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Advancing Consumer-Centric Energy Flexibility: Strategies for Demand Response Engagement

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Academic Year: 2023/2024

July 20, 2024

Acknowledgements

I would like to greatly thank Ms. Carmen Valor Martínez for guiding me throughout this learning process and always being there by my side. I feel like although I haven't been ever been taught class by her, she has been instrumental in helping me harness some of the skills that an Industrial Engineer from ICAI must have.

Also, I would like to thank my parents for helping me pursue the dream of being an Engineer and all of my grandparents, but specially to my 'Avi'. I will become an Engineer as you and I know you will be proud from wherever you see this. This is dedicated to you.

Abstract

Incentive-based policies for demand-side energy flexibility have been developed and tested in the existing literature, yet these studies generally stop short of illustrating the specific incentives that lead end consumers to participate or reduce their energy consumption. This study fills this gap using an experimental design to evaluate the relative effectiveness of different incentives (an economic discount in electricity bill, social recognition, a discount in the municipality's bill and tree planting).

Using a randomized experimental design that had each participant exposed to only one incentive observed, the research examines demographic characteristics affecting the potency of these inducements, yielding an empirical foundation of when certain incentives would resonate with particular consumer segments.

These responses provide important insight on the preferences and drives behind different consumer groups, which can guide how to implement programs enabling energy flexibility. The knowledge gained from this article can be utilised by policymakers, and energy providers to design interventions well-suited for enhancing participation in demand response as efficiently one may consume energy.

This work, therefore, contributes to the success of applying demand-side flexibility for energy efficiency and sustainability in Spain. This level of detailed analysis creates actionable insights and drives the energy transition further in creating a more sustainable future.

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1 Introduction

1.1 Context and Justification of the Study

This study tackles an important aspect of the energy transition: the decarbonization of the environment, which can be achieved through an increased electrification and increased usage of renewable energies. This is were demand flexibility comes into play, as it is very important when we think about the intermittent nature solar and wind power, among others. This intermittent nature however only compounds matters to an energy grid already struggling to match supply with demand. Since we are utilizing more of these renewable energies, it becomes even more important to understand that the key paleo principle still holds true - i.e., maintain a good balance between the load and your system generations so you can keep your power system in top condition. [1].

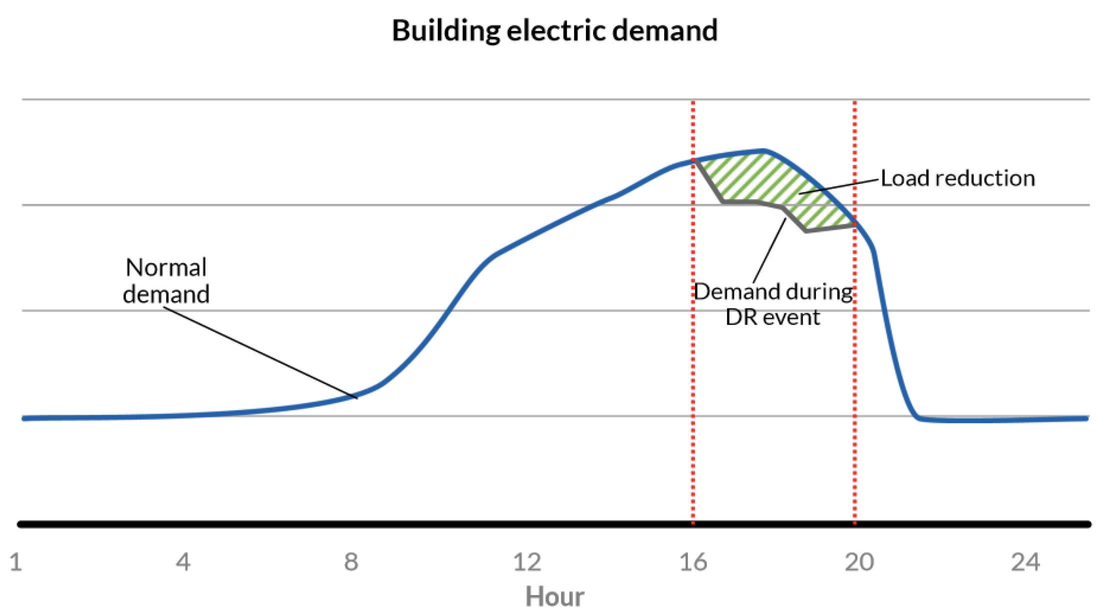


Figure 1: Demand Response graph example [2]

The contributions of consumer-side management - where residential or small-scale users actively participate in demand flexibility programs - to improve the stability and overall efficiency of the grid are widely recognised [3]. By prompting consumers to alter usage in response to signals or rewards, they can reduce the volatility introduced by renewables that ultimately makes the whole system less reliable.

Demand-side flexibility has a long history, with leading countries like U.K [4] and Japan [5] as champions in implementing and testing different approaches. These methods include demand flexibility, or consumers adjusting their usage automatically based on grid signals; as well as demand response programs where consumers are provided an incentive to reduce or shift their energy usage manually during peak hours.

This research was driven by the twin imperatives of slowing down climate change and ensuring energy security. As renewable energy increasingly penetrates the market, new solutions are needed to work with the variable output of these energy sources. Also determining how to best motivate widespread consumer participation involving the most efficient types of incentives can lead to more significant deployment of these programs [6]. The study in this regard attempts to further our understanding of the way residential consumers can be incentivized so that they participate in energy flexibility programmes and test how effective different incentive models are.

Two fundamental problems remain unresolved from energy flexibility. The practical issue is how to entice consumers to alter their energy usage. Consumer involvement is very important because demand flexibility programs would not work without it; however, getting the consumer involved is easier said than done. Existing methods largely involve economic nudges, like giving discounts off electricity bills or paying people directly to cut consumption during peak hours. Unfortunately, these incentives are not always strong enough or successfully to persuade and attract all consumer segments. [6]

There is also the theoretical problem. The existing literature maps the landscape with monetary incentives reflection, at a cost of ignoring other motivations/incentives for consumers towards given target behavior. Consumers may react to a range of factors other than pure money, e.g. the environment, social recognition or personal values This was about exploring different kinds of incentives that if incorporated, could yield what appears to be a more complete demand flexibility program and improve consumer engagement along with improving grid stability. In this line, the objective in this study is to also provide insights of these non-monetary incentives also checking (in a speculative part), how it could affect consumer participation. [7, 8, 9, 10]

1.2 Research Objectives

This dissertation has as a main goal to measure different prices in order to test which is the optimal one for each kind of customer, based on their profiles and willingness-to-pay, encouraging participation on demand-side flexibility programs. Intermittency in renewable resources forces the need for more advanced solutions as penetration increases on both transmission and distribution energy grid systems. It is essential to ensure the stability and efficiency of a grid because it encourages energy consumers to adopt different habits in terms of usage according with signals or incentives.

Research today tends to treat flexibility incentives as though people are *Homo Economicus*. However, there are also alternative explanations for why consumers might be flexible that evidence is growing in support of. The objective of this study is to categorise different incentives and investigate the response, or lack thereof, of residential consumers in providing flexibility through incentive-based mechanisms.

Designing programs that can successfully decrease demand during peak times, and increase the overall value of DSR depends on understanding what incentives work best. This is highly relevant for policy-makers and energy providing stakeholders as it will help to design demand-side flexibility programs that are more effective, but at the same time also more inclusive, ultimately contributing towards a solid and resilient grid.

