal Moral Norms and Self-Determined Motivation with the Theory of Planned Behaviour strengthens the role of Attitudes in predicting Intention, but the impact of Personal Moral Norms remains ambiguous and the Intention-Behaviour link is still non-significant, while adding Past Behaviour highlights Attitude and Past Behaviour as significant predictors of Intention but does not result Behaviour prediction.

Key findings

1. The automation of appliances with Measurable.energy sockets shows improved energy efficiency and reduced CO_2 emissions compared to manual operations, highlighting their effectiveness in managing energy and reducing environmental impact.

2. Automation of the coffee machines led to increased energy consumption in some cases, indicating that the benefits of automation vary depending on the specific operational context.

3. High-energy appliances, such as those in bar settings and coffee machines, show the most favorable payback periods, typically around 2 months, making automation a financially attractive option for these areas.

4. There is a significant gap in training regarding the measurable.energy traffic light system, with varied interpretations of color codes and a lack of clear guidance, emphasizing the need for improved training.

5. Past behaviour and attitudes significantly predict energy-saving intentions, they do not strongly predict actual behaviour, suggesting that additional factors and clearer pathways are needed to translate intentions into effective energy-saving actions.

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List of abbreviations

m.e = Measurable Energy

TPB = Theory of Planned Behaviour

INT=Intention

BEH=Behaviour

ATT=Attitude

PBC = Perceived Behavioural Control

SN = Subjective Norms

PMN=Personal Moral Norms

PBH=Past Behaviour

SDM=Self-Determined Motivation

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1. Introduction

The University of Reading has pledged to achieve Net Zero Carbon by 2030, exemplifying its ongoing leadership in mitigating environmental impacts. Attaining this objective will position the University as a global frontrunner in climate change mitigation. The University is recognized as a leader in reducing operational carbon emissions. In 2016, the University achieved its 35% carbon emissions reduction target (compared to its 2008/09 baseline), earning the EAUC Green Gown Award for Carbon Reduction. Importantly, by January 2020, the University's emissions were 44.1% below baseline levels, nearing its next goal of a 45% reduction by July 2021. This accomplishment places the University among the top five higher education institutions in the country for carbon emissions reductions, including the leading research-intensive university. The cumulative reductions of 133,517 tCO_2 e are equivalent to removing all road traffic from the Borough of Reading for an entire year. Financially, the cumulative direct savings for the University amount to £34 million.

In the context of energy monitoring, the University of Reading began exploring a solution that would allow it to measure carbon emissions at the device level, provide remote access and report savings in electricity consumption. One solution was provided by measurable.energy intelligent sockets, which allow for the monitoring and management of appliances in real-time. Following their installation in Park Eat, just two months of a trial eliminated 872 kWh of small power waste (or standby power)—equivalent to charging 58,075 mobile phones. Additionally, they have prevented 148 kg of carbon emissions, which is comparable to the amount absorbed by two tree seedlings over a decade.

In this report, two Undergraduate Research Assistants, Axel and Zahrah, conducted a comprehensive analysis on how smart automatization can be applied towards the reduction of energy consumption in non-residential buildings. The smart sockets were strategically located at various points within the Park Eat restaurant to assess energy consumption across different areas. The specific locations and number of sockets investigated were as follows:

- Reception Desk: 2 sockets
- Kitchen: 4 sockets
- Front of House: 4 sockets
- Bar: 3 sockets
- Coffee Machine Area: 3 sockets

Each of these locations was selected to provide a comprehensive overview of the energy usage patterns within the restaurant, allowing for a detailed analysis of potential savings and optimization opportunities. Their study focused on various time frames, including the start and end of term, the summer vacation period and the beginning of the new academic year, to capture the full range of appliance usage patterns. This analysis aimed to identify potential energy savings and cost reductions that could be achieved through optimized scheduling and usage of devices.

Furthermore, the students administered a survey to investigate the impact of a traffic light system on human behaviour. This system, designed to provide real-time feedback on energy usage, was evaluated for its effectiveness in encouraging sustainable practices among staff and students. Axel and Zahrah sought to understand how visibility and immediate feedback could influence energy-saving behaviours.

Overall, their research provides valuable insights into the potential for energy optimization and cost savings within the University of Reading's facilities, contributing to the broader goal of achieving net-zero carbon emissions.

1.1. Gaps, aims and objectives

While there are several studies that have investigated the adoption of smart devices in residential homes, fewer studies have explored how these smart technologies function and influence behaviour in institutional settings such as restaurants. Therefore, our aim was to assess the feasibility of replacing human intervention with automation through the use of measurable.energy sockets in institutional settings such as restaurants.

Our objectives in this study are:

- Conduct a detailed analysis of energy consumption patterns at various points within the restaurant, including reception, kitchen, front of house, bar and coffee machine areas.
- Quantify energy savings and reductions in carbon emissions achieved through the use of smart sockets.
- Investigate how the traffic light system of smart sockets influences staff behaviour towards energy usage.
- Determine if automation can effectively replace human intervention in promoting energy-saving behaviours.
- Explore the norms and sustainable practices promoted by the visibility and functionality of smart technologies.

- Identify challenges and best practices for the meaningful incorporation of m.e sockets in restaurant operations.

2. Driving Carbon Neutrality: Monitoring Appliance Energy Consumption and Proposing Technology replacement and Automatisation at the University of Reading's Park Eat Restaurant

Our investigation started with the review of the University of Reading's ambitious Net Zero Carbon Plan. The University of Reading has committed to achieving carbon neutrality by 2030, which necessitates a substantial reduction in energy and gas consumption. In alignment with this objective, a significant project was undertaken in 2021, led by Dr. Samantha Mudie, who managed the installation of 16 new, energy-efficient catering ovens across seven on-campus food outlets. This initiative, funded by Salix, replaced 18 outdated and inefficient ovens, some of which were over two decades old. The replacement ovens not only improved operational reliability but also yielded substantial environmental and financial benefits (Figure 1). The project resulted in a reduction of 326,214 kWh in annual energy consumption and a decrease of 67.9 tonnes in carbon dioxide emissions (Sustainability Reading, 2023).

Figure 1. Old versus new catering owens.

Dr. Mudie, applying her expertise from her PhD research, conducted a meticulous assessment of the project’s outcomes. Her evaluation involved an application of a model that accounted for factors such as appliance capacity, temperature settings and food preparation processes. This detailed analysis facilitated an accurate measurement of the energy savings achieved through the new equipment (Mudie et al., 2016).

Subsequently, Dr Mudie applied similar energy-saving principles to another project using Measurable Energy smart plugs to monitor the energy consumption of bottle fridges. This technology provides real-time analytics on energy usage, enabling the identification of inefficiencies. In a follow-up study, the smart plugs were used to evaluate the energy profiles of five double bottle fridges. The data revealed substantial energy wastage, leading to the decision to replace these fridges with more efficient sockets. The upgrade resulted in an 87% reduction in energy consumption, yielding annual cost savings of £11,953 and a projected total savings of £60,000 over five years, along with a reduction of over 20 tonnes of carbon emissions (Measurable Energy, 2024).

In our reading of case studies from the Measurable Energy website, the use of Measurable Energy smart plugs significantly improves energy management and supports sustainability objectives. These smart plugs are used in various environments, including construction sites, offices, restaurants and more, providing significant savings on energy consumption. These devices enable precise monitoring and detection of energy-inefficient appliances, which are crucial for informed maintenance decisions and timely equipment upgrades. However, the effectiveness of such technologies may vary across different types of equipment and operational contexts, suggesting the need for further research into their broader applications and long-term impacts.

What was not clear to us is how end users domesticate these m.e sockets and what kind of education or training is provided to better connect with the m.e sockets. This aspect of user engagement and training is crucial to ensure that the end users fully understand how to utilize the smart plugs effectively and integrate them into their daily routines to maximize energy savings and sustainability benefits.

For instance, a case study at Stink Studios demonstrated a 25% reduction in energy use and a 22% drop in CO_2 emissions due to the installation of measurable.energy's sockets (Measurable Energy Case Studies, 2026). These sockets allowed for automated and remote control of equipment, with LED lights on the sockets raising awareness and encouraging energy-saving behaviours. Lorraine, the director, praised the automation feature and the ability to visualize energy savings, highlighting the convenience and impact of the technology. While the director praised the traffic light system on m.e sockets, there remains a question regarding how these smart plugs change customer behaviour. Specifically, do these devices increase sustainability knowledge among users? Do people manage their energy savings better? Do they consume less energy or choose to consume energy when the grid's carbon intensity is lower? If these outcomes are not being achieved, what can be proposed to improve the adaptability of the m.e smart plugs and enhance user's understanding of the traffic light system?

In summary, all m.e case studies demonstrate the potential of integrating advanced monitoring technologies in institutional decarbonization efforts and provides a framework for other organizations seeking to reduce their carbon footprint. Future research should explore the application of smart plug technology to other high-power appliances and assess additional features, such as predictive maintenance capabilities, to further enhance energy management strategies.

However, the behavioural aspects need further research. Do the m.e plugs make staff members more sustainable? What are the dominant norms, attitudes and intentions influenced by the m.e plug's traffic light system? It would be interesting to quantify the energy savings on weekdays versus weekends, as well as the hourly consumption patterns. Analyzing this data can help determine the optimal schedule for using energy-intensive equipment to maximize benefits. These are some of the many questions we brainstormed for discussion.Later, we started to review literature to identify if our ideas had already been researched or what kind of academic evidence supports our approach.

3. Exploring Definitions, Consumer Perceptions and Operational Barriers to Sustainability in the Foodservice Sector

Since our investigation was focused on the Park Eat catering restaurant we began reviewing the academic literature to understand what it means to be a green restaurant and how these sockets contribute to making Park Eat more environmentally friendly.

In the academic literature, we found that green restaurant practices are associated with balancing operational efficiency and environmental sustainability. Choi and Parsa (2007) provided a foundational definition of a green restaurant, identifying three broad areas of concern: health, environmental impact and social responsibility.

- Health Concerns: Green restaurants should focus on serving organic, nutritious and balanced food options to support healthy lifestyles. This includes serving nutritionally balanced food, organic foods, healthy and low-fat options and eliminating the use of antibiotics in livestock.

- Environmental Concerns: To protect the macro environment and the community, restaurants should engage in environmentally friendly practices. This includes operational and procedural modifications at production sites, such as recycling paper products (e.g., napkins and paper cups), reducing the use of fluorocarbons and minimizing plastic tubs and jars. Sustainable practices also involve energy conservation and pollution reduction.
- Social Concerns: Green restaurants should focus on community engagement and equitable human resource practices. Many restaurants set up programs for senior citizens and donate time and money to support local communities. Additionally, many restaurateurs engage in socially responsible design practices to prevent and minimize ecological disasters and adopt socially responsible marketing strategies.

The Green Restaurant Association further refines this definition by establishing eight categories that set standards for green restaurants: (1) water efficiency, (2) waste reduction and recycling, (3) use of sustainable durable goods and building materials, (4) sustainable food practices, (5) energy conservation, (6) use of reusable and environmentally preferable disposables, (7) chemical and pollution reduction and (8) transparency and education. According to these criteria, a green restaurant is defined as one that strives for a balance between human and environmental well-being through a variety of green practices. These include minimizing pollutants and solid waste, conserving energy and resources, recycling and composting, using non-toxic cleaning products, employing sustainable building materials and educating employees. Green restaurants also feature menus with locally sourced, organic and healthy ingredients.

Our next step was to understand how and which psychological and cognitive aspects of consumer behaviour towards green restaurants contribute to resource efficiency in commercial kitchens. Studies have shown that adopting energy- and water-efficient equipment, coupled with regular maintenance, can lead to significant savings. For example, improvements in water-use efficiency in California's commercial kitchens could potentially achieve a 20% reduction in water consumption without compromising functionality (Gleick et al., 2003). However, barriers such as inconvenience, time constraints and perceived high costs often hinder the adoption of these sustainable practices. In the UK, small business managers recognized the cost-effectiveness of energy efficiency and waste reduction but were unsure about implementation strategies. Managers often perceived energy use as a minor issue, lacked knowledge about reducing it and questioned the cost-effectiveness of investing in energy-efficient equipment (Revell and Blackburn, 2007). Additionally, challenges such as higher costs and inconsistent availability of green food procurement were cited as significant obstacles.

Government policies and programs, such as incentives and educational initiatives, have been identified as effective means to promote sustainable practices by addressing these barriers (Chou et al., 2012). Providing environmental education to employees can increase their understanding of sustainability and foster positive attitudes towards green practices. Despite growing interest in green foodservices, challenges such as cost, lack of expertise and entrenched attitudes remain, underscoring the need for supportive measures to facilitate the transition to more sustainable practices.

Operational behaviours also play a critical role in resource use in commercial kitchens. Behaviours such as leaving equipment on during free times, keeping doors open, not fully loading equipment and leaving lights on can lead to increased resource consumption. Studies have shown that untrained employees using the same equipment can lead to significant variations in energy consumption, highlighting the importance of operational behaviours (Batty et al., 1988). Modifying staff behaviour is recognized as a low-cost method to reduce energy use in commercial kitchens.

Kitchen equipment is frequently left on when not in use for various reasons. A study of energy consumption in five foodservice facilities revealed that equipment was often turned on much earlier than necessary and left on all day to ensure readiness for immediate use. Kitchen managers preferred this practice as it takes a long time for equipment to warm up if turned off (Revell and Blackburn, 2007). Such practices significantly affect resource use, emphasizing the importance of employee actions in promoting sustainability.

Operational behaviours in kitchens can become ingrained, necessitating continuous reminders for sustained change. For example, energy usage declined when staff knew it was being monitored but reverted shortly afterward, indicating the need for ongoing reinforcement (Batty et al., 1988). Similarly, outdated practices, such as pre-cooking and storing food in hot cupboards, persisted due to historical routines (Batty et al., 1988).

Other barriers to green practices have been identified:

- Physical Barriers: Inefficient kitchen layouts and limited space for waste separation bins can hinder sustainable practices (Batty et al., 1988; Revell and Blackburn, 2007).
- Time Constraints: Staff often lack time for additional tasks such as waste sorting (Revell and Blackburn, 2007).
- Operational Procedures: Existing organizational procedures can complicate sustainability efforts (Batty et al., 1988).

- Lack of Knowledge: Even with educational tools, a lack of specific knowledge on resource saving can be a significant barrier (Kaplowitz et al., 2012).
- Fear of Quality Impact: Employees may be concerned that energy saving efforts could negatively impact the quality of their work (Kaplowitz et al., 2012).

Addressing these barriers effectively requires a comprehensive approach. Recommended practices include:

- Monitoring resource use and operational behaviours.
- Communicating goals and reasons for changes clearly.
- Collecting and acting on employee feedback.
- Measuring and sharing resource usage and reductions.
- Rewarding participation and demonstrating changes through leadership.

Training staff on the efficient use of equipment and using timed switches can help manage energy consumption. However, there is a gap in research regarding the impact of specific behaviours on sustainability and the effectiveness of programs that focus on behaviour change. Implementing a shutdown schedule ensures that lights and equipment are turned off during the night. Despite these recommendations, the overall effectiveness of such programs has yet to be thoroughly assessed.

4. Exploring the Extended Theory of Planned behaviour: Hypotheses and Applications in Sustainable Behaviour Research

Over the last fifty years, various psychological sockets have been proposed to elucidate individual behaviours. One prominent model addressing voluntary behaviours is the Theory of Reasoned Action (TRA), developed by Ajzen and Fishbein. The TRA posits that people make decisions rationally, leading to reasoned choices influenced by behavioural intentions, which in turn can be affected by multiple factors (Ajzen and Fisben, 1988). Ajzen later extended this model to create the Theory of Planned behaviour (TPB) which incorporates additional variables to comprehensively explain both voluntary and involuntary behaviours (Ajzen, 1991). The TPB integrates three key psychological constructs: attitude, subjective norms and perceived behavioural control (PBC). Attitude reflects an individual's overall evaluation of a specific behaviour, subjective norms denote perceptions of others' opinions on the behaviour and PBC assesses the perceived ease or difficulty of engaging in the behaviour. Besides intention, PBC is another critical factor linked to behavioural outcomes and decision-making processes.

According to the literature the TPB remains a pivotal framework in environmental psychology, widely employed to analyze various environmentally friendly behaviours such as recycling, public transportation use, organic food consumption, sustainable consumption practices, household energy conservation and behaviours within the hotel management sector. However, some research indicates that certain TPB variables may not significantly predict specific pro-environmental behaviours.

When the TPB is applied to investigate sustainable behaviour, it suggests the following:

- Attitude has either a moderate (Thøgersen, 2002) or a weak (Grob, 1995) relationship with ecological behaviour.

- The relationship between subjective norm and sustainable behaviour ranged from non-significant (Shaw and Shiu, 2003) to fairly strong (Arvola et al., 2008).

- There is inconsistent findings in the literature about the strength of this relationship between PBC and sustainable behavioural intention, with reports ranging from non-existent (Arvola et al., 2008) to very positive relationship (Kaiser and Gutscher, 2003).

- Kaiser and Gutscher (2003) found that attitude, subjective norm and PBC explained 81% of the variance in an individual's sustainable behaviour intention and intention determined 51-52%of that individual's sustainable behaviour.

Drawing on the literature, this study proposes five hypotheses within the Theory of Planned Behaviour (TPB):

- H1: Staff attitude positively correlates with energy-saving intention in the University of Reading's catering department.
- H2: Staff subjective norms positively correlates with energy-saving intention in the University of Reading's catering department.
- H3: Staff perceived behavioural control positively correlates with energy-saving intention in the University of Reading's catering department.
- H4: Staff perceived behavioural control positively correlates with energy-saving behaviour in the University of Reading's catering department.
- H5: Staff intention positively correlates with energy-saving behaviour in the University of Reading's catering department.

In the academic literature, we identified extended and modified versions of the TPB for diverse contexts, often integrating moral-normative factors to increase its explanatory capacity (Acheampong and Cugurullo, 2019). Moral norms, which reflect personal values in specific situations, have been shown to significantly influence intentions to engage in environmentally friendly behaviours. Additionally, past behaviour plays a crucial role in socio-psychological frameworks, with studies indicating its significant impact on decision-making processes related to pro-environmental behaviours in various domains, including hospitality and tourism. Integrating past behaviour into predictive sockets has been found to enhance their effectiveness.

When applying the extended version of the Theory of Planned behaviour (TPB) to investigate sustainable behaviour, the following suggestions arise:

- Harland et al. (1999) found that including personal norms could increase the proportion of explained variance of behavioural intention. Shaw and Shiu (2003) found a significant positive relationship between personal norms (eg. in this case ethics) and behavioural intention.
- Thøgersen (2002) suggests that positive past experiences with sustainable practices would strengthen the relationship between attitude and intention.

Therefore, the preceding discussion suggests two additional hypotheses for the extended TPB model I (Figure 2):

- H6: Staff personal norms positively correlates with energy-saving intention in the University of Reading's catering department.
- H7: Staff past behaviour positively correlates with energy-saving intention in the University of Reading's catering department.