In this study I have tested the four incentives that I personally consider to be the most promising according to previous literature. These incentives will be explained in the following chapters.

The specific objectives of this research are the following:

- **Which incentives work best to drive demand side flexibility:** The research will test multiple incentive models including but not limited to monetary and non-monetary, in order to establish the incentives that are most attractive for consumers. This knowledge is essential to design programs that can minimize the need for reductions in demand and increase the benefits of demand-side flexibility. In this study I have tested the four incentives that I personally consider to be the most promising according to previous literature. These incentives will be furthered explained in the following chapters, and they are:

    1. Discount on the electric bill (1-3 € per hour of demand flexibility)

2. Tree Plantation for each hour of participation in the program
3. Discount on the electric bill for the local schools, sports centers or public lighting.
4. Public Acknowledgement

- **Understanding which population groups are most responsive to each kind of incentive.** Certain demographics may be more/less likely to be incentivized by each type of reward. The goal of this aim is to delineate patterns of responsiveness to incentives by **age, gender, income, education, environmental awareness, employment, family structure and location**. It is essential to consider this information in order to improve the implementation of demand-side flexibility programs within each of these groups.

- **Provide specific, evidence-based recommendations for policymakers and electric utilities:** The primary objective of this work is to derive actionable insights that can be put forth to public authorities and electric utilities. The resulting insights are intended to inform policy and measures that drive demand-side flexibility uptake, in support of a cleaner, more resilient energy system.

Meeting these goals will deliver a holistic view on how to increase the success of consumer engagement within DSR programmes helping the grid integrate more renewable generation and increasing energy systems stability and resilience. This study provides key insights aiming to better inform both energy policy and future practice on green energy development and utilization.

Individuals will randomly be exposed to a single type of incentive and have no knowledge of other possibilities. Given that the presented incentive is motivating, this technique makes possible to maintain cognitive bias constant alongside all possible incentives shown and make the results more accurate. [11].

Primary research questions are how to incentivize demand-side flexibility (which types of incentives in money / not-money) is the most effective. Moreover, it is important to explore how these type of incentives would affect different types of demand and to ascertain the barriers/facilitators for the implementation of DSF programs in Spain. An extensive questionnaire including demographic qualities and behavioral intentions have been sent out through Google Forms. As per the recommendations from the domain experts, the interviewees had to be representative of a mixed demographics group, so a professional team has been payed to distribute the questionnaire, as I personally believe that getting the most accurate possible responses would make the study more reliable and of higher quality. [12]

Subjects were assigned randomly to one of four groups: each group received a different type of incentive. This randomization approach is important in that it means that any discrepancies in responses among participants can be attributed to the incentives themselves rather than to existing differences between those taking part [12].

These questionnaires were analyzed with a variety of statistical methods in Python to find the key trends and patterns based on the data. After this analysis, performed the same with Jamovi® for a much more granular breakdown of consumer trends and behavior. This methodological framework is be explained in coming sections of this research. [13].

1.3 Study Contribution

The findings of this study are important to help the future academia research and serve as a reference guide for the practical work energy management. The flux of the global energy landscape towards more widespread renewable generation, however, also introduces significant challenges with respect to grid stability as such energy sources have an intermittent character. This paper aims to contribute insights into cost-effective flexibility provision on the demand-side, as this could sustainably realise the balancing of supply and demand for energy, which is a prerequisite in effectively integrating variable renewable energy sources.

Also, the research underscores the importance of non-financial incentives for the consumer participation in DR programs. Knowing how different incentives drive behavior can help design better programs to promote the uptake and success of demand-side flexible services. While this has some major implications for energy providers and policymakers, it also presents considerable advantages to customers who would be able to finally expect more regular service from energy systems and less volatility over time.

The results of this research could be determinant for public policies and practical implementations, especially in Spain. This can help inform the development of consumer-driven demand-side flexibility programs based on the preferences and motivators of different demographics by identifying best incentives. Ultimately, this will work towards a more resilient and flexible energy system with greater levels of renewable penetration, long term reliability while maintaining efficiency.

By doing so, the study aims at contributing to a better understanding of demand-side flexibility and how it can be implemented in practice, with useful lessons that could help bring about a sustainable energy future. Right now most of the existing literature to the author's best knowledge purely focus on trials that do not differentiate between incentives besides some cases [8]. Knowing which of these incentives would be more suitable for each demographic group could make a huge difference in the establishment of DF in Spain and other parts of the world.

1.4 Motivation

This research project is born both from personal motivation and extend a solid commitment to tackle few of the largest challenges of our times: climate change, and energy poverty. As a resident in Altea, a beautiful coastal town south of Alicante I have seen first-hand the dramatic shifts in our home climate. The freezy frost winters of my early years have been replaced with hot summer-vibe winters - proof climate change has already moved our temperatures to a more subtropical climate similar to the one in the Canary Islands.

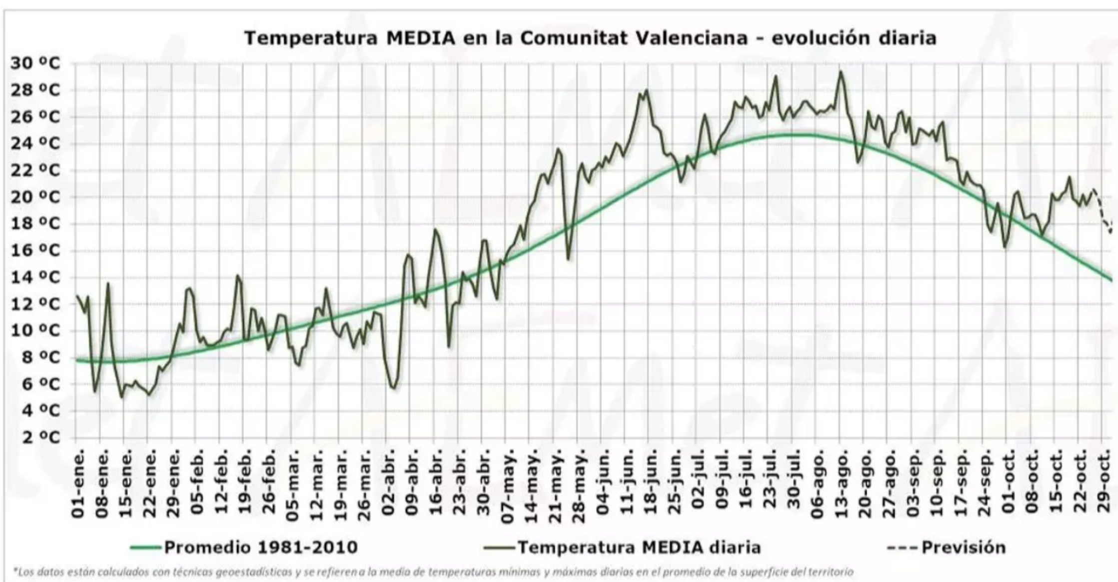


Figure 2: Evolution of Temperatures in the Valencian Community [14]

This personal experience has since spurred a desire to be a better environmental steward and to do more, however small, in the fight against climate change. Energy flexibility can also improve our renewable transition of energy system significantly, giving us the opportunity to absorb better the non dispatchable energies in 24 hour-a-day consumption scheme [13].

The path of a student who choose to study in engineering made my determination to solve these issues even stronger. In the past years I have made research about the problem of energy poverty, which got me thinking that what is even more unmistakable to me is that there are sustainable energy solutions and they must be made available to all-comers irrespective of their socio-economic circumstances. This experimental assessment of incentives that can decrease disparities in energy extends current understanding and contributes to identifying ways to make lower-impact living practices feasible across a range of communities.

It also creates a strong sense of guilt, avowing my technical skills as an engineer to solve problems that should not just counteract climate change, but use principled solutions to fight the root cause for energy inequity. This project is an act more than an academic exercise; it is a call to action in real life, born out of a shared commitment to sustainable futures and social justice.

2 Theoretical Framework

2.1 State of the Art & Importance of Flexibility in the Current Context

The switch to renewable energy sources (RES), e.g., solar and wind power, is essential in tackling climate change. But the variable output from these sources means they are not always available, creating big problems for keeping a predictable and efficient energy system up and running. Because renewable energy is fluctuating, it is also irregular and difficult to predict. The highest value of wind power generation is obviously controlled by the wind speed, and solar energy production relies on sunlight availability, which varies on daily and seasonal scales. As the share of these variable RES in the energy grid is rising, new approaches are needed to strike a balance between supply and demand [6, 15].

Figure 3: EVx Graviational Battery located in Rudong, China [16]

Demand-Side Flexibility (DSF) is defined as the capability of the electricity consumers to alter their power consumption in relation to time, price, and incentives communicated by the grid. This can come in a series of ways, like for example reducing total electricity consumption during times when everyone is using power (mid-afternoon), or consuming energy when the renewable sources are in their peak of production (sunny and/or windy days). It is important to consider that the energy we consume is being produced in nearly real time (if the user has an app, with little lag), therefore during the times when the renewable sources are not producing the total pollution will be higher, and depending on the market prices can peak. Some solutions are being studied in besides DR programs in this field, such as residential electrical batteries or even gravitional batteries, such as the one located in Rudong, China. [16]

These gravitational batteries work by using electricity during the times when production is high and demand is low to produce work and lift either water (in the case of a damn) or these massive blocks of concrete (in the case of EVx Gravitional Battery) to store the energy as potential energy. When demand is higher and production is lower, these huge masses can be released and used to move turbines or other types of generators on their way down.

Although these solutions could be appealing on their own, I really see them as a complement to DR programs. Combining the ability to store electricity in a safe and reliable way with the with demand-side flexibility, RES variability can be compensated, improving grid stability and reliability [17].

DR programs have a large list **benefits**, but some of the most important of them not only for residential consumers but also for companies:

- Earning revenue through DR economic incentives
- Supporting the community by moderating emissions and help improve the grid's stability
- Gaining a better reputation in terms of sustainability in the case of companies
- Empowering others by promulgating the example
- Build a more resilient power system in the community
- Mitigate the risk of damages, loss of productivity or other inconvenients due to power outages

Technology, and in particular smart meters and home energy management systems, are making demand-side flexibility easier to implement. Customers can use smart meters to see energy consumption in real-time, adapting their energy usage on the basis of dynamic pricing signals or grid demands. Home energy management systems can automate these adjustments, making participation in demand response programs more convenient for consumers [18].

Whereas in the US monetary incentives have been dominant (REF) the examples of UK and Japan show that they have been at the forefront of adopting demand-side flexibility programs. National Grid ESO and Octopus Energy have launched a trial in the UK to test demand flexibility in the winter of 2021-2022, finding that consumers were more reactive to non-monetary rewards (e.g., contributing to environmental sustainability) than purely financial rewards [19]. Similarly, Japan has enabled numerous demand response programs by employing economic and non-economic incentives to boost consumer participation [20].

One of the key factors determining whether demand-side flexibility programs work is set by the type of incentives available to consumers. Monetary compensation and energy bill discounts are all types of traditional economic incentives. Nevertheless, new studies confirm that environmental benefits and social recognition drive as many participants (if not more) to these programs than do moral incentives. For example, the UK trial found that households could do more to reduce energy use when they considered the environmental actions in which those actions translate [21].

The role of regulatory landscape in the uptake of demand-side flexibility is crucial. Smart policy instruments, such as smart grid rollout and adoption, dynamic pricing, and consumer education are key in creating an environment that encourages this low-hanging fruit of demand response. European countries such as France, Finland, or Italy have been the most advanced in this sense - having already opened their capabilities to get flexibility only based on a marketplace for their DSOs [22]. These regulatory mechanisms work not only to facilitate innovation but also to ensure that the value brought by demand-side flexibility extends across the whole energy system [22].

Demand-side flexibility is key to the successful integration of renewable energy sources in a global energy transition. It assists in reducing the intermittency challenges caused by RES, supports grid stability, and allows for increased utilization of green power. If overall more informed efforts at incentivization can result, such that the average consumer need do little over and above the usual buying cycle behavior to participate in a wide array of programs. This is an ambition the research in this paper contributes to, testing for the effectiveness of different incentive models able to motivate their residential consumers into taking part in energy flexibility opportunities [23].

2.2 Explicit *vs.* Implicit Flexibility

2.2.1 Definition and Comparison

There has been and there is quite some confusion when it comes to defining the terms Explicit and Implicit demand flexibility. However, with this research, one of my goals is to help devise all this confusion and point exactly at what these concepts truly mean. According to [24], *"The main feature that differentiates the two of them is the way flexible demand is used. On the one side, implicit demand flexibility (IDF) only takes advantage of flexible demand by incentivizing consumers with different electricity tariffs to consume or generate at certain hours....On the other side, explicit demand flexibility (EDF),refers to committed consumers in acting to increase or decrease load or distributed generation in response to system needs"*.

As an introduction the reader can see a brief graphic below, in which the concepts of Explicit and Implicit flexibility are differentiated and provide an overview of the discussion, in which we will deep-dive in the following points:

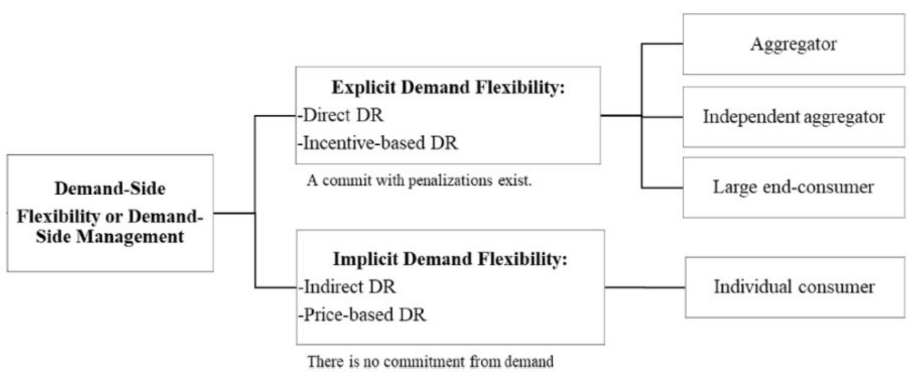


Figure 4: Differences between Explicit and Implicit Flex

Explicit Flexibility

Following the explanation above, we can define Explicit Flexibility as the one which, through signals sent by the grid operator, induces consumers to actively curtail or reschedule their electric consumption within those timeframes. This kind of flexibility implies the consumer acts after receiving a communication and receiving some kind of incentive for it, whether it is monetary or economic

An **example** for Explicit Flexibility is Critical Peak Pricing (CPP). In an extremely hot summer day, when demand for air conditioning is high, the grid could be at risk of a blackout. A day before, the next afternoon is deemed critical peak period, and consumers are alerted that electricity rates will skyrocket this time the next day. The homeowner might also do his or her laundry later in the evening, increase their thermostat a couple of degrees and turn off non-essential appliances during that peak period.