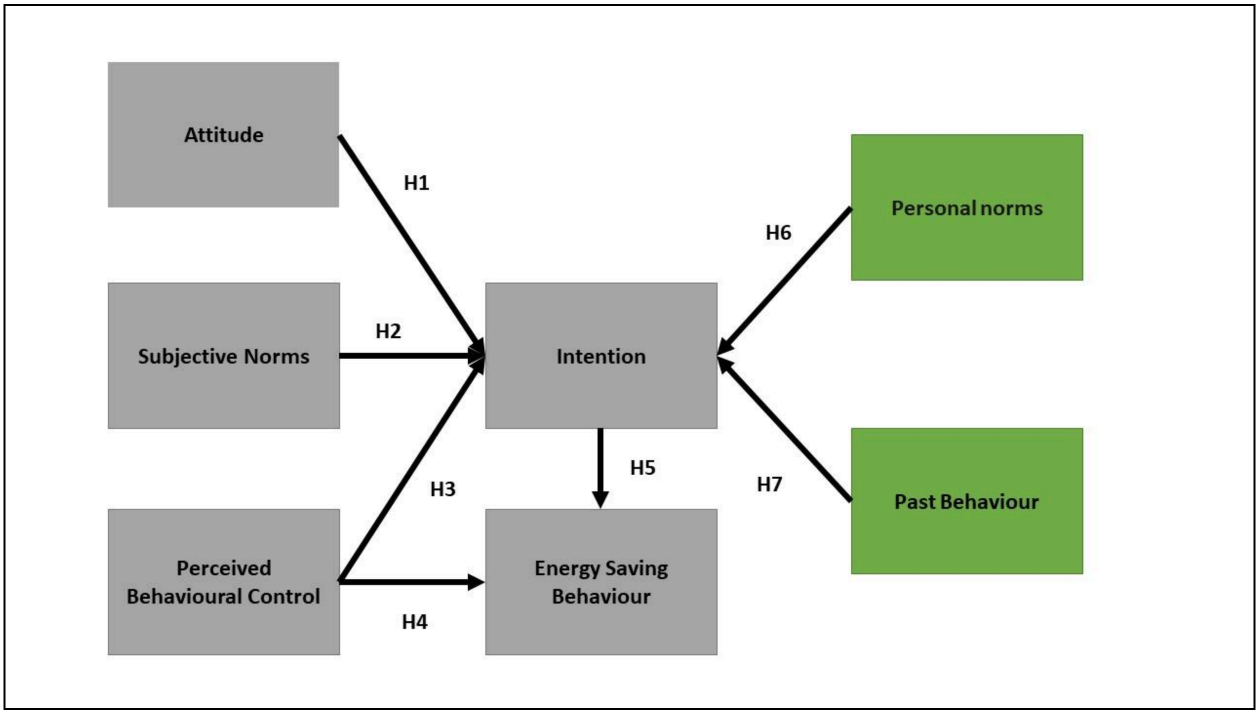


Figure 2. The employed extended version of TPB I and related hypotheses

In addition to personal norms and past behaviour, empirical research has identified self-determined motivation as another potential predictor. Self-determined motivation is a concept derived from self-determination theory (Gagné and Decei, 2005) and the model of goal-directed behaviour. It encompasses internal driving sources of motivation, such as the need to acquire skills, knowledge and independence. Studies have highlighted the significant role of self-determined motivation in promoting pro-environmental behaviours. For example Kaiser et al. (1999) argued that even though knowledge may be the basis for any attitude, it would not have a strong relationship with sustainable behaviour because sustainable attitude and behavioural intention reduce its power.

Based on the academic literature on this topic, this research proposes two additional hypotheses for Extended TPB II (Figure 3):

- H8:Staff self-determined motivation positively correlates with energy-saving intention in the University of Reading's catering department.

- H9: Staff self-determined motivation positively correlates with energy-saving behaviour in the University of Reading's catering department.

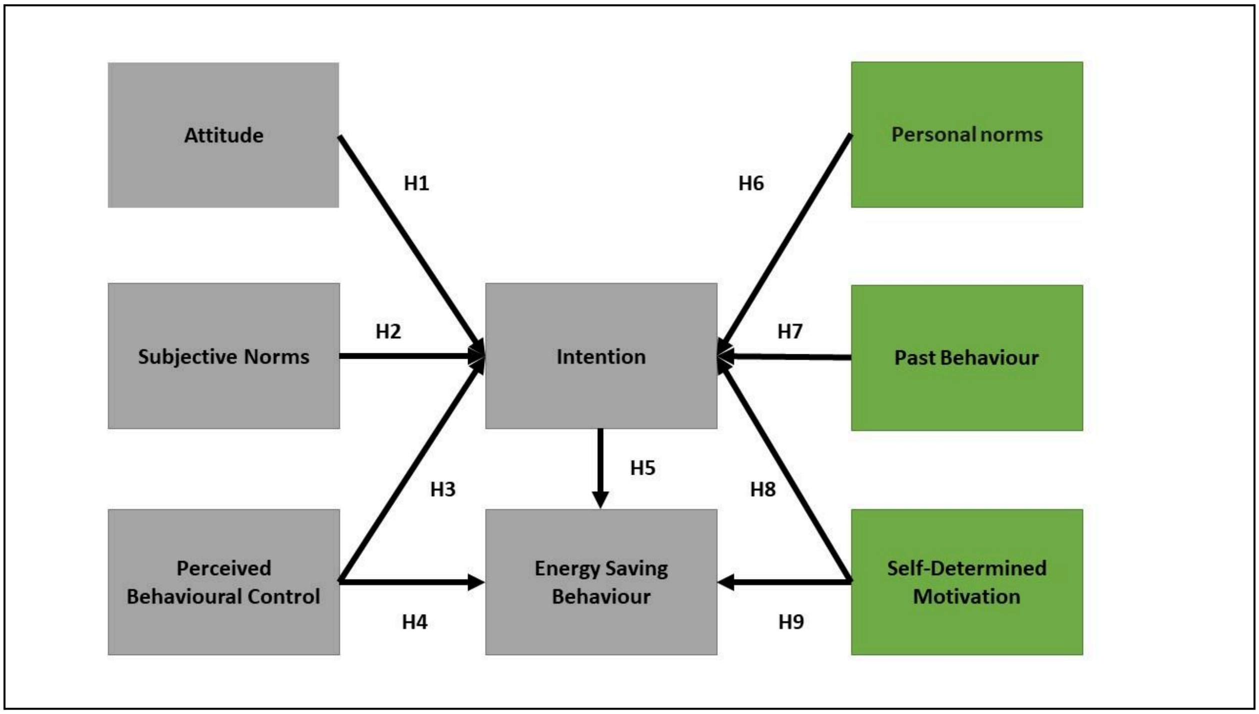


Figure 3. The employed extended version of TPB II and related hypotheses

In sum, in this chapter, we examined the TPB and its extensions to explore sustainable behaviour. We began by outlining the foundational TPB constructs—attitude, subjective norms and PBC—and their application to environmental behaviours such as recycling and energy conservation.We then proposed five hypotheses related to energy-saving behaviours in the University of Reading's catering department, focusing on how staff attitudes, subjective norms, PBC and behavioural intentions influence these behaviours. Building on the literature, we introduced extended TPB sockets that incorporate moral norms and past behaviour, proposing additional hypotheses to assess their impact on energy-saving intentions. Finally, we explored the role of self-determined motivation as an influential factor in sustainable behaviour, suggesting two more hypotheses to investigate its effects on energy-saving practices. Next, we will delve into the research design and methodology employed to investigate the hypotheses proposed in relation to the extended TPB.

5. The m.e Socket, Platform Description and the Extended TPB Questionnaire Design

The Park Eat offers a range of dining options and has a snooker table for guests to enjoy. The establishment also includes a bar. The opening hours are from 8am to 12pm, Monday to Sunday during term time. The venue is closed on bank holidays. At the beginning of the project, we conducted a site visit to the Park Eat restaurant, where we closely inspected the m.e smart plugs (Figure 4).

Figure 4. Park Eat restaurant dining area, front of the house

At Park Eat restaurant, a total of 87 m.e smart sockets have been strategically installed across various locations to optimize energy management. Examples of locations include:

- Cellar: Used for storing beverages and other goods requiring refrigeration.
- Corridors**:** Serving as passageways where various electrical devices (such as fridges) might be connected.
- Bar: Equipped with sockets to support catering equipment such as the chillers.
- Drink Machines: Positioned at the back of coffe machines and water taps.
- Reception Desk: Located at the front desk to accommodate devices used for customer service and operations (such as PC or mobile phone charges).

- Salad Bar: Where sockets support refrigeration units and other appliances used for food preparation, example of appliance are toasters.
- Servery**:** Positioned in areas where food is served, enabling control of equipment used for maintaining food temperature and quality.

Upon inspection, it was observed that some of these sockets are actively supporting appliances, while others remain unused with no devices plugged in. Some were visible and easily accessible to both customers and staff, while others were concealed behind bar chillers or coffee machines (Figure 5). This distribution highlights the variability in how energy is consumed and managed across different areas of the restaurant. Monitoring and analysis of these sockets will provide insights into energy usage patterns, potentially identifying areas for improved efficiency and cost savings. This initial observation was crucial for understanding the diverse contexts in which the smart plugs were operating.

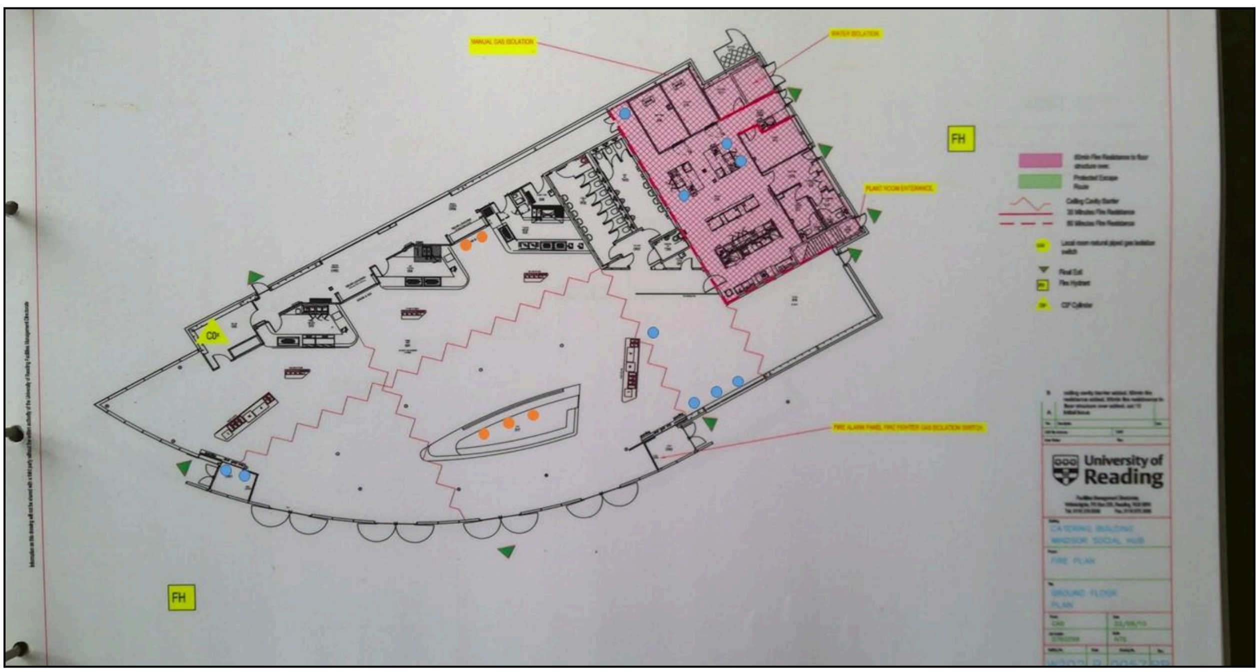


Figure 5.[2] Park Eat floor plan and the locations of the m.e sockets
(orange timed-sockets and blue manual sockets).

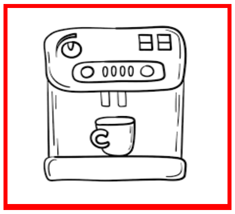
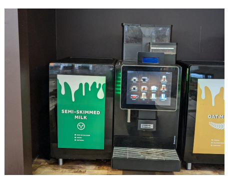
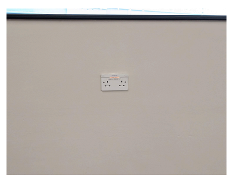
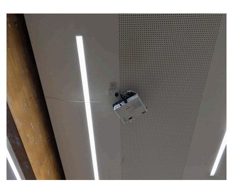
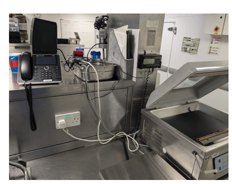
[2] One coffee machine is missing because we could not locate the corresponding socket.

Following our site inspection, we held a meeting with representatives from measurable.energy. They provided comprehensive training on how to effectively use the m.e platform, which is instrumental in monitoring and managing the smart plugs. This training not only equipped us with the necessary skills but also prompted us to reconsider our initial approach to the deployment and placement of the plugs.

After the training, we selected the smart sockets (Table 1) based on the key criteria: their visibility of the traffic light system, their automation functions and their practical use by the staff. In the following, we provide a detailed explanation of the key selection criteria:

1. Traffic light visibility: We chose sockets with clear and accessible traffic light indicators to ensure that the staff and customers could easily observe and interpret the real-time feedback on energy sources and consumption.
2. Automation functions: We prioritized sockets with established automation capabilities that could run on different time schedules.
3. Practical use by staff: We evaluated how the smart sockets would fit into the daily operations of the staff. The selected sockets needed to be located in areas where they would be actively used and interacted with, ensuring that the m.e would integrate smoothly into their routines and provide actionable insights.

Table 1. List of selected m.e sockets and its location

Group 1: Timed m.e smart sockets		Group 2: Manual (non-timed) m.e. sockets		
Bar[3]	Coffee machines[4]	Front of House	Kitchen	Reception desk
DG2-100-0-048 	DG2-100-0-140[5] 	DG2-100-0-112 	DG2-100-0-037 	DG2-100-0-115 
DG2-100-0-133 	DG2-100-0-298 	DG2-100-0-291 	DG2-100-0-043 	
DG2-100-0-210 	DG2-100-0-482 	DG2-100-0-472 	DG2-100-0-114 	
		DG2-100-0-493 	DG2-100-0-287 	

[3] We were unable to access the m.e plugs located behind the chillers. So, we made the assumption that the photos we have correspond to the plugs that are connected to the chillers.

[4] Similar to the situation with the bar m.e plugs, we could not access the m.e plugs located behind the coffee machines. As a result, we assumed that the photos we have accurately match the sockets to which the coffee machines are plugged in.

[5] Unfortunately, we were unable to locate this specific smart socket. However, we utilized the data collected by the m.e. platform to proceed with our analysis.

In the early stages, we discussed establishing a control group and developing a specific intervention to assess the impact of the smart plug traffic lights system more rigorously. However, due to time constraints, we were unable to implement these elements in our research.

In the below sections of this report, we will provide a detailed analysis of the functioning and design of the m.e. sockets. Additionally, we will discuss the development and application of the TPB questionnaire, which was employed to evaluate the impact of the smart sockets on energy-saving behaviour within the University of Reading's catering department.

5.1. M.e smart sockets description

The m.e. smart sockets integrate seamlessly with your existing Wi-Fi network, ensuring they remain operational even if the internet connection is lost. These sockets are equipped with built-in memory, allowing them to maintain any pre-set rules and continue monitoring energy consumption even during network interruptions. You can also switch-off individual appliances using the m.e sockets.

A notable feature of these smart sockets is their ability to indicate the source (eg. renewable/mixed/non-reneable energy) of the electricity being used. This is visually represented by the colour of the LED light on the socket, as illustrated in Figure 6 below.

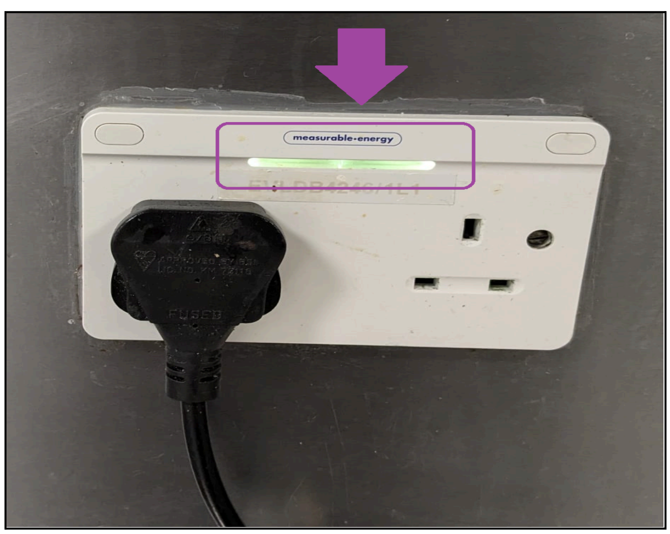


Figure 6: Measurable-energy traffic light system socket inside the Park Eat restaurant kitchen

The National Grid's carbon intensity API offers an indicative trend of carbon intensity for the electrical grid of Great Britain up to 48 hours in advance. This forecast is represented by the m.e sockets, which use an LED light display to show one of four colors, each corresponding to a different type of energy source:

- Green: This indicates that the energy is primarily derived from renewable sources, such as wind or solar power.

- Yellow and amber: These colours signifies that the energy is a combination of renewable and non-renewable sources, including fossil fuels (coal, natural gas and oil) and nuclear energy. Yellow signifies a moderate level of carbon intensity. In some color-coding schemes, amber may be used to indicate a warning or a higher level of emissions compared to yellow, signifying a greater reliance on fossil fuels or less efficient energy generation.

- Red: This indicates that the energy comes solely from non-renewable sources.

The LED light provides consumers with a straightforward visual cue about whether their power is sourced from renewable or non-renewable resources (Figure 7). Customers are expected to respond to the colour changes of the smart sockets. For instance, when the m.e socket's colour turns red, indicating high grid carbon intensity, it is anticipated that people will unplug devices from the socket. A practical example is unplugging a laptop charger during periods of high carbon intensity to help reduce the overall carbon footprint associated with the energy used. Similarly, staff could unplug their mobile phone chargers or catering equipment tablets used for taking orders during such periods.