Implicit Flexibility

In this model, implicit flexibility involves the end-consumers modifying their electricity consumption pattern in response to **scheduled** prices or automatically reacting on a signal basis. This approach is less direct in dealing with consumers, but focuses on creating an economic climate that makes the use of energy more efficient a clear market advantage. Real-Time Pricing (RTP) is a type of implicit flex, which consists of electricity prices that change hourly based on the conditions of the market. For **example**; An individual household is signaled the price of electricity will be ’X’ amount if they use it at 2 AM, which is lower than the price ’Y’ at the moment. The homeowner then switches their dishwasher from after-dinner to 2 AM so they can run it on a time-delayed start without having to think about cost every time.

Time-of-Use (TOU) rates is another type of implicit flex, where prices are fixed in advanced, like the situation we have in Spain with the ’Peak’ hours and ’Valley’ hours. Knowing this information in advance, users may chabge their consumption habits to for example charge the electric vehicle during these ’Valley’ hours and save up some money. In a nuthsell, the goal of implicit flexibility is to implement gradual changes in behaviour via the price signals that are integrated into daily routines. It has less to do with quick changes and more the overall behavioral change.

Embedded flex is in a class of its own, being half of the way between Explicit and Implicit Flex. This is the most advanced type of flex available, and it requires intelligent appliances such as systems or buildings that can self-automate the consumption and can be tailored to automatically change their electric demand signals without user intervention based on grid signals or predefined conditions. This variation on the concept of flexibility eliminates any requirement for consumer action as these adjustments will be made by automated systems. One example may be a smart thermostat that responds to control signals delivered over by the grid operator, or just being able to respond to RTP rates, but without any intervention of the user. For example, on a hot day when electricity prices are high the thermostat will cool your house down for you in the morning when rates are low and allow it to get warmer during afternoon peak pricing. This would allow the homeowner to stay comfortable, as thermostat adjusts on its own. Embedded flexibility provides the ultimate customer convenience because technology handles energy usage on its own, without interrupting users' daily life and adapting consumption to grid requirements. [25]

Consumer and Grid Operator Participation, Pricing Formulation and Behavior Expectations are the key differences between these flex types. Explicit flexibility requires consumer high involvement to execute 'at-the-moment' demand management in reaction to time of use signals (such as CPP), and needs to receive signals from the Grid Operator. Implicit flexibility, like RTP and TOU also involves lower consumer engagement that promotes habitual changes over time based on continuous pricing signals. Embedded flex is the lowest in this regard. Customers need little to no involvement, as systems automatically change energy settings in response to changing conditions.

The table below summarizes the main ideas of the the different types of flexibility:

Type of Flexibility	**Definition**	**Characteristics**	**Examples**
Explicit	Requires active consumer participation, usually in response to direct signals or incentives.	Direct interaction	Consumers receive notifications to reduce or shift usage.
		Financial or non-financial incentives	Discounts on bills, incentives for reducing usage during peak times.
		Reaction to signals sent by the Grid Operator	Turning off appliances during peak hours, manual thermostat adjustments.

Type of Flexibility	Definition	Characteristics	Examples
Implicit	Encourages habitual changes through economic signals, such as price changes, without direct requests to consumers.	Pecuniary Rewards	Time-of-use (TOU) pricing, Real-time pricing (RTP).
		Automatic adjustments by consumers based on already-known tariffs	Shifting laundry or dishwashing to off-peak times in response to lower prices.
		Less intrusive	No direct intervention required from utilities.
Embedded	Automatic adjustments by appliances or systems to reduce or shift energy use based on predefined settings or external signals.	Technology-driven	Utilizes smart appliances and home energy management systems.
		Real-Time responses	Smart thermostats adjusting settings automatically based on external signals.
		Enhances convenience	Optimizes energy usage without user intervention.

2.3 Existing Literature Review

2.3.1 Barriers

The present literature review on demand flexibility in energy systems will start with barriers for its implementation and performance. The litany of obstacles involved are crucial to appreciate fully if we want to understand both why incentives are needed and how they can be better designed and applied in light of the challenge. This analysis builds on two key studies: 1) Gooda et al [26] with an extensive categorization of barriers and enablers for demand response in the context of smart grid, as well as; 2) Annala et al [27] where similar themes are explored emphasizing in regulatory/technical/social barriers.

When overlaid, we can break down these barriers found in both papers to see the broader challenge our industry faces when it comes to implementing demand response.

This recognition underlines not just the importance of well-designed incentives but also lays down the framework for debating policies on how to induce large-scale deployment and realize socio-economic gains that demand flexibility can provide.

Regulatory and Market Barriers

Uncertainty in Regulation and General Inconsistency: High regulatory uncertainty acts as a deterrent factor for the adoption of demand response technologies than does slow pace at which regulations are adapted. Demand response as a resource has failed to scale primarily due to inconsistency in regulations from region, lack of market rules that allow full participation for new technologies like demand response aggregators and modern communication infrastructures. Those regulatory lags do not keep pace with the ever-quickening cycle of technological innovation and market demand, and as a result they under-value consumer-sited demand flexibility in meeting electric power system needs. Businesses and utilities need to be able to plan and invest in technologies that can support greater grid reliability, efficiency through demand response but there are no transparent regulatory frameworks. [26, 27]

Market Access and Structure : Current market rules represent significant hurdles to the participation of aggregated demand response loads in electricity markets. They typically mostly restrict the participation in demand side flexibility provision to participants from existing, large electricity market actors which are not always best placed and equipped for grid optimization and maximum energy savings. It also disincents the take-up of demand response programs, as costs are not cased through to consumers and businesses where these can be passed on due to lack of market mechanisms that supply cost reflective pricing. This seems not only to suppress innovation in demand response technologies but also inhibits economic signals for the end-users to join such programs, thereby limiting large scale deployment of demand flexibility solutions.[26, 27]

Technical and Infrastructure Barriers

Shortcomings in ICT and Automation: Many problems arise from insufficient information, communication technology (ICT) resources for sensing, computing, and communication which are necessary to enable effective demand response deployments. These technology holes are holding back utilities and service providers from being able to understand, control or manage electricity consumption for demand response applications in real-time - which is necessary if it were ever going to realize the true power of a full demand response market. Further, inadequate automation in current systems also means that more sophisticated demand response strategies - i.e. where they are required to adjust smartly and quickly for changes within the electricity supply-and-demand field - will be difficult if not impossible to establish; The benefit of richer demand flexibility that becomes possible only when the deployment advanced metering infrastructure (AMI) and other necessary technologies, is yet to be completely realized because progress in enabling these possibilities are early-stage deployments fraught with challenges.[26, 27]

Integration Challenges: The integration of demand response technologies into the established energy systems in terms technological as well as standardization issues pose significant difficulties. Meanwhile, a dearth of standardized interfaces and protocols for communication among the pieces means it is difficult to talk from one energy device or grid operator to another. This creates inefficiencies and diminishes demand response effectiveness. Problems are further exacerbated by the varying and sometimes conflicting legacy systems that exist throughout energy, all of which need significantt reengineering to work with new demand-side response technology. Integration is a key aspect of ensuring an effective demand response, capable to operate seamlessly with the present grid infrastructure and one amongst the most difficult barriers that require most resources as well.[26, 27]

Economical and Financial Barriers

High Implementation Costs: The upfront cost to set up large-scale demand response programs can be very expensive for many stakeholders, such as smaller utilities or residential customers. This includes the costs associated with smart meters and energy management systems, as well as software and integration expenses required to make these tools part of an existing infrastructure. The lack of cost-effectiveness is compounded by a more nebulous future return on investment, rendering the economic case hard to justify unless large subsidies or incentives are in place.[27]

Under compensation: More generally, demand-side financial benefits are not always adequately correlated with performance; compensated parties might have little incentive to provide the grid services their actions generate. This misalignment leads to deter participation; not enough value perceived by potential contributors to DR programs versus the perceived risks and efforts in changing energy consumption behavior.[26, 27]

Information and Awareness Barriers

Lack of Clear Information: DR programs are so complex that the average consumer will never figure out what is really going on. Consumers may hesitate to participate if they are not provided with up front program details such as potential benefits and what is required from them. This barrier is especially pronounced in a residential customer base that often does not regularly consume energy management solutions and may find the surroundings for DR difficult to grasp.[26, 27]

Lack of Knowledge in DR Benefits: Individual and corporate energy users do not know enough about the financial benefits, on both state scale as well as global/ local warming problems fighting advantage so let often underestimate what they can take for themselves from participate in demand response. An absence of a clear, evidence-based proof on these benefits demotivates the shift in consumption or the investment for enabling technologies.[26, 27]

Technological and Operational Barriers

Incompatibility or Interoperability issues: A major technical challenge is the absence of a common operating platform linking demand response systems and devices. Without being able to communicate, devices and systems hold back the efficiency as well as effectiveness of running DR strategies. This problems extend well into older legacy platforms that have issues with newer DR technologies that require upgrades, overhauls and/or replacements.[26, 27]

Technological Reliability and Performance: If DR technologies do not work properly or compromise performance, they won't be used. Potential participants may choose not to participate if they believe that DR systems will fail, especially at the times it needs most. At the same time, the catapult of DR state to an old-fashioned stage due to rapidly changing technology can also be a barrier.[26, 27]

Behavioral and Social Barriers

Behavioral Resistance and the Status Quo: A significant societal barrier to DR adoption is human reluctance for change, especially when this means sacrificing personal comfort or day-to-day practices. Still, a lot of people do not want to adjust thermostats or change lighting use without a clear and immediate self-interest, which is the case with many consumers. Addressing or overcoming this inertia calls for focused behavioral interventions that go beyond mere economic incentives.[26, 27]

Lack of Trust in the Energy Providers: The lack of trust mechanism is negatively correlated with consumers willingness to participate in DR schemes. If consumers are concerned about the benefits and/or motives of utilities (which can often be due to experiences or perceptions in less consumer-centric energy markets), they tend not to yield control over their own consumption behaviour, even if relatively simple smart controls like connected thermostats ("nudge technology") could guide them more automatically towards a desired behavior. Building this trust is a very multifaceted process, with utilities and DR program admins needing to develop an effective combination of positive engagement on behalf their constituents over time.[26, 27]

In the figure below there is a brief info grahic where it can be seen how DSO's (Distributing System Operators) and Retailers see these barriers, with a higher percentage indicating that a higher number of them see that specific barrier as important:

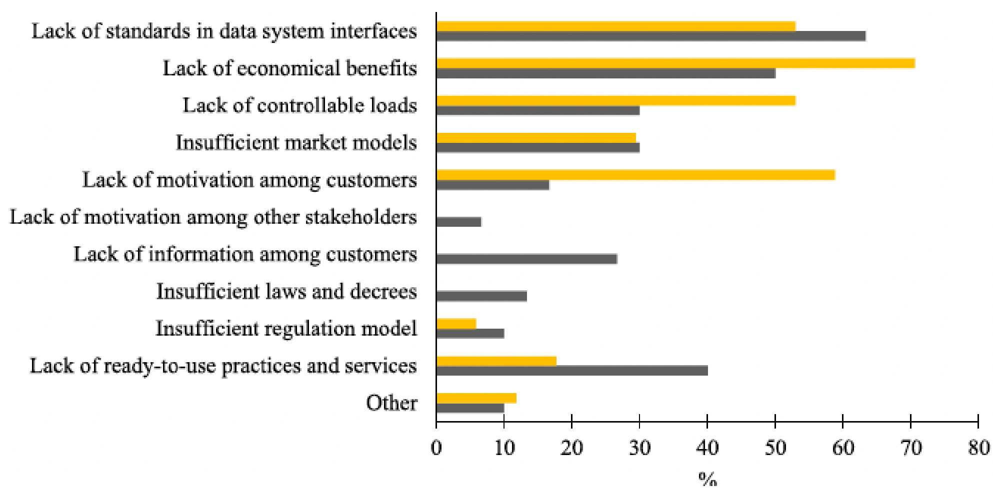


Figure 5: Percentage of DSO's and Retailers interviewed in [26] that think these specific barriers are of relevance

As we have been able to see in this section, there are many barriers that DR programs have to overcome in order to become of significant importance in society, and be adopted by the majority of us. Therefore, it is very important that DSO's and retailers start to provide incentives for people to adhere to these programs, and testing these incentives is the contribution of my study.

To the author's best knowing, right now there is very scarce literature on incentives testing. However, there are some findings that have to be taken into account before starting the testing. These findings will be covered in the following section.

2.3.2 Review of past studies

After examining the literature on the topic, to the author's best knowledge, very important findings have already been made and I feel it is very important to list them all to gather in one place the most important information. Moreover, this Will give the reader a more holistic view of the issue and a better understanding of why the study contribution is presented in the way it is.

The most important findings are listed below, in a schematic way to make it more readable and easily understandable to the reader:

1. Financial vs. Environmental Incentives

Finding: Consumers respond much more to financial incentives than they follow environmental ends when it comes to engaging with flexibility programs. Yet using incentives both financial and environmental, is the most effective. [8, 10]

Explanation:

- Text messages were sent to households asking them to shift demand for electricity in a large field experiment conducted as part of a study in Denmark. The messages contained a mix of both financial and eco-friendly rewards [8].
- Financial rewards for recycling emerged as the strongest motivators largely due to their immediate and concrete effects on household budgets[8].
- Long-term, environmental incentives were welcomed for energy savings on properties. Customers liked the environmental side of things but needed a greater financial prize to do so[8].
- The biggest trend in the behavior emerged as a result of combining both types of incentives together: thus, it was expected that while consumers want to be seen environmentalists and like (eco-social), using money will increase significantly their participation[8].

- An example of this could be providing discounts on electricity bill for shifting use away from peak hours and conveying the message of having lesser carbon footprints. This could people more engaged.

2. Characteristics of Flexibility Adoption by Demographic

Finding: When it comes to adopting flexibility measures as well, women and members of older generations are more likely than others to engage and obtain benefit out of DF programs.

Explanation:

- For elderly people and women, a study in Denmark showed they were more inclined to participate in flexibility programs[8].
- This demographic understanding can be great news when it comes to customizing demand response programs, so they experience optimal participation and impact[8].
- A possible explanation is that women and elderly people have more flexible schedules than other demographic groups. For instance, elder people can have a coffee at 8 am or at 10 am without any tradeoffs, while people who are in working age may not be able to be at home during other times of the mornings due to work. Also, women tend to stay at home more than men as they usually take care of the children in a higher rate, and that explains partly this event.
- Integrated communication strategies for these segments, which might include personalized messages or community-based programs can also be very successful.