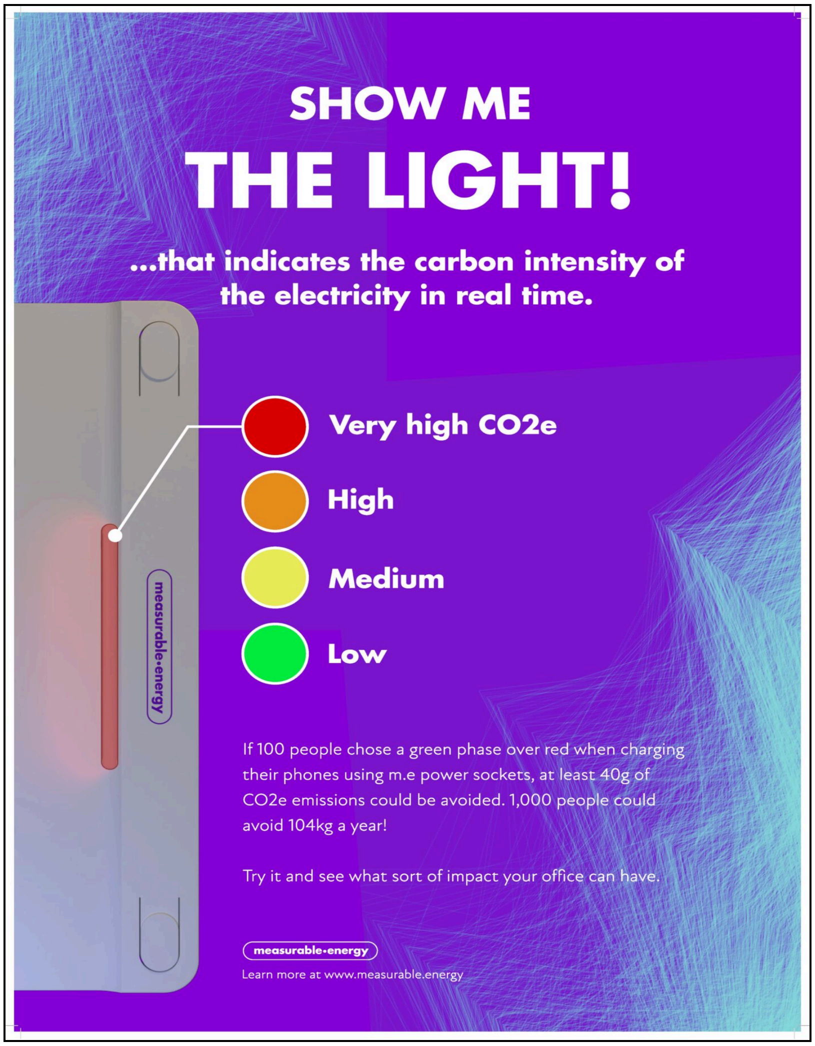
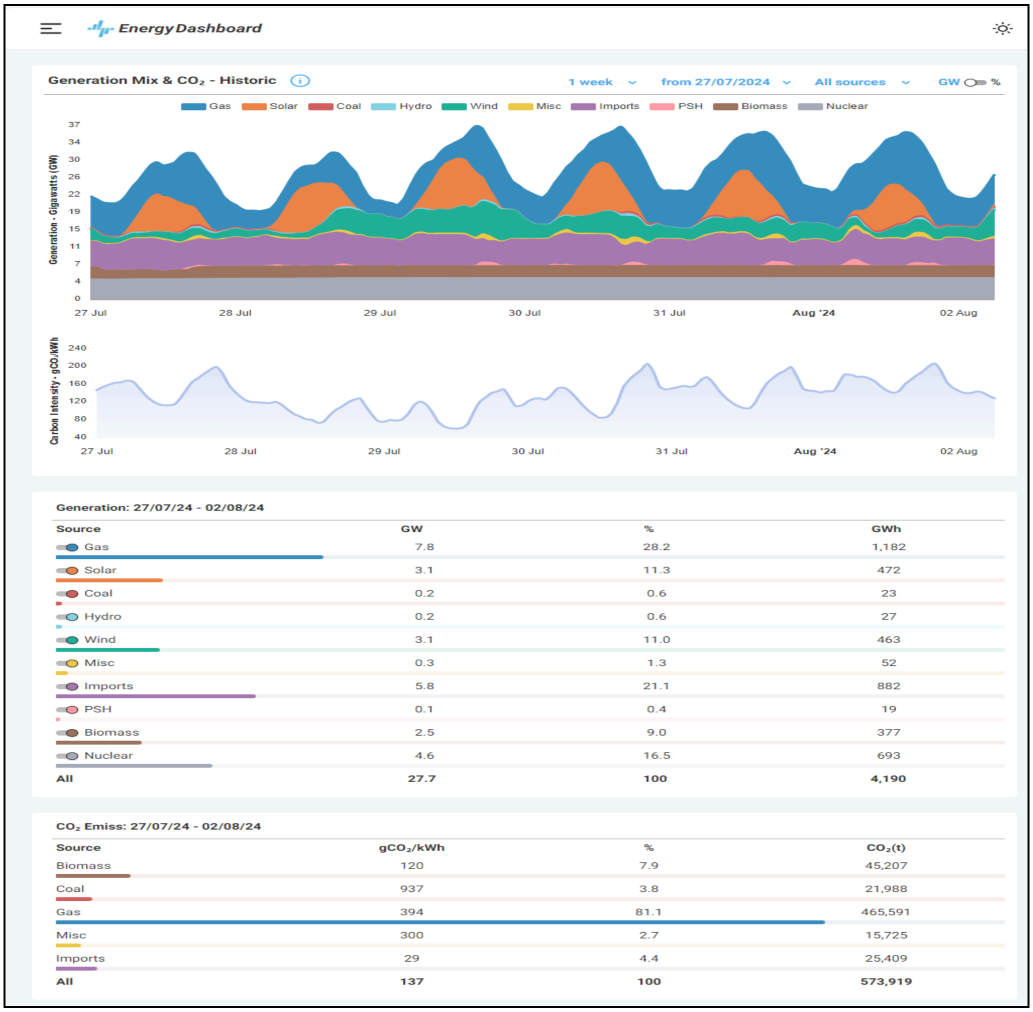


Figure 7: Measurable Energy Sockets Traffic Light System (Source: Park Eat website, https://www.hospitalityuor.co.uk/casual-dining/park-eat/)

In calculating the GHG emissions, the m.e Platform uses data from the Carbon Intensity API (Figure 8). This API provides details on the various types of energy contributing to the UK National Grid, including Gas, Coal, Biomass, Hydro, Nuclear, Oil, Solar, Wind and imports. It calculates and updates a dynamic gCO2/kWh value every 30 minutes. We align this carbon intensity data with your energy consumption in the corresponding 30-minute intervals. This enables us to show both the carbon emissions associated with your energy use and the emissions saved by turning off appliances.



Generation: 27/07/24 - 02/08/24

Source	GW	%	GWh
Gas	7.8	28.2	1,182
Solar	3.1	11.3	472
Coal	0.2	0.6	23
Hydro	0.2	0.6	27
Wind	3.1	11.0	463
Misc	0.3	1.3	52
Imports	5.8	21.1	882
PSH	0.1	0.4	19
Biomass	2.5	9.0	377
Nuclear	4.6	16.5	693
All	27.7	100	4,190

CO_2 Emiss: 27/07/24 - 02/08/24

Source	gCO_2/kWh	%	$CO_2(t)$
Biomass	120	7.9	45,207
Coal	937	3.8	21,988
Gas	394	81.1	465,591
Misc	300	2.7	15,725
Imports	29	4.4	25,409
All	137	100	573,919

Figure 8. The mix of technologies supplying Great Britain's electricity between 27/07/2024 and 02/08/2024 (Source: Energy Dashboard - real time and historical GB electricity data, carbon emissions and UK generation sites mapping, https://www.energydashboard.co.uk/historical)

In addition to providing real-time feedback on energy sources, these smart sockets facilitate long-term electricity monitoring. They enable users to record and analyze energy consumption data over extended periods, offering valuable insights into usage patterns and potential areas for efficiency improvements.

5.2. M.e smart sockets dashboard

In addition to its precise measuring capabilities, the socket offers the significant advantage of power demand control, which is crucial for effective energy management. These sockets are Wi-Fi enabled, allowing them to communicate in full duplex mode with a central software system. This advanced connectivity facilitates continuous, real-time monitoring of power consumption at any given moment, enabling a comprehensive understanding of energy usage patterns across different devices and locations.

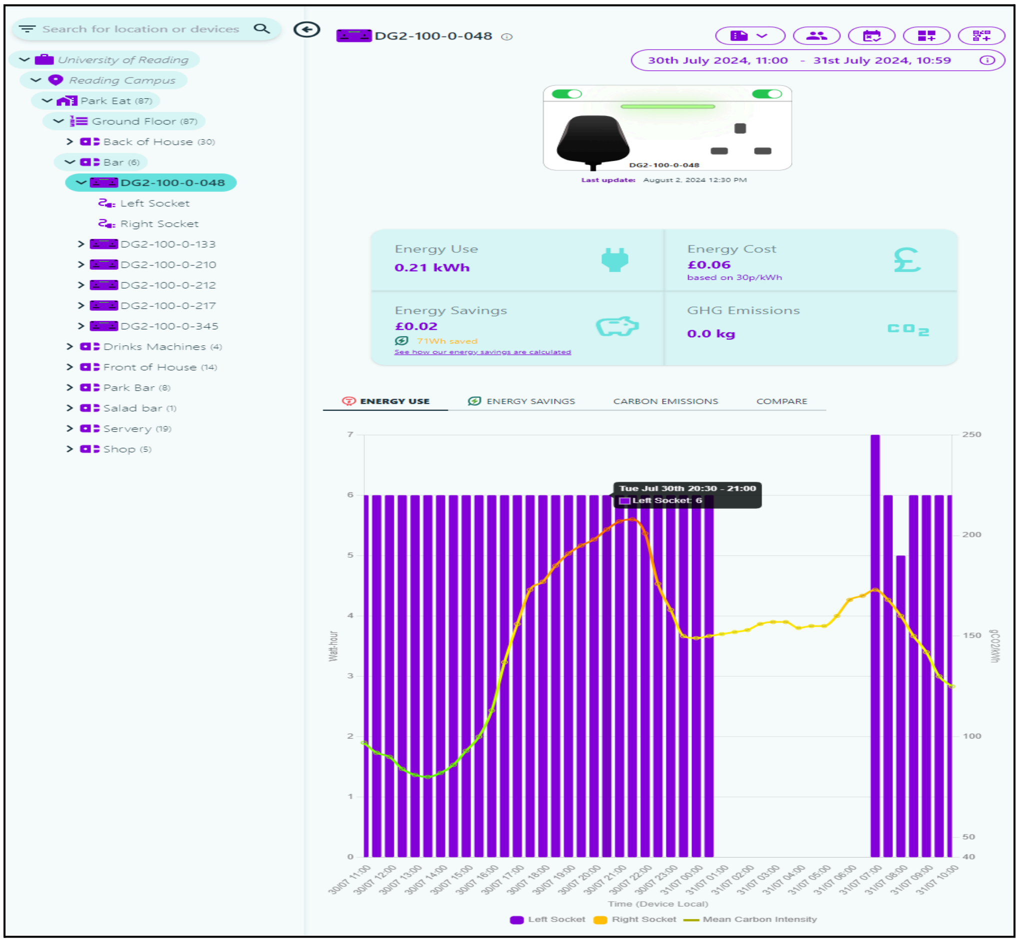


Figure 9: M.e platform graphical user interface

Moreover,dashboard provides a robust platform for managing these smart sockets (Figure 9). Through this platform, users can access detailed analytics and reports on energy consumption, helping identify opportunities for reducing waste and optimizing efficiency. One of the key features of this system is the ability to set specific rules and schedules for individual sockets. These rules can automate the turning on and off of devices based on predefined criteria, such as time of day, energy prices, or carbon intensity levels. This automation not only helps in reducing unnecessary power usage but also aligns energy consumption with more sustainable and cost-effective practices. For example, during periods of high grid carbon intensity, the software can automatically disconnect non-essential devices to reduce the overall carbon footprint. Conversely, during periods of low carbon intensity, it can enable devices to operate more freely, thus balancing operational needs with environmental considerations. The table below (Table 2) summarizes the key features and outputs of the m.e dashboard, providing a clear overview of the platform's capabilities:

Table 2. The m.e dashboard capabilities

Capabilities	Description
Detailed in-depth reading of power consumption	The smart sockets offer precise and comprehensive monitoring of power consumption at any given time. This feature allows users to obtain real-time data on how much energy each socket is drawing, enabling granular insights into energy usage patterns and identifying potential areas for efficiency improvements.
Carbon intensity details	The technology provides real-time information on the carbon intensity of the electricity being consumed. Having this data available helps users make informed decisions about their energy use, especially in efforts to reduce their carbon footprint.
Energy cost information	Alongside power consumption and carbon intensity, the smart sockets also offer detailed information on the cost of the energy being used. This feature allows users to track and manage their energy expenses more effectively, promoting cost savings
Comparison of two periods	The technology includes the capability to compare energy consumption, carbon intensity and costs across two different time periods. This comparative analysis is valuable for assessing the impact of energy-saving measures and understanding seasonal variations.

Automated control with customizable rules	On the platform, users can set specific rules for each socket to automate the switching on and off of devices based on predefined schedules. This automation can be tailored to match operational needs, peak and off-peak energy times, or carbon intensity levels, thereby optimizing energy usage without manual intervention.
Traffic light system	The smart sockets feature an intuitive LED indicator that displays the source of the power being consumed. The indicator uses different colors to show whether the electricity is being generated from renewable sources (such as wind or solar), a mix of renewable and non-renewable sources, or non-renewable sources. This immediate visual feedback helps users quickly understand the environmental impact of their energy consumption and encourages more sustainable practices.

5.3. The extended TPB survey design

In this research, we employed a questionnaire-based survey to collect self-reported data from catering staff members. Initially, we distributed the survey in a printed format to the catering team. Later, we also made the questionnaire available online. Staff members who completed the questionnaire had the opportunity to enter a draw to win a £20 Amazon voucher.

We received a total of 22 completed questionnaires, with 9 submitted online and 13 through face-to-face interactions. The primary reasons for the limited response were the busy schedules of the catering staff and the perceived length of the survey.

The questionnaire comprised four sections: respondents' sociodemographic information, a traffic light system for assessing psychological characteristics and an evaluation of energy-saving behaviours. To increase the number of responses, one suggestion was to use the snowball sampling technique. However, this approach did not result in any additional responses.

The questionnaire comprised four sections:

- Section 1: Focused on demographic information, including sex, age and job status.
- Section 2: Included questions on the m.e. socket traffic light system and the frequency of energy-saving inductions in the workplace.
- Section 3: Contained 21 questions based on the literature, covering the psychological variables of the extended TPB across six dimensions: attitude, subjective norms, PBC, moral norms, past behaviour and intention.
- Section 4: Evaluated the self-reported performance of staff in four typical energy-saving behaviours in campus restaurants.

In both of these sections, all items were responded to with the same 5-point Likert scale, ranging from 1 (completely disagree) to 5 (completely agree). The questions in Sections 3 and 4 are presented in the table (Table 3) below.

Table 3. The extended TPB Section 3 and 4

Construct	Code	Survey Question
Attitude	ATT-1	I think conserving energy when working at the University of Reading's catering department is

		beneficial for protecting the environment.
	ATT-2	I think that practicing energy conservation behaviours at the University of Reading's catering department is beneficial for protecting the environment.
	ATT-3	I think energy conservation behaviours at University of Reading's catering department are valuable for the University of Reading's Net Zero Carbon Plan.
Subjective Norms	SN-1	I think my family members want me to save energy when at the University of Reading's catering department.
	SN-2	I think my boss and colleagues want me to save energy when at the University of Reading's catering department.
	SN-3	I think that people who are important to me want me to save energy when at the University of Reading's catering department.
Perceived Behaviour Control	PBC-1	It is difficult for me to engage in energy conservation behaviours when at the University of Reading's catering department.
Personal Moral Norms	PMN-1	Saving energy at the University of Reading's catering department is a moral imperative for me.
	PMN-2	I would feel guilty if I did not save energy at the University of Reading's catering department.
	PMN-3	My ethics do not allow me to waste energy at the University of Reading's catering department.

Past Behaviour	PBH-1	Two months ago, during the academic term, I engaged in energy-saving behaviours at the University of Reading's catering department.
	PBH-2	Two months ago, during the academic term, I made efforts in energy-saving behaviours at the University of Reading's catering department.
	PBH-3	My efforts to save energy at the University of Reading's catering department increased two months ago, during the academic term.
Intention	INT-1	I am willing to save energy when at the University of Reading's catering department.
	INT-2	I am willing to make efforts to save energy when at the University of Reading's catering department.
	INT-3	I am willing to follow the energy-saving guidelines at the University of Reading's catering department.
Self-Determined Motivation	SDM-1	I will feel pleased if I can contribute to the environment.
	SDM-2	I will gain recognition from others by performing energy-saving behaviours at the University of Reading's catering department.
	SDM-3	Engaging in energy-saving behaviour at the University of Reading's catering department is an integral part of my life.
	SDM-4	I will feel guilty if I do not do energy-saving behaviour at the University of Reading's catering department.
	SDM-5	I engage in energy-saving behaviours to avoid

		criticism from the public.
Behaviour	BEH-1	I performed well in practicing sustainable air conditioning use behaviours, such as opening doors/windows instead of adjusting the air conditioning system at the University of Reading's catering department.
	BEH-2	I performed well in sustainable appliance use (e.g. turning off appliances that I was using instead of leaving them on standby) and lighting use while working at the University of Reading's catering department.
	BEH-3	I performed well in conserving hot water while working at the University of Reading's catering department.
	BEH-4	I performed well in motivating and encouraging others to conserve energy while working at the University of Reading's catering department.

In practice, before the start of the survey, we included an ethical form that explained the research aim, emphasizing that participation was voluntary and that data would be handled confidentially. This form assured participants that no action would be taken based on their responses. This measure was also intended to reduce social desirability bias by reassuring respondents that their honesty was valued and that their answers would remain anonymous and without repercussions.

6. Results

On Figure 10 we compare half-hourly energy consumption for two restaurants, "Eat at the Square" and "Park Eat," from July to December 2023. "Eat at the Square" consistently shows higher energy consumption, with daily peaks reaching up to 400 kWh, while "Park Eat" rarely exceeds 100 kWh daily.

A substantial level of standby power consumption is evident in "Eat at the Square," as energy use remains noticeable even during non-operational hours, indicating that appliances are left on or in standby mode. In contrast, "Park Eat" has a lower baseline of energy consumption during non-operational hours, suggesting better management of standby power. Seasonal variations show increased energy use in both restaurants during the summer (July and August) and in the colder months (September to December). The peak hours for energy use can be identified as follows:

- For "Eat at the Square," peak energy consumption typically occurs between 10:00AM and 4:00PM. This trend is consistent across all the months shown in the plot, with the highest spikes often seen around midday.
- For "Park Eat," peak energy consumption also tends to occur between 10:00AM and 4:00PM. However, the peaks are less pronounced compared to "Eat at the Square," indicating lower overall energy usage during these hours.

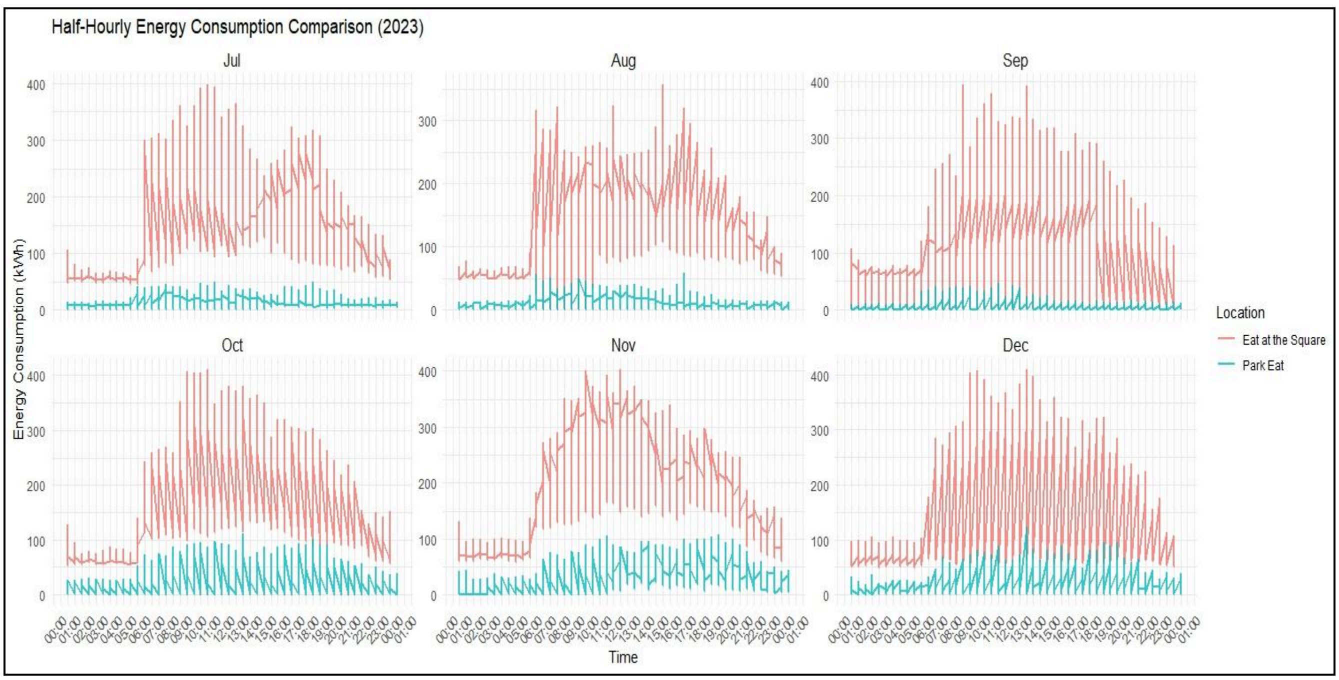


Figure 10. Park Eat and Eat at the Square electricity consumption

6.1.1. Bar Sockets vs. Coffee Machines: Energy Usage Patterns of Timed Appliances

Coffee machine automation and bar sockets reveal both similarities and differences in their energy consumption and CO_2 emissions patterns (Figure 11). The usage shows seasonal variations, with increased energy use and CO_2 emissions during colder months, such as January to March and reduced levels in the summer months, like June to August. Specifically, both coffee machines and bar sockets experience peak energy use and CO_2 emissions during winter, with lower values observed in the summer. However, significant differences emerge in the degree of seasonal variability and efficiency across application. For instance, coffee machines, including sockets DG2-100-0-298 and DG2-100-0-482, display considerable fluctuations, with substantial peaks in specific months such as November and July, indicating higher variability in energy consumption and CO_2 emissions. In contrast, bar sockets, such as DG2-100-0-048, exhibit more consistent patterns with minimal fluctuations throughout the year. Furthermore, bar sockets demonstrate clearer distinctions in efficiency among different sockets; for example, DG2-100-0-210 is markedly more energy-efficient compared to DG2-100-0-048. Conversely, coffee machine efficiency varies less distinctly across sockets.