3. How Notifications Affect Consumer Behavior

Finding: Alerts highly affect the consumer behavior in a good way with load shifting to low off peak hours.

Explanation:

- The German study [28] demonstrated the success of delivering push notifications to consumers about opportunities in different energy applications, for example with electric vehicle charging.

- These prompts were highly effective, with consumers receiving these notifications willingly modifying their behavior accordingly[28].

- A case in point is a notification that encouraged electric vehicle charging during non-peak periods, which had the effect of flattening peak demand[28].

- This helps not just to balance the load on the grid, but also to increase consumer participation through clear and immediate instructions[28].

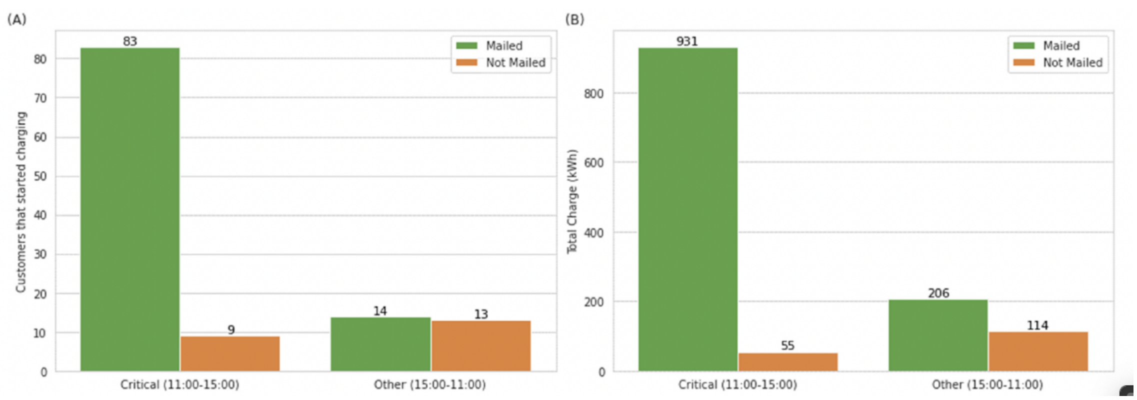


Figure 6: The participants who were emailed engaged significantly higher that those who didn't [28]

4. Accuracy of Demand Prediction

Finding: Electricity demand can be predicted with high accuracy a day ahead, something vital in effective electricity management.

Explanation:

- The Japanese sample [9] did well at forecasting electricity demand. Below is a graph of the accuracy obtained:

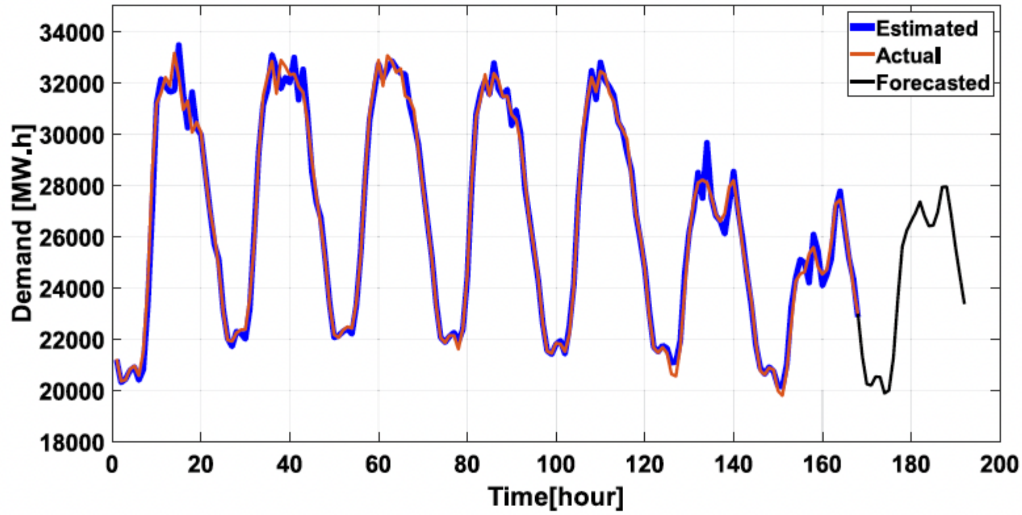


Figure 7: Demand could be accurately predicted in this study [9]

- Ensuring that supply meets demand puts less strain on resources and allows for better planning[9].
- Predictability is important to better implement demand-side management strategies and design pricing schemes that incentivize the most efficient use of energy[9].
- Utilities could, for instance, harness predictive analytics capabilities to forecast periods of high demand and take pre-emptive action-like offering discounted rates in exchange for conservation during expected peak hours.

5. Daily Peak Load Reduction: TOU Pricing vs. RTP

Finding: Time-of-Use (TOU) pricing is more effective than Real-Time Pricing (RTP) in achieving demand response.

Explanation:

- This study that took place in Japan clearly showed that TOU was way more effective in engaging customers than RTP.
- TOU pricing also created a more conducive environment for energy cost management, according to consumers who said that it was simpler and easier to adjust their behaviors in response.

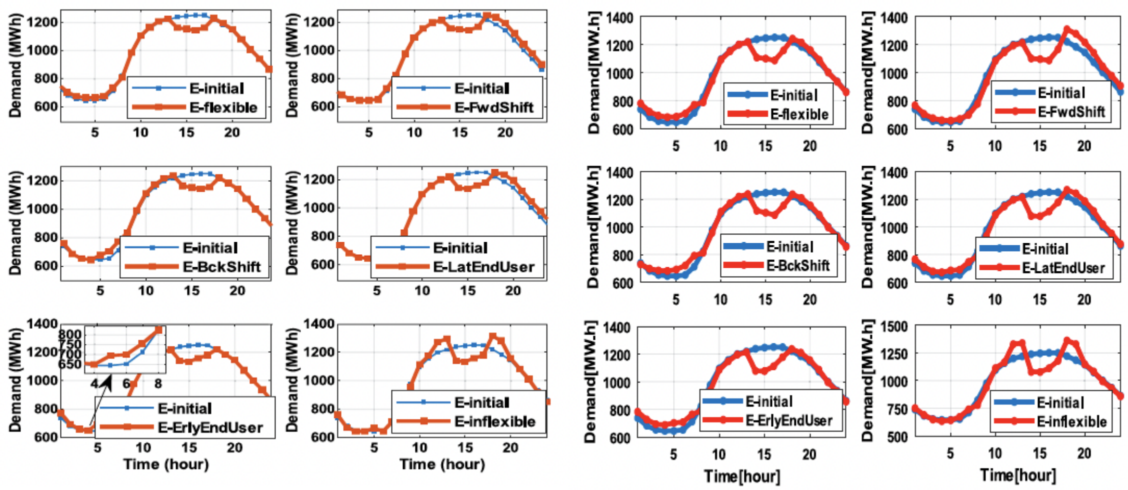


Figure 8: TOU proved to be more effective than RTP in engaging clients[9]

- The more predictable nature of TOU pricing resulted in a much clearer shift in consumption patterns and consumers were able to base their activities around known price changes, whereas the constant variable rate under RTP made it difficult for customers with higher marginal costs (e.g. residential customers) to adjust their use accordingly.
- In a future, when Embedded Flexibility is more established, it is possible that we see a shift in this pattern, as the consumer wouldn't have to dedicate so much time to check the prices and everything could be done seamlessly.

6. Environmental Concerns & Non-Financial Motivation

Finding: Customers who had participated in previous demand programs and were more educated presented better results. Also the ones that had better access to technology and the ones who were driven by environmental factors profited more from the trial in UK.

Explanation:

- The English trial showed that non-financial motivations were an important factor in consumer willingness to accept flexibility programs, especially environmental reasons.

- Environmentally aware consumers were also more likely to engage in reducing energy consumption.
- Furthermore, technology including smart meters and home energy management systems helped consumers to get involved with access to active participation through giving the right tools and data for responsible decision making.
- Part of being more responsive was related to previous experience in flexibility programs, where consumers who had previously been involved tended to know the ropes and understand how they would benefit.

Conclusion

These studies both highlight the need a holistic approach in order to design effective demand-side flexibility programmes. Monetary rewards are strong drivers, but even stronger when they resonate with our environment, pulling at the economic as well and ecological leverage. These programs can be better suited to specific demographics, such as women or the elderly and in ways more likely increase participation. Additionally, notifications have proven to be incredibly successful in frictionlessly getting the customer to shift their energy use from peak times - which contributes towards load management. To enable effective planning and resource allocation, accurate demand prediction is essential as Time of use (TOU) Pricing supersedes Real-Time Pricing (RTP) with its higher predictability enabling consumers to better plan usage.

Environmental concerns are a powerful motivator in driving consumer responsiveness as well, but the prevailing narrative highlights financial incentives. This will enable engagement, facilitated by technology such as smart meters and home energy management systems - making sure we have the right scaffolding around us to allow full participation. Furthermore, past flexibility program experience facilitate self-activation and long-term engagement. As such, the effective implementation of demand side flexibility programs necessitates marrying financial and environmental reward structures to demographic datasets through communication channels coupled with predictive analytics for accurate supply forecasts along relatively reasonable price mechanisms. The house or industry will consume the energy both effectively and efficiently, its occupants can be incorporated in it, making them active actors of their own use but also for general participation in a renewable system.

2.3.3 Proposals

Once the barriers and findings are clear, it is of upmost importance to revise the current literature in search of proposals that can help eliminate said barriers. Below is a compilation of the most interesting proposals made by the scientific community and based in the findings exposed above.

Some of these proposals have shaped the study that I have developed in Spain, which will be later discussed. Said proposals are the following:

1. **Establish Push Message as a standard**: Use the push message to inform users of recommended energy use, such as charging an electric vehicle at night when it costs less so that peak demand can be reduced and load management improved. [28]

2. **Promote Off-Peak Charging**: Incentivize off-peak electric vehicle charging through targeted incentives and information campaigns.[28]

3. **Coordinate Financial Incentives and Environmental Objectives**: There need to be a way in which the subsidies can match with broader environmental benefits. While they suffice as stand-alone solutions, financial incentives combine with the environmental factor can have even more impactful results.[8]

4. **Formulate Communication Strategies meant for Specific Demographics**: Target women and elderly, who are considered more amiable penetration draws towards adaptability measures. Personalized messaging can improve the rates of engagement and participation.[8]

5. **Simple Communication Leveraging**: Send direct communications to prompt shifts in energy usage and use basic methods of communication like SMS. These methods have been found, especially in the same day.[8]

6. **Push forward non-monetary motives**: Study the non-pecuniary incentives that people tend to prefer the most and try to include them in DR programs.[10]

7. **Expand Technology Access**: Make smart meters and home energy management systems available to consumers, empowering them with the data they need to make smarter decisions regarding energy usage. Technology availability increases the level of engagement and response drastically [10].

8. **Build upon experience**: Leverage the consumer's experience in flexibility programmes to encourage participation. Understanding how the process works and what it achieves offers continued involvement whilst minimising push back.[10]

9. **Implement TOU pricing over RTP**: Implement TOU pricing in the absence of automated devices that could make possible embedded flexibility.[9]

10. **Improve Demand Prediction**: Focus on developing technologies and processes that deliver higher rates of accuracy in predicting demand, resulting in better planning and efficient resource utilization.[9]

11. **Improve Consumer Education**: Increase the marketing towards consumer education and how consumers can contribute to the program. For example, consumers need to be aware of the ways they can save money and help the environment.[24]

12. **Develop Aggregation Services**: Promote the development of services that will allow small consumer load to participate in DR programs through aggregators, thus ensuring it is easier for individual households to contribute with a structural capacity towards grid stability.[24]

13. **Strengthen Regulatory Support**: Refine the regulations to create a more favorable environment for DR projects. This would include setting the right conditions for TOU tariff adoption and financial incentives.[24]

14. **Advanced Metering Infrastructure (AMI) Deployment**: Encourage AMI deployment for timely information on energy use which is essential to facilitate dynamical rating and DR programs.[25]

15. **Automation Technologies**: Incentivize digitally controlled appliances and home energy management systems, which can automatically adjust energy flow in response to real-time price signals providing Embedded Flexibility to the customer.[25]

16. **Develop Tailored DR Programs**: Design segment-specific programs to meet the potential of residential, commercial, and industrial users in order to increase participation levels that lead towards better results.[25]

17. **Standardize Appliance Interfaces**: Implement regulatory requirements to standardize appliance interfaces so that DR actions can be more easily integrated and automated.[26]

18. **Advance Public Sector Leadership**: Encourage the public sector to use DR resources in public buildings and promote energy efficiency and demand response capabilities.[26]

19. **Forced High-Potential Consumer Participation**: Force high-potential consumers, including those with electric heating for example, to participate in DR.[26]

20. **Development of New Business Models**: The creation or enablement of new business models that bundle DR services in combination with other energy services such as solar PV and EV charging.[27]

21. **Consumer Price to Reflect Pricing in Wholesale Market**: Promote price-responsive consumer behaviors by allowing for dynamic pricing based on real-time wholesale market prices, so that consumers can respond to the most accurate signal of changes in electricity costs.[27]

2.4 Two Hypothesis; *Homo Economicus vs. Homo Moralis*

Regarding the motivations for consumer participation in demand-side flexibility (DSF) programs, two hypotheses, which are opposed to each other can be confronted: ***Homo Economicus*** and ***Homo Moralis***. These hypotheses refer to what moves the consumer more when it comes to the Spanish energy market, economic incentives or convictions and defence of the environment.

Homo Economicus Hypotheses

According to the hypothesis of **Homo Economicus**, we should be effecting choices based on financial beneficial property aiming to optimize personal utility. Under this hypothesis, DSF programs are markets; consumers will primarily participate if they see a direct personal financial benefit. Such people are likely to be motivated by economic incentives, including cash incentives, bill discounts and cost savings [10].

This is corroborated by the previuosly analyzed studies that convincingly demonstrated the effectiveness of economic incentives in altering consumer behavior. For example, in a study in Denmark [8]. Financial incentives were shown to be effective in Denmark in getting households to move their electricity consumption . Similarly, the British study [10] discovered that economic incentives worked well for driving up participation in DSF schemes.

Especially when it comes to countries such as Spain, where a family's electricity costs can make up as much as 1/3 of its monthly expenses, some questions pop up.