Comparing the energy consumption and CO_2 emissions of coffee machines and bar sockets for July-December 2023 and January-July 2024, significant differences emerge. For coffee machines running on automation in 2024, energy consumption for DG2-100-0-140 increased by 13.9% from 36.75 kWh to 41.85 kWh, while CO_2 emissions decreased by 5.4% from 5.6 g to 5.3 g. DG2-100-0-298 saw a 20.3% rise in energy consumption from 251.03 kWh to 301.80 kWh, with CO_2 emissions increasing slightly by 1.3% from 39.0 g to 39.5 g. DG2-100-0-482 also experienced a 27.7% increase in energy use from 260.52 kWh to 332.71 kWh, accompanied by a 5.2% rise in CO_2 emissions from 40.1 g to 42.2 g.

Figure 11. Timed coffee machines at Park Eat restaurant

In contrast, the energy consumption trends for bar sockets in 2024 demonstrate different patterns (Figure 12). Socket DG2-100-0-048 shows a slight increase in energy use, rising by 3.9% from 65.35 kWh in June-December 2023 to 67.89 kWh in January-July 2024. Correspondingly, CO_2 emissions decreased by 13.3%, from 9.8 g to 8.5 g. Socket DG2-100-0-133 experienced a 6.6% increase in energy use, increasing from 57.44 kWh to 61.24 kWh, while CO_2 emissions fell by 11.5%, from 8.7 g to 7.7 g. Socket DG2-100-0-210 saw a modest increase in energy consumption of 7.6%, rising from 16.00 kWh to 17.22 kWh and CO_2 emissions decreased slightly by 8.3%, from 2.4 g to 2.2 g.

Overall, while the coffee machines show increased energy consumption with mixed results on CO_2 emissions, bar sockets benefit substantially from automation with notable reductions in both energy use and CO_2 emissions (Figure 12). Further details are available in Annex 4 and Annex 5.

Figure 12. Bar chillers running on a timed setting at Park Eat restaurant

Based on Figure 13 socket DG2-100-0-048, socket DG2-100-0-133 and socket DG2-100-0-210, there is a noticeable trend of negative savings in electricity consumption during the early months of the year, specifically January through March, followed by relatively smaller negative figures in April and May. This suggests a pattern where automatisation expenses tend to be higher at the beginning of the year and decrease slightly as the year progresses.

Socket DG2-100-0-048 shows a consistent decrease in electricity usage from January (-3.69 kWh) to May (-2.04 kWh), with variations between -2.75 kWh to -3.38 kWh in between. Similarly, socket DG2-100-0-133 shows a reduction in electricity usage from January (-3.27 kWh) to May (-2.35 kWh), with figures ranging from -1.99 kWh to -3.06 kWh during the months in between. Socket DG2-100-0-210 displays a similar pattern with electricity usage decreasing from January (-0.89 kWh) to May (-1.04 kWh), with figures varying between -0.86 kWh to -1.5 kWh throughout the intervening months. This seasonal trend indicates that the costs associated with automatisation, represented by negative savings, tend to peak in the first quarter of the year and then stabilize or reduce slightly in the second quarter. This could be due to various factors such term dates.

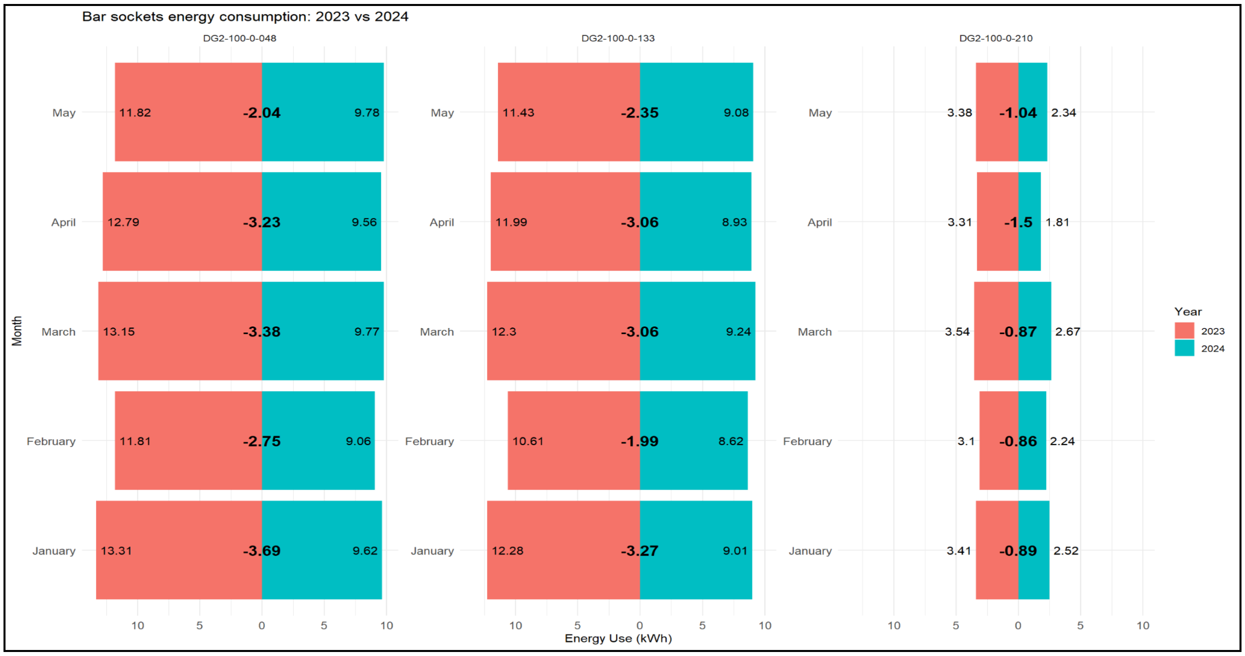


Figure 13. Park Eat bar sockets energy consumption before and after automatisation

The data for automatisation of the caffe machines across different plugs shows distinct seasonal variations (Figure 14). In the following, we compare the electricity consumption for June and July in 2023 (before automation) and 2024 (after automation) to identify notable changes. For socket DG2-100-0-140, there is a significant shift from June to July, with electricity usage droppping from 3.69 kWh in June to 1.13 kWh in July. We should note that the plug DG2-100-0-140 was set on a timer in July 2023, which may affect the interpretation of the energy consumption results. As this automation was introduced partway through the year, it is important to consider its potential impact on the data. This change could have influenced the energy usage patterns and may not fully reflect the comparative efficiency of automation versus manual operation over the entire year. Consequently, caution should be exercised when interpreting the results and drawing conclusions about the overall effectiveness of automation based solely on this data. Socket DG2-100-0- 298 demonstrates a substantial decrease in electricity consumption from June to July, Socket DG2-100-0-482, demonstrates a similar increasing trend, with electricity consumption increasing from 12.55 kWh in June to 15.85 kWh in July. This trend could highlight a potential issue with this socket,such as malfunctioning equipment. Overall, while plug DG2-100-0-140 and plug DG2-100-0- 298 experienced a decrease in electricity consumption in July, plug DG2-100-0-482 showed an increase in electricity consumption.

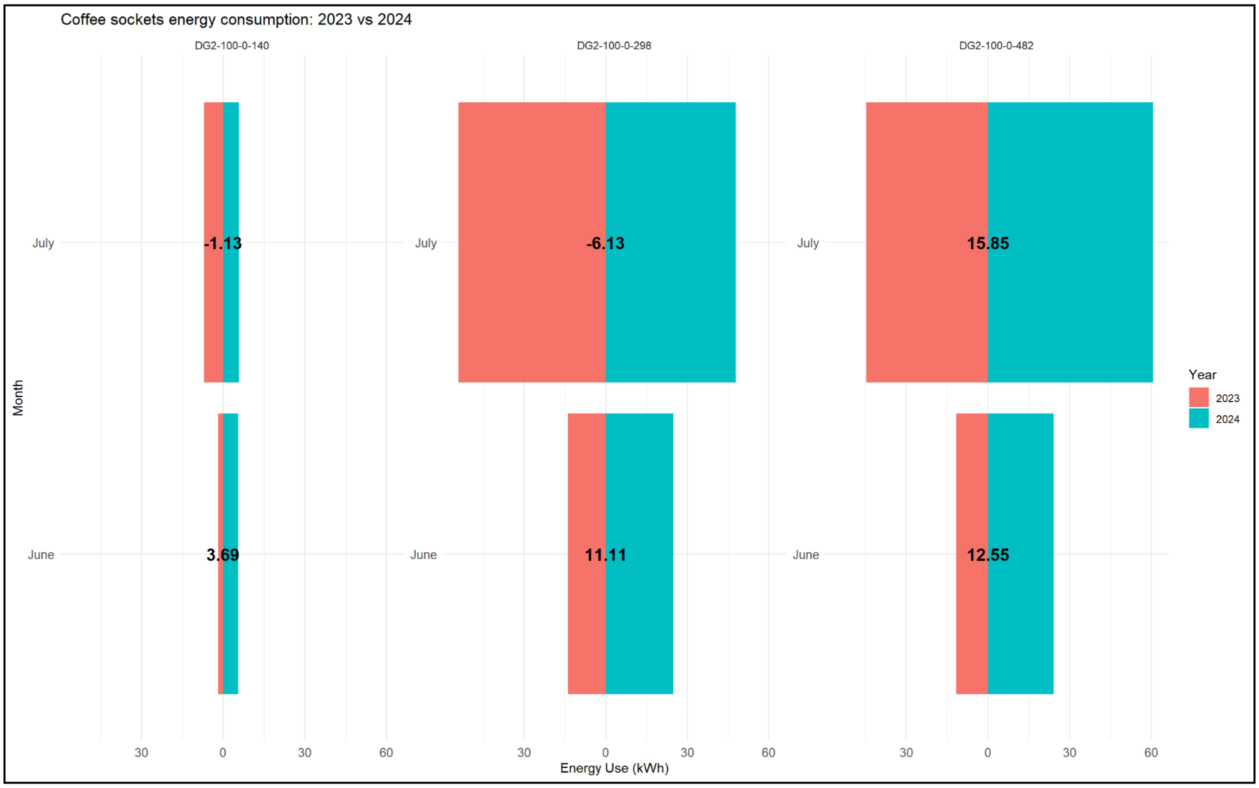


Figure 14. Coffe bar sockets energy consumption with(2024) and without (2023) automatisation

The energy use heatmap of DG2-100-0-482 socket in July reveals distinct patterns for weekdays and weekends (Figure 15). On weekdays, energy consumption peaks from 1 PM to 7 PM, with the highest use between 2 PM and 5 PM. A noticeable increase starts around 6 AM, likely as the workday begins and usage remains high until about 10 PM. Weekends show a different pattern, with generally higher and more consistent energy use throughout the day. Weekend peak hours extend longer, from about 9 AM to 9 PM, with high consumption spread across afternoon and evening hours. There's less of a clear morning ramp-up on weekends, suggesting later start times.

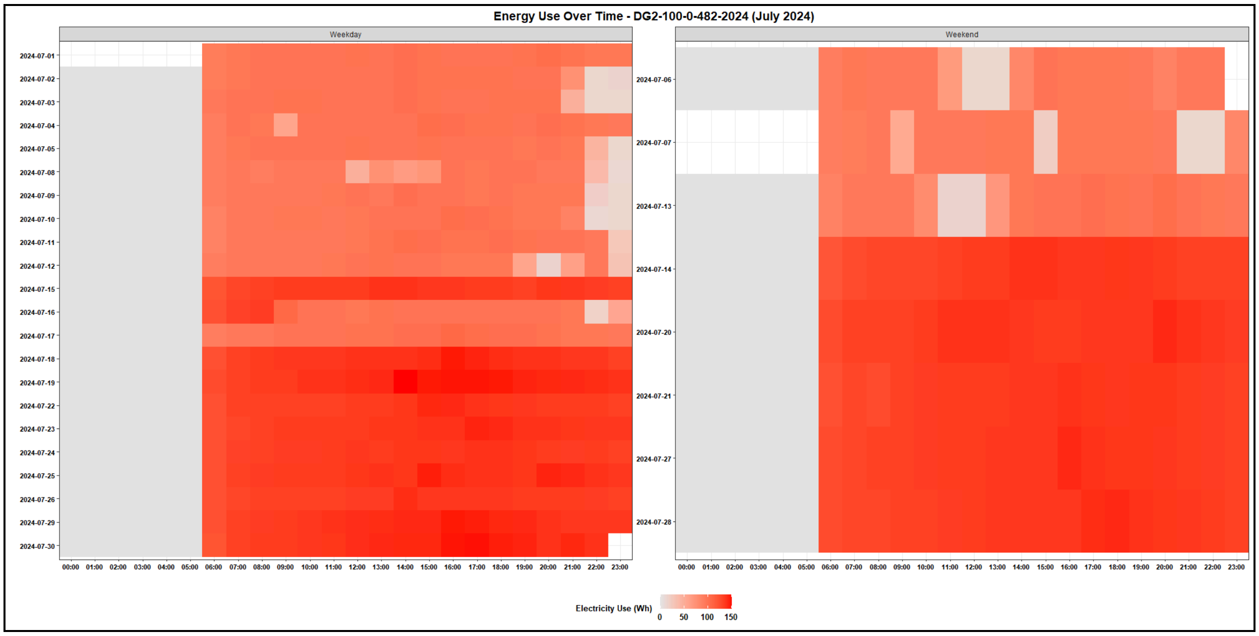


Figure 15. DG2-100-0-482 Coffee bar sockets energy consumption weekday versus weekend day

In sum, weekday afternoons see the highest energy consumption, this period might coincide with energy-intensive events like graduation ceremonies or conferences.

6.1.2. Front of House Sockets vs. Reception Desk Energy Usage Patterns

Given that there is no automation on the reception desk and front of house sockets (Figure 16), the observed differences in energy consumption and CO_2 emissions can be attributed primarily to the usage patterns and operational demands of these areas.

The reception desk, which is continuously occupied throughout the day, exhibits a steady energy consumption pattern and relatively stable CO_2 emissions due to its constant operational demands. For the DG2-100-0-115 socket, energy use increased from 6.56 kWh in August-December 2023 to 6.97 kWh in January-July 2024, representing a 6.3% rise. CO_2 emissions decreased slightly from 1.1 kg to 0.9 kg, a reduction of 18.2%. The DG2-100-0-132-f socket, however, shows a dramatic shift, with energy use surging from 29.84 kWh in August-December 2023 to an astonishing 501.12 kWh in January-July 2024, CO_2 emissions also soared from 4.8 kg to 75.1 kg.

Figure 16. The front of house manually used m.e. sockets

In contrast, front of house sockets demonstrate more variable energy usage and CO_2 emissions due to fluctuating guest traffic. For example, the DG2-100-0-112 socket saw a decrease in energy use from 3.30 kWh in January-July 2023 to 2.05 kWh in January-July 2024, marking a 37.8% reduction, with CO_2 emissions decreasing from 0.4 kg to 0.3 kg, a 25% drop. The DG2-100-0-291 socket also experienced a notable reduction in energy use from 2.91 kWh to 1.17 kWh, a 59.8% decrease and CO_2 emissions fell from 0.4 kg to 0.2 kg, a 50% reduction. The DG2-100-0-472 socket saw a 23.2% decrease in energy consumption, from 4.22 kWh to 3.24 kWh and a 42.9% reduction in CO_2 emissions, from 0.7 kg to 0.4 kg.

Figure 17. Front of the house DG2-100-0-493 socket and projector

Meanwhile, the DG2-100-0-493 socket's energy consumption increased by 50.0%, from 183.85 kWh to 275.42 kWh, though CO_2 emissions rose by 25.4%, from 30.1 kg to 37.7 kg (Figure 17).

The data highlights that while the front of house sockets, primarily used by dining guests and cleaners, show some improvements and fluctuations in efficiency, the reception desk sockets, due to their constant use, maintain a more consistent but higher level of energy consumption and CO_2 emissions. This distinction is evident in the percentage changes observed between the two areas. This comparison highlights the significant impact of operational patterns on energy use and carbon footprint and suggests that automation could further optimize performance and reduce emissions across both front of the house and perception desk. Further details are available in Annex 6 and Annex 8.

Figure 18. Front of the house projector without an m.e socket

In the process of locating the m.e sockets (Figure 18), we identified an additional projector that appeared to be connected to a socket not currently monitored for energy consumption. It seems this projector's energy usage is not being tracked. Therefore, we suggest installing m.e socket for monitoring the projector’s energy usage.

6.1.3. Kitchen Energy Usage Trends

From January to July 2024, the analysis of energy consumption and CO_2 emissions across various sockets reveals diverse outcomes, highlighting the impact of non-automated systems. The DG2-100-0-037 socket, which recorded an almost unchanged energy consumption of 675.98 kWh in 2023 compared to 677.62 kWh in 2024, showed a minimal increase of 0.3%. However, its CO_2 emissions decreased significantly by 15%, from 103.5 kg to 88 kg, reflecting improved energy efficiency or a shift towards less carbon-intensive energy sources. In contrast, the DG2-100-0-043 socket demonstrated a notable reduction in both energy use and CO_2 emissions. Its energy consumption fell from 35.60 kWh to 23.50 kWh, a substantial 33.9% decrease and CO_2 emissions decreased by 39.2%, from 5.1 kg to 3.1 kg. This reduction suggests possibly less frequent use. The DG2-100-0-114 socket experienced a slight decline in energy consumption from 41.22 kWh to 40.62 kWh, representing a modest 1.5% reduction, while CO_2 emissions dropped by 19%, from 6.3 kg to 5.1 kg. These small changes indicate limited but ongoing usage.

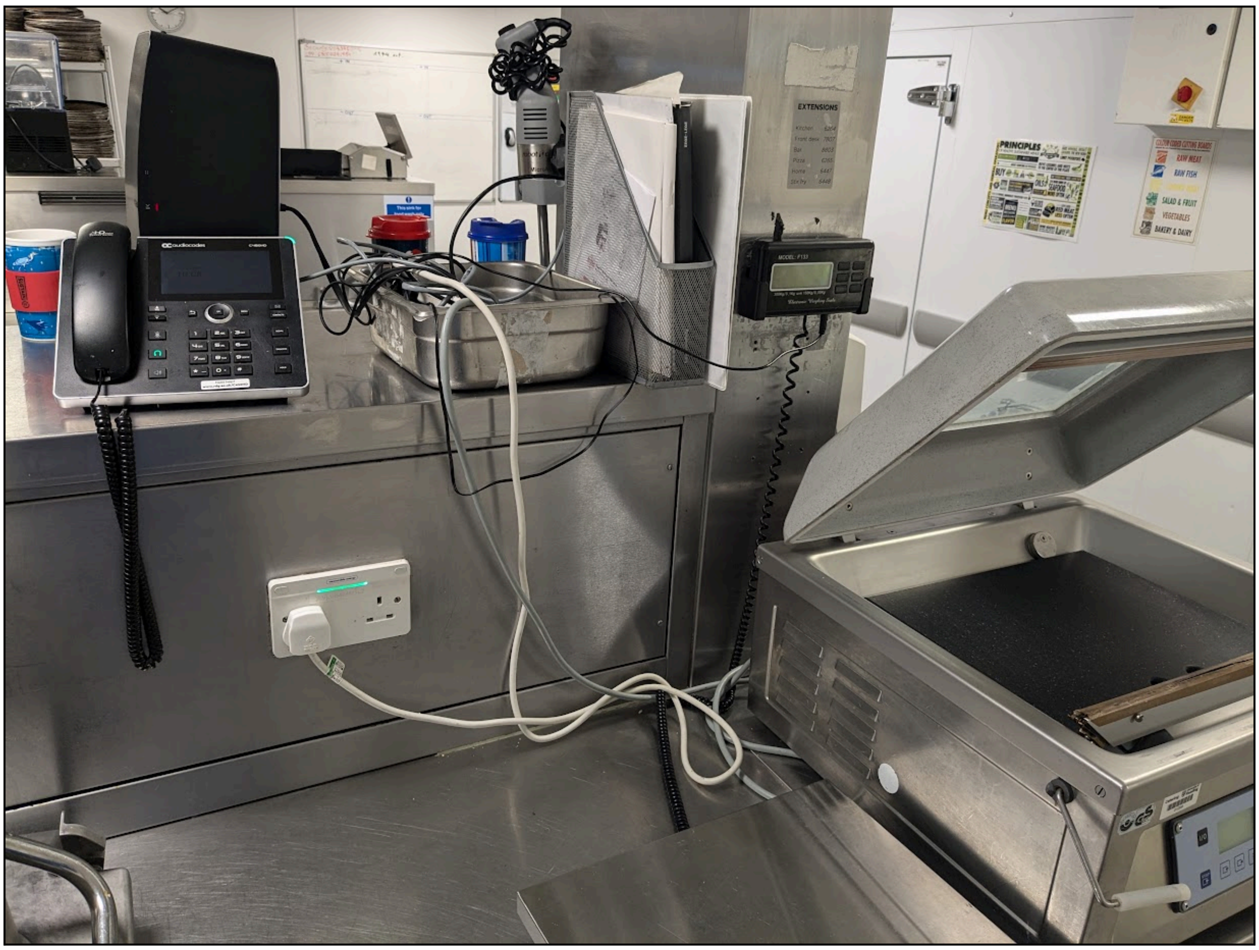


Figure 19. Kitchen DG2-100-0-287 socket

Conversely, the DG2-100-0-287 socket showed a significant increase in energy consumption from 44.41 kWh to 58.53 kWh, a rise of 31.8%, though CO_2 emissions only increased slightly by 2.7%, from 7.4 kg to 7.6 kg (Figure 19). This suggests that despite a considerable rise in energy usage, efforts or conditions might have mitigated the corresponding rise in CO_2 emissions. Overall, the absence of automation has led to varied results, with some sockets showing substantial reductions in CO_2

emissions, while others highlight the challenges of managing energy use and emissions without automated systems. Further details are available in Annex 7.

6.1.4. Evaluating Automation Versus Manual Operation: Is Automation Better?

The analysis of energy consumption and CO_2 emissions provides compelling evidence that automation generally offers significant advantages over manual operation, particularly in terms of efficiency and environmental impact.

Automated coffee machines demonstrate varied results in energy consumption and CO_2 emissions. For instance, DG2-100-0-140 saw a 13.9% increase in energy consumption from 36.75 kWh to 41.85 kWh between July-December 2023 and January-July 2024, while CO_2 emissions decreased by 5.4% from 5.6 g to 5.3 g. Similarly, DG2-100-0-298 experienced a 20.3% rise in energy use but a slight increase of 1.3% in CO_2 emissions. Despite these increases, automation can still contribute to overall efficiency improvements by optimizing operational schedules and reducing manual intervention.

The impact of automation on bar sockets reveals a mixed but generally positive trend. For instance, DG2-100-0-048 showed a slight increase in energy consumption of 3.9% from 65.35 kWh to 67.89 kWh, but a reduction in CO_2 emissions by 13.3%, from 9.8 g to 8.5 g. DG2-100-0-133 also saw a 6.6% rise in energy use, increasing from 57.44 kWh to 61.24 kWh, while CO_2 emissions decreased by 11.5%, from 8.7 g to 7.7 g. Similarly, DG2-100-0-210 experienced a 7.6% increase in energy consumption, rising from 16.00 kWh to 17.22 kWh and CO_2 emissions dropped by 8.3%, from 2.4 g to 2.2 g. These trends indicate that while automation can improve efficiency and reduce CO_2 emissions in some cases, the overall impact varies and may not always lead to significant reductions in energy use.

The front of house sockets, primarily used by dining guests and cleaners, show improvements with automation but still exhibit variability. For example, DG2-100-0-112 and DG2-100-0-291 both experienced notable reductions in energy consumption and CO_2 emissions, with decreases of 37.8% and 59.8%, respectively. However, socket DG2-100-0-493 saw a 50% increase in energy use and a 25.4% rise in CO_2 emissions, indicating that fluctuations in guest traffic and operational demands can affect the efficiency of automated systems.

The reception desk sockets, due to their constant use, present a more stable but higher energy consumption and CO_2 emission profile. For instance, the DG2-100-0-115 socket showed a 6.3% increase in energy consumption but an 18.2% decrease in CO_2 emissions, reflecting a relatively steady efficiency. Conversely, the DG2-100-0-132-f socket exhibited an alarming increase in energy use and rise in CO_2 emissions, highlighting the inefficiencies associated with manual operation in areas with high and consistent usage demands.

The kitchen sockets reveal diverse impacts of non-automation. For instance, DG2-100-0-043 demonstrated a 33.9% reduction in energy consumption and a 39.2% decrease in CO_2 emissions, suggesting a positive outcome for less frequent use. In contrast, DG2-100-0-287 experienced a 31.8% increase in energy use with a slight rise in CO_2 emissions. This variability underscores that while automation could potentially offer benefits, the effectiveness largely depends on usage patterns and operational adjustments.

In sum, the evidence indicates that automation generally provides considerable advantages over manual operation in terms of reducing energy consumption and CO_2 emissions. While manual operation can sometimes exhibit stable patterns, as seen with the reception desk sockets, automation consistently delivers better results in optimizing energy use and minimizing carbon footprints. Thus, integrating automation into both operational and high-demand areas is likely to result in substantial benefits, as demonstrated by the data presented.

6.2.1. Return on Investment for New Sockets Based on Appliance Performance

Investing £25[6] in new sockets demonstrates different economic return depending on the appliance performance.

From Table 4 the DG2-100-0-048, the total energy costs for January-March 2023 were £19.40 and for June-October 2023, it was £13.68, resulting in a total of £33.08. For 2024, the costs were £14.85 for November-March and £11.56 for April-July, totaling £26.41. A 20% reduction in energy consumption for DG2-100-0-048 would save approximately £6.62 in 2023 and £5.48 in 2024. Thus, the aggregated savings for 2023 and 2024 would be around £12.10, leading to a payback period of about 2 months.

For DG2-100-0-133, the total energy costs for January-March 2023 were £18.17 and for June-October 2023, it was £11.82, totaling £30.99. In 2024, the costs were £13.84 for November-March and £10.03 for April-July, aggregating to £23.87. A 20% reduction in energy use would save approximately £6.20 in 2023 and £4.84 in 2024, giving a total savings of £11.04. Thus, the payback period for DG2-100-0-133 would be about 2 months.

[6] Price considered according to https://measurable.energy/pricing

For DG2-100-0-210, the total energy costs for January-March 2023 were £5.19 and for June-October 2023, it was £3.24, summing up to £8.43. In 2024, the costs were £3.89 for November-March and £2.86 for April-July, totaling £6.75. A 20% reduction would save around £1.68 in 2023 and £1.35 in 2024, resulting in aggregated savings of £3.03. Consequently, the payback period for DG2-100-0-210 would be approximately 8 months.

Table 4 illustrates the payback periods for different bar appliances across two periods in 2023 and 2024. The DG2-100-0-048 device shows a varied payback period, with 19.40 kWh costing £13.68 from November to March and 14.85 kWh costing £11.56 from April to July. The DG2-100-0-133 device reflects a similar trend, with a consumption of 45.59 kWh costing £13.68 in the initial period and 33.44 kWh costing £10.03 later in the year. The DG2-100-0-210 sockets, which has the lowest energy usage, demonstrates a cost of £6.00 for 5 kWh in the earlier period and £5.19 for 17.30 kWh in the subsequent period. In 2024, the DG2-100-0-048 sockets is projected to have a payback period with a cost reduction, reflecting lower consumption costs of £14.85 and £11.56. The DG2-100-0-133 will similarly see reduced costs, with £13.84 and £10.03, while the DG2-100-0-210's payback period benefits from even lower costs, with £3.89 for 12.97 kWh. The analysis indicates that as consumption costs decrease over time, the payback periods for these devices are expected to improve.

Table 4. Bar appliances consumption cost

<table>
<tr><td></td><td></td><td colspan="2">November-December-January-February-March</td><td colspan="2">April-May-June-July</td><td colspan="3">Payback period (Months)</td></tr>
<tr><td rowspan="4">2023</td><td>Device</td><td>kWh</td><td>£</td><td>kWh</td><td>£</td><td>DG2-100-0-048</td><td>DG2-100-0-133</td><td>DG2-100-0-210</td></tr>
<tr><td>DG2-100-0-048</td><td>64.65</td><td>19.40</td><td>45.59</td><td>13.68</td><td rowspan="6">5</td><td rowspan="6">6</td><td rowspan="6">20</td></tr>
<tr><td>DG2-100-0-133</td><td>60.58</td><td>18.17</td><td>39.40</td><td>11.82</td></tr>
<tr><td>DG2-100-0-210</td><td>17.30</td><td>5.19</td><td>10.79</td><td>3.24</td></tr>
<tr><td rowspan="3">2024</td><td>DG2-100-0-048</td><td>49.50</td><td>14.85</td><td>38.54</td><td>11.56</td></tr>
<tr><td>DG2-100-0-133</td><td>46.12</td><td>13.84</td><td>33.44</td><td>10.03</td></tr>
<tr><td>DG2-100-0-210</td><td>12.97</td><td>3.89</td><td>9.54</td><td>2.86</td></tr>
</table>

Based on Table 5, which outlines the consumption costs of coffee machines, the payback periods for these appliances are highlighted for different months in 2023 and 2024. In 2023, the DG2-100-0-140 device exhibited varied costs: £2.78 for 9.25 kWh in June-July, £17.28 for 17.28 kWh in August-September and £12.26 for 12.26 kWh in November-December. The DG2-100-0-298 had higher energy consumption and costs: £20.97 for 69.91 kWh in June-July, £111.52 for 111.52 kWh in August-September and £84.16 for 84.16 kWh in November-December. The DG2-100-0-482 device, with even greater consumption, showed costs of £17.36 for 57.88 kWh in June-July, £127.70 for 127.70 kWh in August-September and £87.33 for 87.33 kWh in November-December. In 2024, the DG2-100-0-140 is projected to have a cost of £3.53 for 11.76 kWh, the DG2-100-0-298 is anticipated to cost £22.54 for 75.15 kWh and the DG2-100-0-482 will cost £26.45 for 88.16 kWh. The payback period for these devices in 2024 will reflect changes in consumption costs.

Table 5.Coffe machines appliances consumption cost

June-July				August-September- October		November-December		Payback period (Months		
	Device	kWh	£	kWh	£	kWh	£	DG2-100-0-140	DG2-100-0-298	DG2-100-0-482
2023	DG2-100-0-140	9.25	2.78	17,280	17.28	12.26	3.68	11	2	2
	DG2-100-0-298	69.91	20.97	111,520	111.52	84.16	25.25			
	DG2-100-0-482	57.88	17.36	127,700	127.70	87.33	26.20			
2024	DG2-100-0-140	11.76	3.53	NA	NA	NA	NA			
	DG2-100-0-298	75.15	22.54	NA	NA	NA	NA			
	DG2-100-0-482	88.16	26.45	NA	NA	NA	NA			

Table 6 provides a detailed overview of the consumption costs and payback periods for the manually controlled sockets across different periods in 2023 and 2024. In 2023, the DG2-100-0-112 socket exhibited relatively low costs: £0.79 for 2.63 kWh in January-February, £0.70 for 2.33 kWh in March-April and a significant increase to £80 for 2.33 kWh in May-June-July. The DG2-100-0-291 socket showed moderate costs: £0.63 for 2.09 kWh in January-February, £0.25 for 0.82 kWh in March-April and £0.35 for 1.17 kWh in May-June-July. The DG2-100-0-472 socket had costs of £0.81

for 3.68 kWh in January-February, £0.46 for 1.53 kWh in March-April and £0.44 for 1.48 kWh in May-June-July. The DG2-100-0-493 socket, however, had the highest costs, with £34.14 for 113.80 kWh in January-February, £21.00 for 69.99 kWh in March-April and £25.40 for 84.65 kWh in May-June-July.

For 2024, the projected costs for these sockets indicate changes: the DG2-100-0-112 is expected to cost £0.45 for 1.51 kWh in January-February and £0.16 for 0.54 kWh in March-April, with no data provided for subsequent months. The DG2-100-0-291 will cost £0.27 for 0.89 kWh in January-February and £0.08 for 0.28 kWh in March-April. The DG2-100-0-472 will have costs of £0.53 for 1.78 kWh in January-February and £0.45 for 1.49 kWh in March-April. The DG2-100-0-493 is anticipated to incur costs of £59.57 for 198.55 kWh in January-February and £23.04 for 76.82 kWh in March-April. Overall, the data highlights significant variations in payback periods for different sockets, with some showing much higher costs compared to others.

Table 6.Front of house appliances consumption cost

<table>
<tr><td colspan="2"></td><td colspan="2">January-
February-
March-April</td><td colspan="2">May-June-July</td><td colspan="2">August- September October-November-December</td><td colspan="4">Payback period (Months)</td></tr>
<tr><td rowspan="5">2023</td><td>Device</td><td>kWh</td><td>£</td><td>kWh</td><td>£</td><td>kWh</td><td>£</td><td>DG2-100-0-112</td><td>DG2-100-0-291</td><td>DG2-100-0-472</td><td>DG2-100-0-493</td></tr>
<tr><td>DG2-100-0-112</td><td>2.63</td><td>0.79</td><td>0.67</td><td>0.20</td><td>2.33</td><td>0.70</td><td rowspan="8">80</td><td rowspan="8">190</td><td rowspan="8">112</td><td rowspan="8">2</td></tr>
<tr><td>DG2-100-0-291</td><td>2.09</td><td>0.63</td><td>0.82</td><td>0.25</td><td>1.17</td><td>0.35</td></tr>
<tr><td>DG2-100-0-472</td><td>3.68</td><td>0.81</td><td>1.53</td><td>0.46</td><td>1.48</td><td>0.44</td></tr>
<tr><td>DG2-100-0-493</td><td>113.80</td><td>34.14</td><td>69.99</td><td>21.00</td><td>84.65</td><td>25.40</td></tr>
<tr><td rowspan="4">2024</td><td>DG2-100-0-112</td><td>1.51</td><td>0.45</td><td>0.54</td><td>0.16</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-291</td><td>0.89</td><td>0.27</td><td>0.28</td><td>0.08</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-472</td><td>1.78</td><td>0.53</td><td>1.49</td><td>0.45</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-493</td><td>198.55</td><td>59.57</td><td>76.82</td><td>23.04</td><td>NA</td><td>NA</td></tr>
</table>

Table 7 provides an analysis of the consumption costs and payback periods for kitchen appliances across periods in 2023 and 2024. In 2023, the DG2-100-0-037 appliance demonstrated significant energy costs, with £123.08 for 410.26 kWh in January-February, £79.71 for 265.70 kWh in March-April and £158.33 for 527.78 kWh in May-June-July, reflecting a payback period of 1 month. The DG2-100-0-043 appliance had costs of £4.82 for 16.05 kWh in January-February, £5.86 for 19.55 kWh in March-April and £16.01 for 53.37 kWh in May-June-July. The DG2-100-0-114 appliance incurred £7.70 for 25.65 kWh in January-February, £4.67 for 15.56 kWh in March-April and £10.01 for 33.36 kWh in May-June-July. Lastly, the DG2-100-0-287 appliance showed £10.77 for 35.89 kWh in January-February, £2.55 for 8.52 kWh in March-April and £11.88 for 39.61 kWh in May-June-July.

For 2024, the DG2-100-0-037 is projected to cost £119.36 for 397.85 kWh in January-February and £84.21 for 280.67 kWh in March-April, with no data for the subsequent periods. The DG2-100-0-043 appliance is expected to cost £5.29 for 17.64 kWh in January-February and £1.77 for 5.90 kWh in March-April. The DG2-100-0-114 appliance will have costs of £7.36 for 24.53 kWh in January-February and £4.87 for 16.22 kWh in March-April. The DG2-100-0-287 is anticipated to incur £10.69 for 35.63 kWh in January-February and £6.92 for 23.08 kWh in March-April.

Table 7.Kitchen appliances consumption cost

<table>
<tr><th colspan="2"></th><th colspan="2">January-
February-
March-April</th><th colspan="2">May-June-July</th><th colspan="2">August- September October-November-December</th><th colspan="4">Payback period</th></tr>
<tr><td rowspan="4">2023</td><td>Device</td><td>kWh</td><td>£</td><td>kWh</td><td>£</td><td>kWh</td><td>£</td><td>DG2-100-0-037</td><td>DG2-100-0-043</td><td>DG2-100-0-114</td><td>DG2-100-0-287</td></tr>
<tr><td>DG2-100-0-037</td><td>410.26</td><td>123.08</td><td>265.70</td><td>79.71</td><td>527.78</td><td>158.33</td><td rowspan="8">1</td><td rowspan="8">9</td><td rowspan="8">9</td><td rowspan="8">7</td></tr>
<tr><td>DG2-100-0-043</td><td>16.05</td><td>4.82</td><td>19.55</td><td>5.86</td><td>53.37</td><td>16.01</td></tr>
<tr><td>DG2-100-0-114</td><td>25.65</td><td>7.70</td><td>15.56</td><td>4.67</td><td>33.36</td><td>10.01</td></tr>
<tr><td></td><td>DG2-100-0-287</td><td>35.89</td><td>10.77</td><td>8.52</td><td>2.55</td><td>39.61</td><td>11.88</td></tr>
<tr><td rowspan="4">2024</td><td>DG2-100-0-037</td><td>397.85</td><td>119.36</td><td>280.679</td><td>84.21</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-043</td><td>17.64</td><td>5.29</td><td>5.90</td><td>1.77</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-114</td><td>24.53</td><td>7.36</td><td>16.22</td><td>4.87</td><td>NA</td><td>NA</td></tr>
<tr><td>DG2-100-0-287</td><td>35.63</td><td>10.69</td><td>23.08</td><td>6.92</td><td>NA</td><td>NA</td></tr>
</table>

Table 8 outlines the consumption costs and payback periods for reception appliances over various periods in 2023 and 2024. In 2023, the DG2-100-0-115 appliance had incomplete data, with costs not recorded for January-February, March-April and May-June, but reported a cost of £2.07 for 6.91 kWh in July-August-September, indicating a payback period of 2 months. The DG2-100-0-132-f appliance's costs were not recorded for the earlier periods but were £9.13 for 30.44 kWh in October-November-December.

For 2024, the DG2-100-0-115 appliance is projected to cost £1.40 for 4.68 kWh in January-February-March and £0.38 for 1.27 kWh in April. The DG2-100-0-132-f appliance is anticipated to incur higher costs of £127.08 for 423.60 kWh in January-February-March and £16.49 for 54.96 kWh in April. This data highlights significant variations in energy costs and payback periods for reception appliances.

Table 8.Reception appliances consumption cost

		January-February-March-April		May-June		July-August-September October-November-December		Payback period	
	Device	kWh	£	kWh	£	kWh	£	DG2-100-0-115	DG2-100-0-132-f
2023	DG2-100-0-115	NA	NA	NA	NA	6.91	2.07	78	2
	DG2-100-0-132-f	NA	NA	NA	NA	30.44	9.13		
2024	DG2-100-0-115	4.68	1.40	1.27	0.38	NA	NA		
	DG2-100-0-132-f	423.60	127.08	54.96	16.49	NA	NA		

6.2.2. Comparing Payback Periods Across Sockets Locations

In evaluating the payback periods for automating different sockets across various operational areas, we observe notable variations based on energy consumption and cost savings. For bar appliances, the DG2-100-0-048 and DG2-100-0-133 sockets show the fastest payback periods of approximately 2 months due to their higher energy costs and potential savings. Similarly, coffee machines with sockets like the DG2-100-0-298 and DG2-100-0-482 also achieve a rapid payback of around 2 months. In the front of house area, sockets such as DG2-100-0-112, DG2-100-0-291 and DG2-100-0-472 exhibit quick paybacks of about 2 months, benefiting from their lower energy consumption. Kitchen appliances demonstrate a wide range of payback periods, with the DG2-100-0-037 achieving the fastest return of approximately 1 month, while others like the DG2-100-0-043 and DG2-100-0-114 have longer paybacks due to their lower energy costs. Lastly, reception area sockets, including the DG2-100-0-115 and DG2-100-0-132-f, also provide quick paybacks of around 2 months. Overall, sockets used in areas with higher energy costs and consumption typically offer faster paybacks, making them more favorable investments for automation.

In our calculations of the payback periods for the different sockets across various operational areas, we made several key assumptions. We assumed that energy costs would remain constant over the evaluation period, ignoring potential fluctuations that could impact actual payback periods. We also assumed stable usage patterns for the appliances connected to these sockets, without significant changes in usage intensity or duration. Additionally, we presumed that the costs associated with installing and maintaining the automation systems would be uniform across different types of sockets and locations. We also considered operational conditions, such as hours of operation and occupancy levels, to remain consistent across the different areas (bar, front of house, kitchen, reception). Financial metrics used in the evaluation are straightforward, not accounting for factors like inflation, discount rates, or opportunity costs that could influence the financial assessment. Lastly, we assumed complete adoption of the sockets to achieve the projected energy savings, as partial or phased adoption could result in different payback periods. These assumptions aim to provide a simplified and consistent comparison of payback periods across different sockets and operational areas, highlighting where automation investments are most financially beneficial.

7. Survey findings

In this section, we report the results of a survey involving 22 participants, focusing on their interactions with the traffic light system for energy usage. The survey assessed respondent’s socio-demographic profiles, their interpretations of the m.e color codes and the effectiveness of energy-saving initiatives..

7.1. User behaviour and Perceptions Regarding Socket Usage and Energy-Saving Initiatives

This section provides an analysis of 22 surveys focusing on user behaviour and perceptions related to socket usage within a specific context. It begins with a socio-demographic overview of the respondents, including their affiliations, gender and age. It then addresses the effectiveness and reception of energy-saving initiatives, with particular emphasis on the m.e traffic light system. The section reviews varying interpretations of the traffic light system's color codes and the associated recommended actions. Lastly, it explores the influence of attitudes, subjective norms, perceived behavioural control, personal norms, past behaviour and self-determination on users' intentions and behaviours related to socket usage.

7.1.1. Respondent's Profile

Figure 20 illustrates the socio-demographic information of the 22 valid responses collected in this research. The data reveals that the majority of respondents are affiliated with either 'Eat at the Square' or 'Park Eats,' each representing 28% of the total mentions, making them the most prominent categories in the dataset. In terms of gender distribution, male respondents constitute 43.5% while female respondents make up 56.5% of the total. The age distribution indicates that 52.6% of respondents are in the 30-39 age range. Additionally, it is noteworthy that most respondents hold permanent contracts.

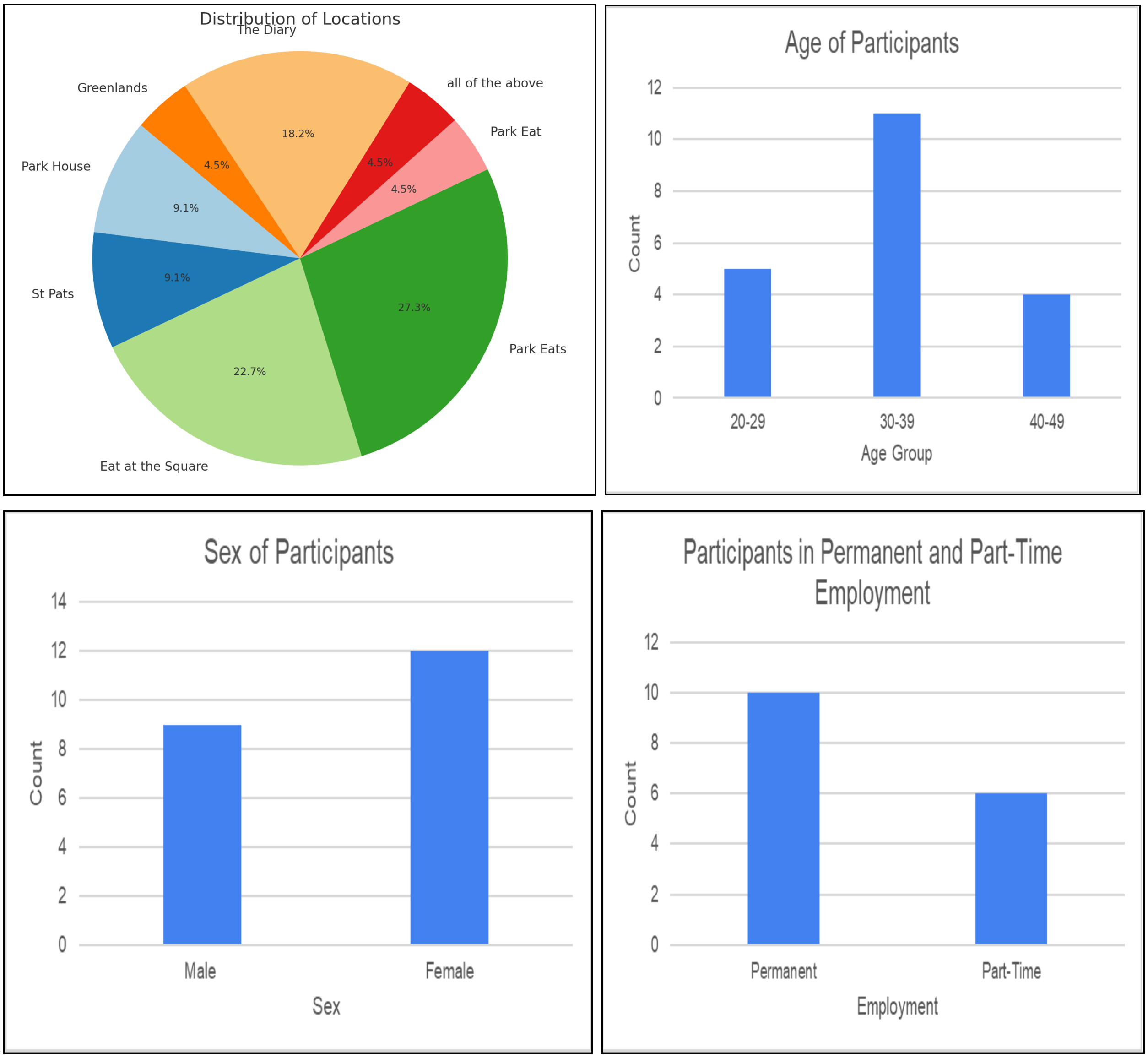


Figure 20. Distribution of location, age, sex and job type from the TPB survey

7.2.1. Respondent's interpretation of the m.e traffic light system

Survey results indicate that none of the respondents received an induction on energy saving when they joined the University of Reading's catering department (Figure 21). Furthermore, 77% of respondents expressed a desire to receive such an induction biannually. This highlights a clear gap in the current training practices and suggests a strong interest among staff for more frequent energy-saving education. Conversely, 22.2% of respondents did not support the idea of receiving induction on energy saving twice a year.

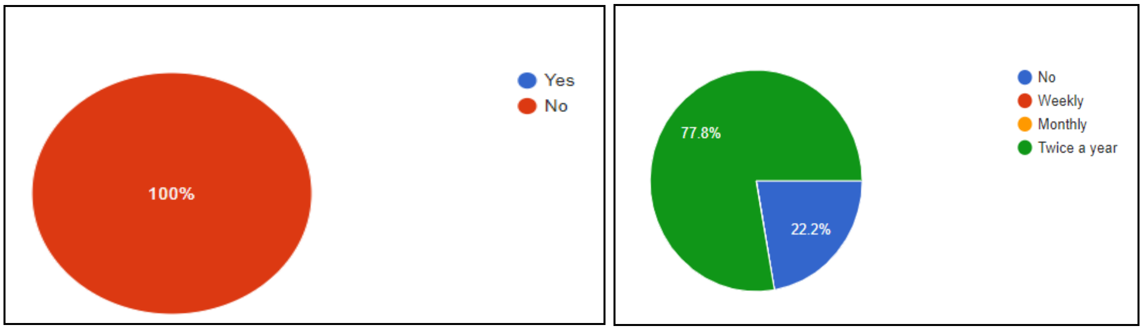


Figure 21. Interest and frequency of energy saving induction

The survey sought to determine whether respondents had observed the smart sockets with a traffic light system in the University of Reading's restaurants. The results indicate that 66.7% of respondents have indeed observed these smart sockets, while 33.3% have not. Among those who have seen the smart sockets, 66% specifically mentioned noticing them in the 'Park Eats' department, while the remaining mentions were not attributable to a specific department.

Survey respondents provided a variety of interpretations regarding the meaning of the traffic light color codes for grid carbon intensity (Table 9). The responses indicate a general lack of clarity, with many participants stating they had "no idea" or that it "was never explained." Specifically, green, which indicates grid carbon intensity generated from renewables, was sometimes interpreted as "safe to use" or "green electricity." Amber, representing a mixed grid, was associated with "medium energy use" or "mixed grid carbon." Red, signaling non-renewable energy sources, was frequently associated with terms like "danger," "high energy consumption," and "carbon heavy grid." Some respondents also mentioned "using too much energy" or "connected device wasting energy," highlighting concerns about energy efficiency. In sum, these varied responses highlight the need for clearer communication and education about the traffic light system's meaning and implications.

Table 9. Respondent’s interpretations of the m.e traffic light system

Red colour	Amber colour	Green colour
Not turned on	Shorted circuit	Safe to use
No idea . Never been explained	No idea never explained	See previous answers
Using too much energy	Don’t know	Using entry effectively
High energy consumption, unplug any unnecessary appliances	Medium energy use	Low energy usage
High energy consumption, unplug any unnecessary appliances	Medium energy use	Low energy usage
High energy consumption, unplug any unnecessary appliances	Medium energy use	Low energy usage
Danger	Stay away	Safe to use
Carbon Heavy Grid	Mixed Grid Carbon	Green electricity
Off	Not sure - haven't been told the traffic light system	On
Connected device wasting energy	Dont know	Connected device using energy efficiently
High usage	Don’t know	Don’t know

Survey responses revealed diverse interpretations of the recommended actions associated with the traffic light color codes for energy usage (Table 10). For the green light, which signifies no immediate action is required, some respondents suggested "use it" or "turn things off" if not using the device, while others noted "nothing" or "use more power." For the amber light, indicating medium energy use, common responses included "unplug from the socket" and "review usage and consider setting a schedule to power off devices." In contrast, the red light, representing high energy consumption, prompted recommendations such as "not use it," "call facilities," or "unplug any unnecessary appliances."

Table10. Respondent’s suggested actions for the traffic light system colours

Red colour	Amber colour	Green colour
Not use it	Call Facilities	Use it
No idea never been explained	See previous answers	See previous answers
If not using turn off plugged in device	Don’t know	Nothing
High energy consumption, unplug any unassaary appliances	Medium energy use	Low energy usage
High energy consumption, unplug any unassaary appliances	Medium energy use	Low energy usage
High energy consumption, unplug any unassaary appliances	Medium energy use	Low energy usage
Not use	Not use	Use it
Turn things off	Think about switching stuff off.	Use more power! :-)
Switch on	Not sure - haven't been told the traffic light system	You can use
Review usage and consider setting schedule to power off device	Dont know	Give yourself a pat on the back
On	Don’t know	Don’t know

The varied responses highlight a general lack of clear understanding of the traffic light system, indicating a need for better guidance and communication regarding the appropriate actions for each color code. Again, the answers highlighted the need for education/training regarding the traffic light system's meaning and the appropriate actions to take for each color code.

7.3.1. Collinearity assessment of the modells

The collinearity test (Table 11) results reveal varying degrees of collinearity among the constructs, as indicated by their Variance Inflation Factors (VIF). Constructs such as ATT-1 and ATT-3 exhibit high VIF values of 6.130 and 6.147, respectively, signaling significant multicollinearity that may distort the accuracy of any regression estimates. Similarly, INT-2 and SDM-3 show moderate VIF values of 4.916 and 3.836, suggesting potential collinearity issues that should be monitored. In contrast, constructs with lower VIF values, such as PBC-1 (1.00), demonstrate minimal collinearity, indicating they are relatively independent of other predictors. Constructs with moderate VIF values, like PMN-2 and HEB-2, fall within acceptable limits but still require attention to avoid potential instability in the model.

The limited sample size of only 22 surveys could exacerbate these collinearity issues, as smaller samples may lead to higher variance in the estimates and less reliable results.

Table 11. Collinearity assessment for the model

Constructs	VIF	Constructs	VIF	Constructs	VIF	Constructs	VIF	Constructs	VIF
ATT-1	6.130	PMN-1	2.054	SDM-1	1.324	INT-1	1.155	HEB-1	2.160
ATT-2	1.008	PMN-2	4.206	SDM-2	1.746	INT-2	4.916	HEB-2	2.564
ATT-3	6.147	PMN-3	3.234	SDM-3	3.836	INT-3	4.625	HEB-3	3.807
SJN-1	2.033	PBH-1	2.042	SDM-4	4.619			HEB-4	2.999
SJN-2	1.914	PBH-2	3.463	SDM-5	1.500				
SJN-3	1.588	PBH-3	2.799						
PBC-1	1.00								

Table 12 represents the coefficient determination (R^2) of the three modells. Based on the provided R^2 values for the TPB, Model 1 and Model 2, it is evident that Model 2 outperforms both TPB and Model 1 in explaining the variance in Intention and Behaviour. For Intention, Model 2 has the highest R^2 value (0.839), indicating it explains 83.9% of the variance, compared to 82.9% for Model 1 and 76.6% for TPB. This suggests that the additional factors or modifications included in Models 1 and 2 enhance their explanatory power for Intention over the traditional TPB. For Behaviour, Model 2 also shows the highest explanatory power with an R^2 of 0.289, followed by Model 1 at 0.241 and TPB at 0.162.

Table 12. The modells coefficient determination (R^2)

	TPB	Model 1	Model 2
	R^2	R^2	R^2
Intention	0.766	0.829	0.839
Behaviour	0.162	0.241	0.289

This indicates that Model 2's additional constructs better capture the variance in Behaviour. Overall, Model 2 provides a more comprehensive understanding of the determinants of Intention and Behaviour.

7.3.2. Modelling results of TPB, Model 1 and Model 2

Comparing Model 1, Model 2 and the TPB using beta values, t-values and significance levels reveals key insights into their effectiveness (Table 13). In Model 2, significant predictors for Intention include ATT ($\beta = 0.655$, $t = 4.884$, $p < 0.001$) and PBH ($\beta = 0.609$, $t = 2.214$, $p = 0.042$), although none of the predictors for Behaviour reach significance. Model 1 shows ATT ($\beta = 0.674$, $t = 5.136$, $p < 0.001$) and PMN ($\beta = 0.299$, $t = 1.064$, $p = 0.303$) as significant for Intention, with SDM approaching significance ($\beta = 0.440$, $t = 2.081$, $p = 0.052$). TPB highlights ATT ($\beta = 0.86$, $t = 7.164$, $p < 0.001$) as a consistently strong predictor for Intention, but lacks significant predictors for Behaviour. TPB has lower R^2 values (0.766 for Intention and 0.162 for Behaviour) compared to Model 2 (0.839 for Intention and 0.289 for Behaviour), indicating Model 2 has better explanatory power for both outcomes. Overall, while Model 2 provides the highest explanatory power, TPB and Model 1 also offer significant insights, particularly with ATT and PMN being notable predictors for Intention across models.

Table 13. Modelling analysis results of the three models

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Constructs	TPB model			Model 1			Model 2		
	β	T-Values	Sig.	β	T-Values	Sig.	β	T-Values	Sig.
ATT-> Intention	0.86	7.164	***	0.674	5.136	***	0.655	4.884	***
SJN->Intention	0.388	1.736	0.101	0.154	0.633	0.536	0.131	0.536	0.6
PBC->Intention	-0.205	-0.89	0.385	-0.066	-0.373	0.714	-0.076	-0.433	0.671
PBC-> Behaviour	0.211	0.917	0.371	0.283	1.266	0.224	0.27	1.207	0.246
Intention-> Behaviour	0.342	1.546	0.139	0.218	0.664	0.516	0.139	0.407	0.69
PBH->Intention				-0.596	-2.987	***	0.609	2.214	**

Constructs	TPB model			Model 1			Model 2		
PMN->Intention				0.299	1.064	0.303	-0.596	-2.987	***
SDM->Intention							0.299	1.064	0.303
SDM-> Behaviour							0.399	1.068	0.301

* p < 0.05, ** p < 0.01, *** p < 0.001

In examining the results across the different models—TPB, Model 1 and Model 2—several key insights emerge. The TPB shows (Figure 22) that the ATT construct is a significant predictor of Intention (β = 0.86, t = 7.164, $p < 0.001$), demonstrating its strong influence. However, it lacks significant predictors for Behaviour, with the intention-behaviour relationship showing a modest beta (β = 0.342) and a t-value of 1.546, with a significance level ($p = 0.139$) that is not below the typical thresholds for statistical significance.

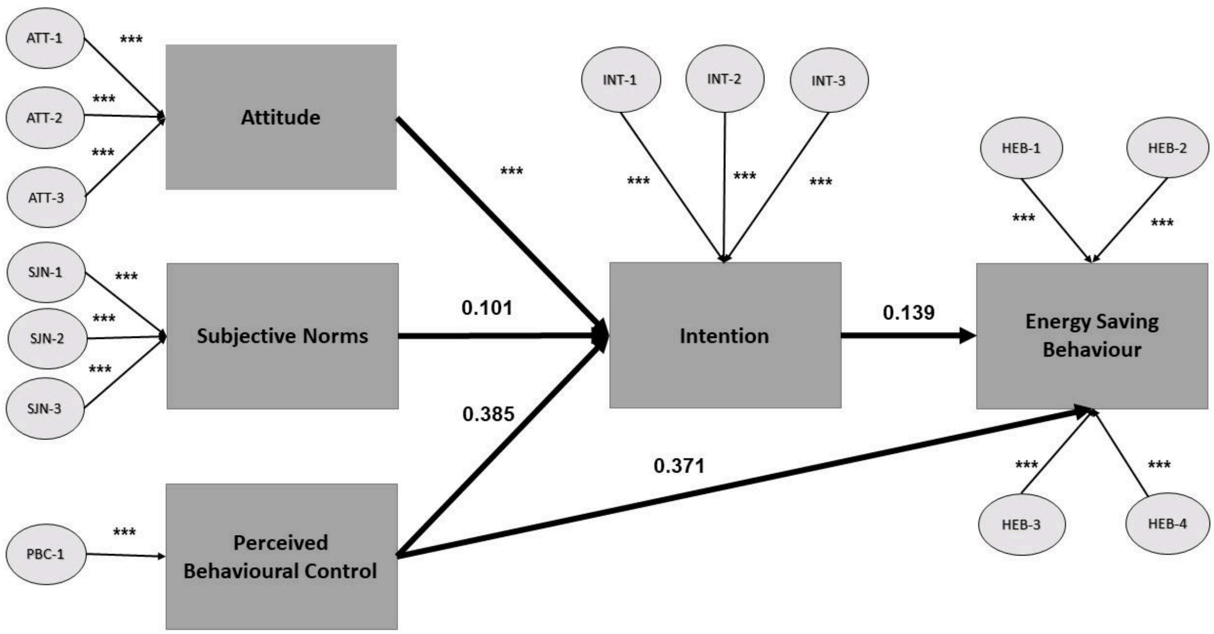


Figure 22. Modelling result TPB

In Model 1 (Figure 23), ATT remains a significant predictor of Intention (β = 0.674, t = 5.136, $p < 0.001$), reinforcing its importance. Additionally, the PMN construct shows some significance with a beta of 0.299 and a t-value of 1.064, though its significance level ($p = 0.303$) is not as strong as ATT. The SDM construct approaches significance with β = 0.440, t = 2.081 and $p = 0.052$, indicating it may have a relevant but less clear impact on Intention. The model's ability to predict Behaviour remains limited, with the intention-behaviour relationship showing β = 0.218, t = 0.664 and $p = 0.516$, suggesting that while intentions are influenced by ATT and PMN, their translation into Behaviour is less clear.

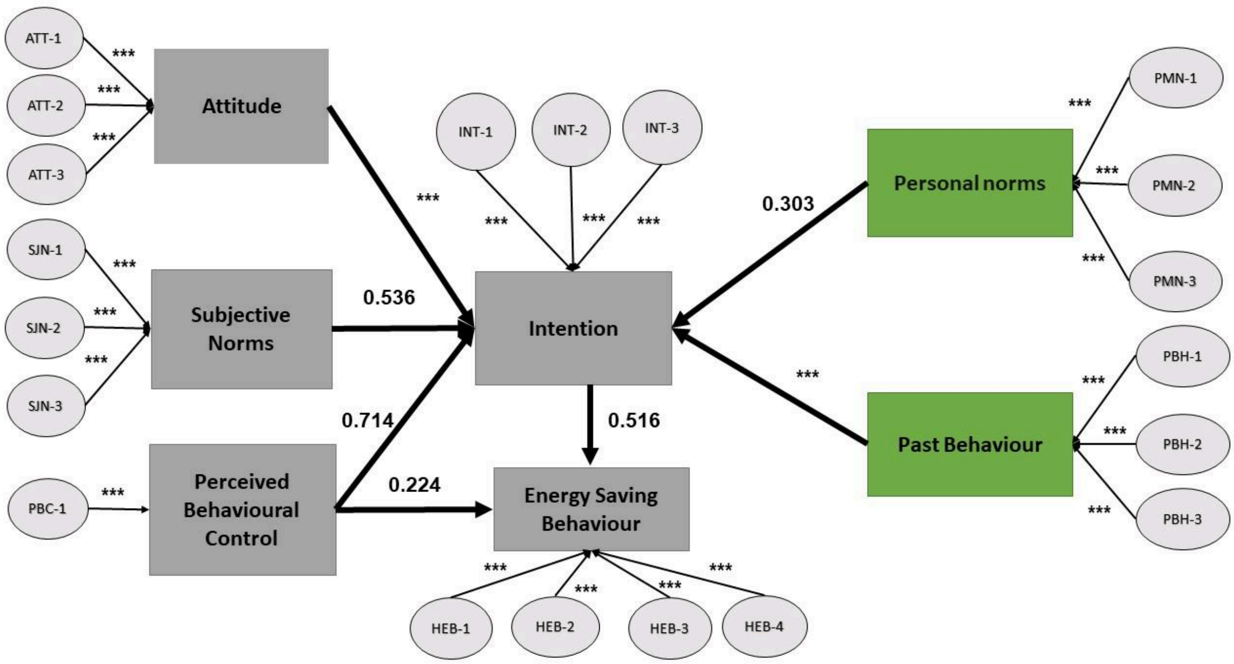


Figure 23. Modelling result Model 1

Model 2 (Figure 24) presents a more nuanced picture. It highlights ATT as a strong predictor of Intention ($\beta = 0.655$, $t = 4.884$, $p < 0.001$), consistent with findings from TPB and Model 1. Additionally, PBH emerges as a significant predictor of Intention in Model 2 ($\beta = 0.609$, $t = 2.214$, $p = 0.042$), which is not present in the other models. However, similar to Model 1, the predictors for Behaviour are not statistically significant in Model 2, with the intention-behaviour relationship showing $\beta = 0.399$, $t = 1.068$ and $p = 0.301$.

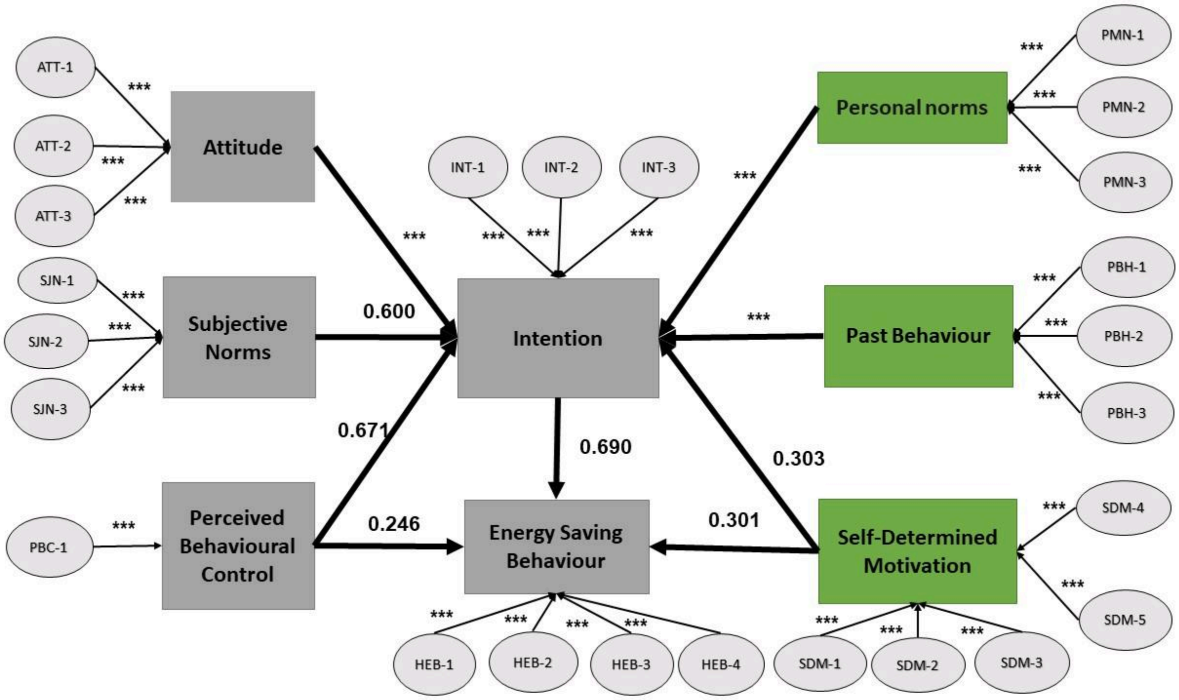


Figure 24. Modeling result Model 2

8. Discussion

The detailed analysis of energy consumption patterns across various areas in the Park Eat restaurant has revealed several key insights into how energy use and carbon emissions vary with the implementation of measurable energy smart sockets. The analysis primarily focused on comparing the energy usage and efficiency of different types of appliances, including bar chillers and coffee machines, as well as examining the energy consumption in kitchen, reception desk areas or dining areas.

The comparison between automated and manual operations reveals that automation typically offers superior efficiency and reduced environmental impact. Automated systems, such as those used in bar sockets, have shown remarkable improvements in both energy consumption and CO_2 emissions. For example, DG2-100-0-048 experienced a slight 3.9% increase in energy consumption but achieved a 13.3% reduction in CO_2 emissions; DG2-100-0-133 saw a 6.6% rise in energy use while CO_2 emissions decreased by 11.5%; and DG2-100-0-210 had a 7.6% increase in energy consumption coupled with an 8.3% drop in CO_2 emissions. These results highlight the benefits of automation in optimizing performance and reducing the carbon footprint. In contrast, coffee machines demonstrated mixed outcomes, with increased energy use in some cases but improved emissions efficiency, indicating that while automation can optimize certain aspects, its impact varies based on specific operational contexts.

The front of house sockets, primarily used by dining guests and cleaners, also benefited from automation, showing improvements in efficiency despite some variability due to fluctuating guest traffic. However, the reception desk sockets, which are in constant use, maintained a relatively stable but higher level of energy consumption and CO_2 emissions, illustrating the challenges of managing high-demand areas manually.

Kitchen sockets further highlight this variability, with some showing notable reductions in both energy consumption and CO_2 emissions, while others experienced increased energy use. Overall, while manual systems can be stable, automation consistently delivers better efficiency and environmental performance, making it a valuable tool for optimizing energy use and minimizing emissions across various applications.

The analysis of payback periods across different sockets reveals notable variations in financial returns. High-energy appliances, such as those used in bar settings and coffee machines, exhibit the most favorable payback periods, generally around 2 months. For example, the DG2-100-0-048 socket, utilized in bar environments and the DG2-100-0-298 socket for coffee machines, demonstrate significant energy savings that translate into quick returns on investment. Similarly, front of house sockets like the DG2-100-0-112, with its efficient energy use, also achieve a payback period of about 2 months.

In contrast, kitchen appliances present a more varied landscape. The DG2-100-0-037 shows a particularly rapid payback period of approximately 1 month, indicating a highly favorable return, while other kitchen sockets display longer payback durations due to relatively lower cost reductions. Reception area sockets, such as the DG2-100-0-115, also achieve swift returns, typically around 2 months.

Overall, this analysis highlights that investing in automation for sockets in high-energy consumption areas offers the most attractive financial returns.

In assessing the effectiveness of energy-saving initiatives, particularly the m.e traffic light system, it is evident that a significant gap exists in training. Notably, none of the respondents received an induction on energy saving upon joining the University of Reading's catering department, though 77% expressed a desire for biannual training. This indicates a strong interest in more frequent energy-saving education among staff, while 22.2% opposed the idea of such training.

Observations of the smart sockets with the traffic light system show that 66.7% of respondents have seen these devices, primarily in the 'Park Eats' department. However, interpretations of the traffic light color codes for grid carbon intensity varied widely. Green, indicating renewable energy, was often misinterpreted as 'safe to use' or 'green electricity,' while amber (mixed grid) and red (non-renewable energy) elicited responses ranging from 'medium energy use' to 'high energy consumption' and 'danger,' respectively. These varied interpretations highlight a significant lack of clarity and underscore the need for improved communication and education regarding the traffic light system's meaning and implications.

Furthermore, respondent’s suggested actions for each color code varied. For the green light, responses ranged from 'use it' to 'turn things off,' while amber prompted actions like 'unplug' or 'review usage,' and red led to recommendations such as 'not use it' or 'call facilities.' These diverse responses reflect a general confusion about the appropriate actions for each color code, reinforcing the need for clearer guidance and training on the traffic light system's proper use.

We could also suggest, as in the case of the fire safety noticeboard, using labels to highlight the importance of the traffic light system. This would ensure that users are continually reminded of the traffic light system importance and are more likely to engage customers with energy-saving practices.

In Model 1, which incorporates PMN and PBH alongside the TPB constructs, ATT remains a robust predictor of Intention ($\beta = 0.674$, $t = 5.136$, $p < 0.001$), mirroring its role in the TPB framework. PMN, though not reaching statistical significance ($\beta = 0.299$, $t = 1.064$, $p = 0.303$), suggests a potential influence on Intention. The SDM construct approaches significance for Intention ($\beta = 0.440$, $t = 2.081$, $p = 0.052$), indicating that motivational factors may play a role in shaping intentions. However, the relationship between Intention and Behaviour in Model 1 remains non-significant ($\beta = 0.218$, $t = 0.664$, $p = 0.516$), which aligns with the findings in TPB where Behaviour is not directly influenced by Intention.

This indicates that while PMN and PBH contribute to Intention, their direct impact on Behaviour is less clear. The addition of SDM in Model 1 suggests that motivation may influence Intention, yet the pathway from Intention to Behaviour remains ambiguous. Thus, while Model 1 provides a deeper understanding of how PMN and SDM might affect Intention, it does not significantly alter the predictive power for Behaviour compared to the TPB model.

Model 2, which integrates SDM alongside PMN and PBH, highlights ATT as a significant predictor of Intention ($\beta = 0.655$, $t = 4.884$, $p < 0.001$) and introduces PBH as a significant predictor of Intention ($\beta = 0.609$, $t = 2.214$, $p = 0.042$). Despite these enhancements, the predictors for Behaviour, including those influenced by PMN and SDM, are still not statistically significant ($\beta = 0.399$, $t = 1.068$, $p = 0.301$). This suggests that while PMN and PBH contribute meaningfully to Intention in both models, their impact on Behaviour remains less clear. The inclusion of SDM in Model 2 adds complexity to the understanding of how motivational factors influence Behaviour, but it does not fully resolve the challenges in achieving significant predictions for Behaviour.

9. Conclusion and future research

The analysis of energy consumption patterns across various sockets and appliances in different areas of the Park Eat restaurantt reveals that automation generally offers significant advantages over manual operation in terms of energy efficiency and CO_2 emissions reduction. The benefits vary depending on the specific appliance and usage patterns, automated systems consistently demonstrate potential for optimizing energy use and minimizing environmental impact.

The economic analysis, the analysis reveals significant variation in payback periods across different socket types and operational areas. Overall, the most favorable investment opportunities for automation are in areas with higher energy costs and consumption, where sockets deliver quicker returns on investment.

The analysis of the survey data reveals significant gaps in energy-saving education and communication regarding the m.e traffic light system. The varied interpretations of the traffic light color codes and the diverse suggested actions highlight the need for clearer guidance and more frequent training to enhance user understanding and compliance. Addressing these issues could increase the uptake of energy-saving initiatives and optimizing energy usage within the Park Eat restaurant.

The addition of Personal Moral Norms and Self-Determined Motivation alongside the Theory of Planned Behaviour components reinforces the role of Attitudes as a significant predictor of Intention, though Personal Moral Norm’s impact remains unclear and the pathway from Intention to Behaviour is still non-significant. The inclusion of Past Behaviour similarly highlights Attitude and introduces Past Behaviour as significant predictors of Intention; however, it does not significantly improve the prediction of Behaviour.

9.1. Limitations

One significant limitation was the low response rate to the survey, resulting in a small sample size that may not accurately represent the broader population. This limitation introduces potential response bias, as those who chose to participate may have different views and behaviours compared to those who did not respond. The low number of respondents could have significantly influenced the results and the generalizability of our findings.

Additionally, the lack of a control group skewed the analysis, making it challenging to attribute changes in behaviour solely to the intervention. Without a control group, it is difficult to determine whether observed changes were due to the traffic light system or other external factors.

The data also did not capture the reasons behind the use of different appliances, nor could it explain sudden spikes in energy consumption. This limitation leaves some aspects of user behaviour unexplored, particularly the motivations and contextual factors influencing appliance usage. Understanding these reasons could provide deeper insights into how and why energy consumption varies, which is crucial for designing more effective energy-saving interventions.

Furthermore, the study did not account for potential variations in term dates, opening hours, bank holidays, summer holidays and other related factors that could influence the findings. Energy consumption patterns may differ across seasons, terms, campus closure etc. affecting the payback periods and the overall effectiveness of the traffic light system.

Lastly, the desirability bias could have influenced respondent's answers, with individuals potentially providing socially desirable responses rather than accurate reflections of their behaviour. This bias could skew the results, making it appear that the intervention was more effective than it actually was.

9.2. Future research

Future research should explore other critical areas of use of the smart socket technology. We suggest further exploration of the application of the m.e socket based on different automation schedules tailored to monthly and seasonal variations in energy consumption. This approach will help identify the most effective timing strategies for energy-saving interventions, ensuring that smart sockets operate optimally throughout the year.

Expanding the scope of research beyond the Park Eat restaurant to include various locations across the campus—such as staff offices, lecture rooms and other communal spaces—will provide a broader perspective on the performance and impact of smart sockets in diverse environments. This broader implementation will help assess the generalizability of the technology and its effectiveness in different settings.

Additionally, exploring the role of visual feedback, such as traffic liht system, on smart sockets could shed light on how such visual cues influence user behaviour and contribute to energy savings.

Understanding how these visual indicators affect user engagement and energy conservation is crucial for refining the design and functionality of smart sockets.

Another important aspect is evaluating the effectiveness of instructional messaging about the traffic light system. Developing and testing various types of educational content, researchers can explore how well these messages improve user understanding and compliance with energy-saving practices.

Moreover there is a concern that the presence of smart sockets, which provide real-time feedback on energy usage, may lead individuals to believe they are consuming less energy than they actually are, potentially prompting them to increase their overall consumption. Understanding how users perceive and respond to this feedback is crucial for accurately assessing the impact of the m.e socket on energy conservation.

Furthermore, distinguishing between energy consumption practices that can be shifted versus those that are fixed will provide insights into which behaviours can be modified through the traffic light system. This understanding will help identify areas where the system can be most effective in influencing behaviour and improving energy efficiency.

These are some suggestions for further research projects that could provide deeper insights into the effectiveness of m.e sockets and its potential to incraese energy efficiency across various contexts.

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Annex

Annex 1 - The bar appliances automatisation (DG2-100-0-048, DG-100-0-133 and DG2-100-0-210 socckets)

Year/Month	On (hh:mm)	Off (hh:mm)
2023-January	No Schedule	No schedule
2023-February	No Schedule	No Schedule
2023-March	No Schedule	No Schedule
2023-April	No Schedule	No Schedule
2023-May	No Schedule	No Schedule
2023-June	05:30	11:30
2023-July	05:30	11:30
2023-August	05:30	11:30
2023-September	05:30	11:30
2023-October	05:30	11:30
2023-November	06:30	00:30
2023-December	06:30	00:30
2024-January	06:30	00:30
2024-February	06:30	00:30
2024-March	06:30	00:30
2024-April	05:30	11:30
2024-May	05:30	11:30
2024-June	05:30	11:30
2024-July	05:30	11:30

Annex 2 - The coffe machine automatisation (DG2-100-0-140)

Year/Month	On (hh:mm)	Off (hh:mm)
2023-January	N/A	N/A
2023-February	N/A	N/A
2023-March	N/A	N/A
2023-April	N/A	N/A
2023-May	N/A	N/A
2023-June	No Schedule	No Schedule
2023-July	05:30	23:30
2023-August	05:30	23:30
2023-September	05:30	23:30
2023-October	05:30	23:30
2023-November	06:30	00:30
2023-December	06:30	00:30
2024-January	06:30	00:30
2024-February	06:30	00:30
2024-March	06:30	00:30
2024-April	05:30	23:30
2024-May	05:30	23:30
2024-June	05:30	23:30
2024-July	05:30	23:30

Annex 3 - The coffe machine automatisation (DG2-100-0-298 and DG2-100-0-482)

Year/Month	On (hh:mm)	Off (hh:mm)
2023-January	N/A	N/A
2023-February	N/A	N/A
2023-March	N/A	N/A
2023-April	N/A	N/A
2023-May	N/A	N/A
2023-June	No Schedule	No Schedule
2023-July	No Schedule	No Schedule
2023-August	05:30	23:30
2023-September	05:30	23:30
2023-October	05:30	23:30
2023-November	06:30	00:30
2023-December	06:30	00:30
2024-January	06:30	00:30
2024-February	06:30	00:30
2024-March	06:30	00:30
2024-April	05:30	23:30
2024-May	05:30	23:30
2024-June	05:30	23:30
2024-July	05:30	23:30

Annex 4 - Bar sockets consumption statistics

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2023	DG2-100-0-048	13.31	Jan	6.72	Sep	2.10	Apr	1.10	Aug	133.12	11.10	17.10	1.42
	DG2-100-0-133	12.30	Mar	6.04	Sep	2.00	Mar	1.00	Aug	99.43	8.28	15.30	1.28
	DG2-100-0-210	3.54	Mar	1.76	Sep	0.60	Mar	0.19	Aug	33.76	2.81	4.10	0.34

2024	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
	DG2-100-0-048	9.78	May	8.89	July	1.70	Jan	0.90	Apr, Jun	56.03	9.34	10.10	1.01
	DG2-100-0-133	9.24	Mar	6.16	July	1.60	Jan	0.70	Jul	58.24	8.32	7.40	1.06
	DG2-100-0-210	2.79	Jul	1.81	April	0.40	Jan	0.20	Apr,Jun	14.78	2.11	1.70	0.24

Energy usage with automatisation	2023		2024	
	June-December		January-July	
	kWh	CO_2	kWh	CO_2
DG2-100-0-048	65.35	9.8	67.89	8.5
DG2-100-0-133	57.44	8.7	61.24	7.7
DG2-100-0-210	16	2.4	17.22	2.2

Annex 5- Coffee machines consumption statistics

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2023	DG2-100-0-140	7.02	Jul	1.80	Jun	1.00	Jul	0.30	Jun	41.4	5.91	4.8	0.69
	DG2-100-0-298	54.05	Jul	30.79	Sep	9.00	Nov	2.10	Jun	227.20	32.46	41.00	5.86
	DG2-100 0-482	52.33	Nov	11.66	Jun	8.60	Nov	1.80	Jun	214.97	30.71	34.80	4.97

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2024	DG2-100-0-140	6.02	Mar	5.49	Jun	1.00	Jan	0.50	Apr	39.68	5.67	4.60	0.66
	DG2-100-0-298	52.87	Mar	24.92	Jun	7.50	Jan, Febr	2.60	Jun	274.86	39.98	37.10	5.30
	DG2-100-0-482	60.63	Jul	24.21	Jun	8.00	Mar	2.50	Jun	256.03	36.86	27.00	3.86

Energy usage with automatisation	2023		2024	
	July-December		January-July	
	kWh	CO_2	kWh	CO_2
DG2-100-0-140	36.75	5.6	41.85	5.3
DG2-100-0-298	251.03	39.0	301.80	39.5
DG2-100-0-482	260.52	40.1	332.71	42.2

Annex 6- Front of house consumption statistics

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2023	DG2-100-0-112	1.27	Sep	0.11	Jun	0.20	Sep	0.00	May	4.70	0.39	0.60	0.05
	DG2-100-0-291	0.73	Mar	0.09	July	0.10	Multiple	0.00	Multiple	4.65	0.42	0.36	0.03
	DG2-100-0-472	0.80	Mar	0.07	Sep	0.20	Febr	0.00	Multiple	6.32	0.57	1.00	0.09
	DG2-100-0-493	53.92	May	0.00	Multiple	8.70	Nov	0.00	Multiple	200.47	18.23	40.58	3.69

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2024	DG2-100-0-112	0.50	Jan	0.08	Jun	0.10	Jan, Febr, Mar	0.00	Apr, May, Jun, Jul	2.96	0.25	0.3	0.03
	DG2-100-0-291	0.27	Apr	0.09	May, Jun	0.00	All months	0.00	All months	1.37	0.19	0.0	0.0
	DG2-100-0-472	0.78	May	0.04	Jun	0.10	Jan, Febr, May, Jul	0.00	Mar, Apr, Jun	2.90	0.24	0.5	0.04
	DG2-100-0-493	59.17	Febr	1.34	Jul	8.10	Febr	0.00	Jan	215.40	30.77	26.37	3.76

Energy usage without automatisation	2023				2024	
	January-July		August-December		January-July	
	kWh	CO_2	kWh	CO_2	kWh	CO_2
DG2-100-0-112	3.30	0.4	2.33	0.4	2.05	0.3
DG2-100-0-291	2.91	0.4	1.17	0.2	1.17	0.2
DG2-100-0-472	4.22	0.7	1.48	0.3	3.24	0.4
DG2-100-0-493	183.85	30.1	84.62	14.4	275.42	37.7

Annex 7- Kitchen consumption statistics

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2023	DG2-100-0-037	163.49	Nov	40.68	Dec	27.80	Nov	8.5	Jun	938.17	78.18	114.8	9.57
	DG2-100-0-043	48.01	Nov	0.21	Dec	11.00	Nov	0.00	Dec	84.64	7.67	16.00	1.45
	DG2-100-0-114	7.82	Nov	3.65	Jul	1.30	Nov	0.50	Jul	74.12	6.01	10.80	0.90
	DG2-100-0-287	11.10	Jan	1.52	Jul	2.21	Jan	0.20	Jul	60.18	5.02	14.80	1.23

	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
2024	DG2-100-0-037	133.98	May	25.53	Jun	21.30	Jan	2.10	Jun	735.25	102.32	73.6	10.51
	DG2-100-0-043	7.47	Febr	1.03	Jul	0.90	Febr	0.10	Jun, Jul	20.89	2.98	3.9	0.56
	DG2-100-0-114	7.11	May	3.81	Jun	1.00	Jan	0.40	Jun	39.27	5.61	6.2	0.89
	DG2-100-0-287	9.80	May	5.98	Jul	1.50	Jan	0.60	Jun	56.90	8.13	9.0	1.29

Energy usage without automatisation	2023				2024	
	January-July		August-December		January-July	
	kWh	CO_2	kWh	CO_2	kWh	CO_2
DG2-100-0-037	675.98	103.5	527.78	84.6	677.62	88
DG2-100-0-043	35.60	5.1	53.37	11.8	23.50	3.1
DG2-100-0-114	41.22	6.3	33.28	5.2	40.62	5.1
DG2-100-0-287	44.41	7.4	39.58	6.5	58.53	7.6

Annex 8- Reception desk consumption statistics

2023	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
	DG2-100-0-115	2.17	Oct	0.00	Multiple	0.30	Oct	0.00	Multiple	6.73	0.56	1.42	0.12
	DG2-100-0-132-f	27.79	Dec	0.00	Multiple	4.50	Dec	0.00	Multiple	30.55	2.54	5.31	0.44

2024	Location	Highest Energy Use (kWh)	Month	Lowest Energy Use (kWh)	Month	Highest CO_2 Emissions (g)	Month	Lowest CO_2 Emissions (g)	Month	Total energy use (kWh)	Average Monthly energy use (kWh)	Total CO_2 Emissions	Average Monthly CO_2 Emissions
	DG2-100-0-115	1.45	Jan	0.49	Jun	0.30	Jan	0.00	Jun	6.72	0.96	1.10	0.16
	DG2-100-0-132-f	177.72	Feb	4.20	Jul	26.00	Febr	0.20	Jul	490.75	70.11	77.60	11.09

Energy usage without automatisation	2023				2024	
	January-July		August-December		January-July	
	kWh	CO_2	kWh	CO_2	kWh	CO_2
DG2-100-0-115	NA	NA	6.56	1.1	6.97	0.9
DG2-100-0-132-f	NA	NA	29.84	4.8	501.12	75.1

Annex 9 - Survey

Design for Sustainable Behaviour: Feedback Interventions to Reduce Institutional Electricity Consumption

Consent Form – Title of Research: Design for Sustainable Behaviour: Feedback Interventions to Reduce Institutional Electricity Consumption

I have been invited to participate in a research study that will examine attitudes and intentions. The purpose of this study is to investigate the primary intentions to save electricity in the campus catering departments. If I agree to participate in this study, I will be asked to rate my beliefs on various issues. The study will only take approximately 12 to 14 minutes. There are no risks associated with this study. The benefits of participation include providing me an opportunity to reflect on my beliefs regarding energy savings.

This study is confidential. The records of this study will be kept private. No identifiers linking me to the study will be included in any report that might be published. Research records will be stored securely, and only the researcher, Zahrah Kanyiki, will have access to the records. If I decide to participate, I am free to refuse to answer any questions that may make me uncomfortable. I can withdraw at any time without my relationship with the university being affected. For any questions about the study, I can contact Zahrah Kanyiki (z.kanyiki@student.reading.ac.uk) or Dr Máté Lőrincz (m.lorincz@reading.ac.uk).

I have read the above information. By ticking the 'I consent' column, I consent to participate in this study. I may choose not to participate in the study by ticking an X in the 'I do not consent' column.

matejanoslorincz@gmail.com Switch account

Not shared

* Indicates required question

Consent form *

- [ ] I consent
- [ ] I do not consent

At which catering department are you working at the University of Reading? (Please specify) *

- ◯ Park Eat
- ◯ Eat at the Square
- ◯ The Diary
- ◯ Other: ______

What is your sex? *

- [ ] Male
- [ ] Female

What is your age? (Please specify) *

Your answer ______

Are you working: *

- ◯ Part-time
- ◯ Permanent

When did you start working at the University of Reading's catering department? (Please specify the year) *

Your answer

Did you receive an induction on energy saving when you at the University of Reading's catering department? *

- ◯ Yes
- ◯ No

If yes, please specify the catering department name: *

Your answer

If not, would you like to receive and induction on how to manage energy? *

- ◯ No
- ◯ Weekly
- ◯ Monthly
- ◯ Twice a year

Have you observed the below smart sockets with traffic light system in the University of Reading restaurants? *

◯ Yes

◯ No

If yes, can you name the restaurant were these sockets are used? *

Your answer

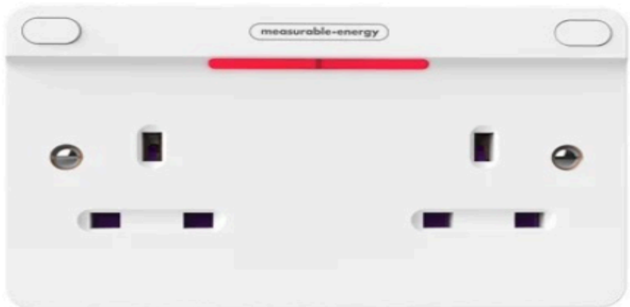
You will see the smart sockets showing different colours on their traffic lights. *
Please identify what each colour means.
The socket traffic light shows a red colour.

This means ... (please specify below)

Your answer

The socket traffic light shows a red colour. *

When seeing this colour on the socket, it is advisable to ... (please specify below)



Your answer

The socket traffic light shows a green colour. *

This means ... (please specify below)

Your answer

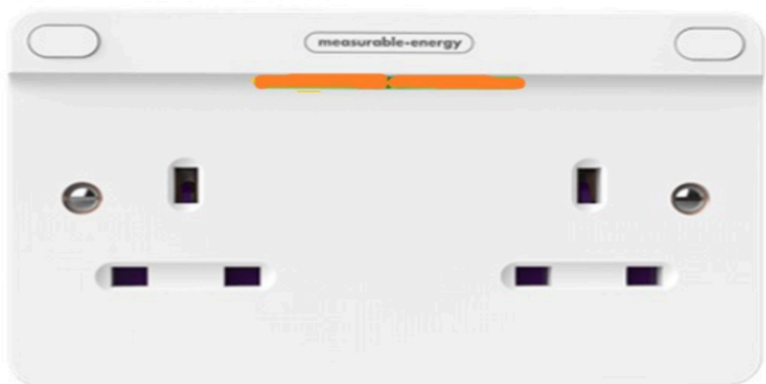
The socket traffic light shows a green colour. *

When seeing this colour on the socket, it is advisable to ... (please specify below)

Your answer

The socket traffic light shows an amber colour. *

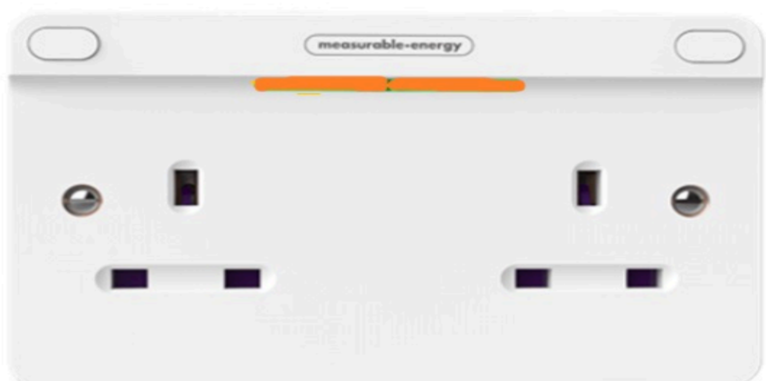
This means ... (please specify below)



Your answer

The socket traffic light shows an amber colour. *

When seeing this colour on the socket, it is advisable to ... (please specify below)



Your answer

I think conserving energy when working at the University of Reading's catering department is beneficial for protecting the environment. *

- ◯ Strongly Agree
- ◯ Somewhat Agree
- ◯ Neither
- ◯ Somewhat Disagree
- ◯ Strongly Disagree

I think that practicing energy conservation behaviours at the University of Reading's catering department is beneficial for protecting the environment. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I think energy conservation behaviours at University of Reading's catering department are valuable for the University of Reading's Net Zero Carbon Plan. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I think my family members want me to save energy when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I think my boss and colleagues want me to save energy when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I think that people who are important to me want me to save energy when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

It is difficult for me to engage in energy conservation behaviours when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

Whether to engage in energy conservation behaviours at the University of Reading's catering department entirely up to me. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

Saving energy at the University of Reading's catering department is a moral imperative for me. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I would feel guilty if I did not save energy at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

My ethics do not allow me to waste energy at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

Two months ago, during the academic term, I engaged in energy-saving behaviours at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

Two months ago, during the academic term, I made efforts in energy-saving behaviours at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

My efforts to save energy at the University of Reading's catering department increased two months ago, during the academic term. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I am willing to save energy when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I am willing to make efforts to save energy when at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I am willing to follow the energy-saving guidelines at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I will feel pleased if I can contribute to the environment. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I will gain recognition from others by performing energy-saving behaviours at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

Engaging in energy-saving behaviour at the University of Reading's catering department is an integral part of my life. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I will feel guilty if I do not do energy-saving behaviour at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I engage in energy-saving behaviours to avoid criticism from the public. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I performed well in practicing sustainable air conditioning use behaviours, such as opening doors/windows instead of adjusting the air conditioning system at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I performed well in sustainable appliance use (e.g. turning off appliances that I was using instead of leaving them on standby) and lighting use while working at the University of Reading's catering department. *

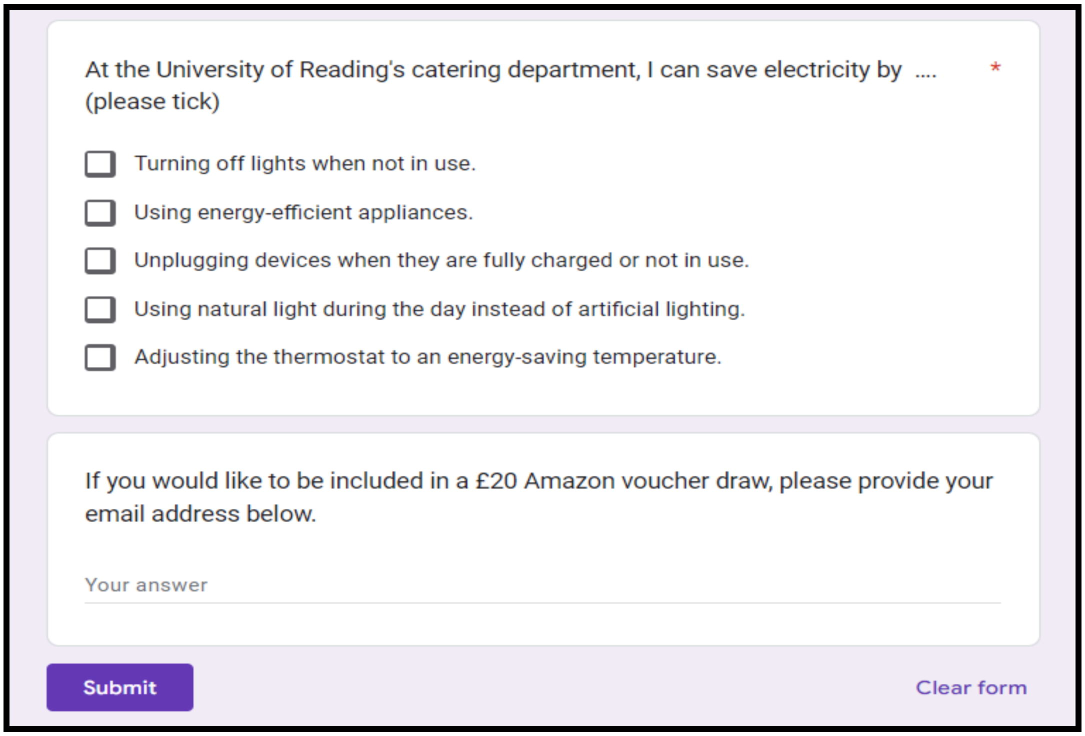
- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I performed well in conserving hot water while working at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree

I performed well in motivating and encouraging others to conserve energy while working at the University of Reading's catering department. *

- Strongly Agree
- Somewhat Agree
- Neither
- Somewhat Disagree
- Strongly Disagree


At the University of Reading's catering department, I can save electricity by .... (please tick) *

- [ ] Turning off lights when not in use.
- [ ] Using energy-efficient appliances.
- [ ] Unplugging devices when they are fully charged or not in use.
- [ ] Using natural light during the day instead of artificial lighting.
- [ ] Adjusting the thermostat to an energy-saving temperature.

If you would like to be included in a £20 Amazon voucher draw, please provide your email address below.

Your answer

Submit

Clear form