- **Are poorer households disproportionately sensitive to energy costs more likely to participate in DSF for money**?
- **Will younger consumers, who have more flexible schedules and fewer financial commitments, respond as readily?**

Homo Moralis Hypothesis

In contrast, the ***Homo Moralis*** theory proposes that people are driven by ethical and environmental concerns rather than just money. According to this hypothesis, consumers are willing to participate in DSF programs provided they feel that they are also making a contribution to the broader social good, such as reducing environmental impact and increasing sustainable economic activity.

There is also evidence for this claim from different studies showing that non-economic incentives can be highly motivating. As we have seen, the British study's scrutiny of DSF has shown that consumers are more interested in participating in DSF programs when presented as an environmental sustainability measure [10]. In addition, the study by Kacperski [28] suggested that combining financial incentives with eco-friendly empowerment led to a significant increase in participation rates.

Being in Spain, a scene blessed with the rapid uprise of environmental consciousness and an established culture of communal living and societal responsibility, some questions arise:

- **Will the participation from higher-income households, which therefore are in a better position to act on moral imperatives, be elevated?**
- **Will future incentives appeal more to older generations with a more ingrained sense of environmental stewardship? [10]**

Demographic Consideration

To comprehend the intersection of economic and moral incentives, nuanced interpretations that account for different demographic features are essential. All prior studies analyzed have indicated that age, income, occupation and educational backgrounds are important determinants of DSF program consumer behavior.

For example, those who are retired may have the ability to adapt their energy consumption habits easier because they have a more open schedule. In contrast, for working professionals DR incentives may be less attractive as work hours are more rigid. In addition, there could also be situations where environmentally friendly incentives overtake the absolute financial ones (e.g. high income households can look beyond pure monetary value and take into consideration a broader societal focus).

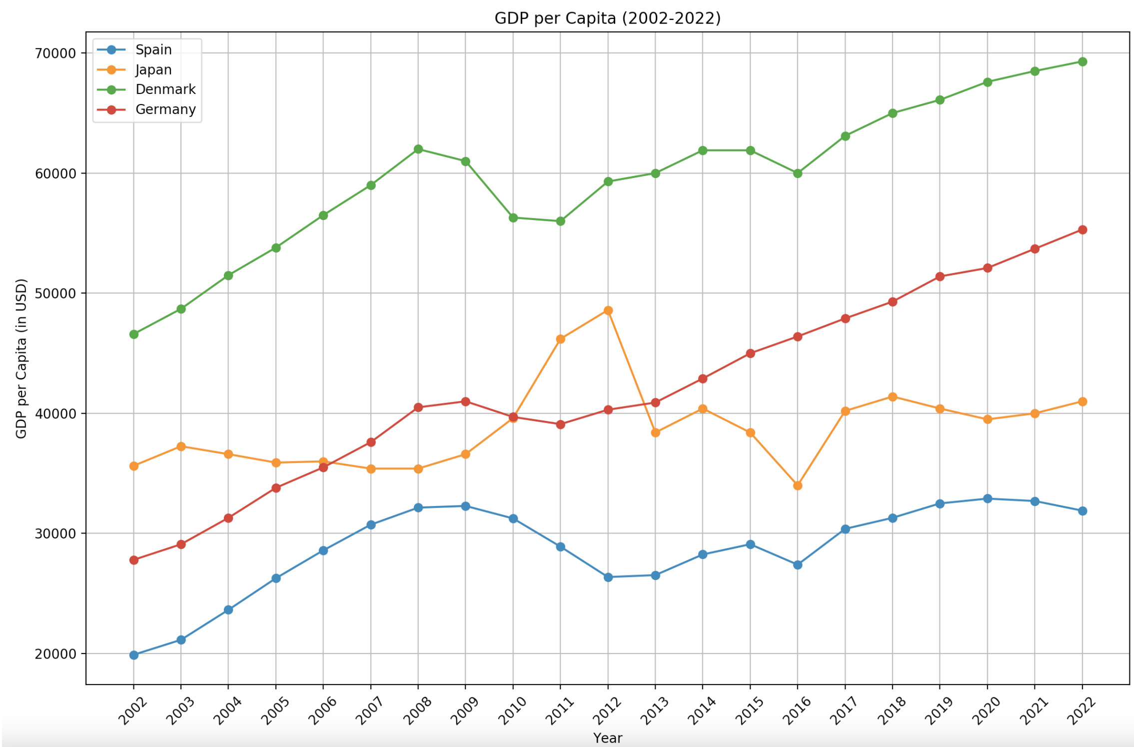


Figure 9: GDP per Capita of Spain vs studied countries [29]

In order to overcome these questions, this research will devise an experiment in order to assess the moral or economic incentives can be more or less effective in Spain. The study will use Google Forms to distribute surveys aimed at a broad demographic in order to ensure that the responses will represent a wide spectrum. After that, we will explain the methodology and each of the survey items in this next sections to guarantee a complete and relevant result.

It is important to note that the countries where the studies mentioned above where conducted had significantly greater GDP per Capita numbers, so I will be interesting to devise how this will affect the results. Will Spanish people be more attracted to monetary incentives due to this? Or are there other variables that have a greater influence in the results?

This study will examine responses to create strategies that leverage the power of combined economic and moral incentives. This way we will be not only better able to understand consumer behavior, but also provide helpful information to policy-makers and energy companies in order design more efficient and inclusive DSF programs in Spain.

3 Methodology

During the design of this research Carmen and I had careful consideration of alternative methods, and this lead to the proposal of the methods that I will later discuss. The overarching objective was to discover potential new ways of uncovering the underlying reasons for demand-side flexibility by energy consumers in research. Historical research in the area of Demand Flexibility Programs seems to have concentrated on high-level incentives, mostly pecuniary ones with perhaps one known pilot previously run at UK level. In these experiments, researchers typically deliver an across-the-board incentive package to all participants without differentiating the opposing impacts of various types depending on consumer demographics.

This gap is filled by means of this research, which explores how different stimuli can experience nuanced indirect effects on individual behavior in customer response, an area insufficiently explored within literature. Our goal is to tease apart these distinctions in a way that allows us to ascertain which motivations work best, and for whom. This granular approach is expected to offer deeper, more actionable insights into specific target segments of population and hence help improve the effectiveness in demand-side flexibility programs.

In the original planning, I suggested to test eight different incentives, but it quickly became apparent that in order to test this many incentives, we would need a large enough sample size to make our results valid and reliable. My analysis suggested an effective sample size for estimating the impacts of each incentive would be at least 400 respondents

(50 per incentive). This was a necessity to obtain proper statistical results and extract valid general conclusions of broader population. Therefore I decided to narrow it down to 4 different incentives to make sure the sample size was obtainable and sufficient.

What makes this study different is its effort to differentiate between types of incentives. Rather than treating incentives as a black box, this research seeks to disaggregate and test them. In this way, we can find what kinds of incentives are more attractive for each demographic and hence tailor the design of demand flexibility programs to be more effective. Not only does this approach add to the academic body of knowledge, but it also offers tangible benefits for policy-makers and utilities looking to lessen peaks in energy consumption, which are thought destabilize grids.

In the following subsections I will explain in-depth which incentives I selected to test and why, how the survey was designed, why I chose this exact methods and all the details about the experiment.

3.1 Incentive Selection and Rationale

The incentives tested in the study are the following:

1. **Electricity Bill Discount**

   Description: An economic compensation is offered to participants in the form of a reduction on their electricity bill, starting from 1 euro per hour up to no more than 3 euros. The discount will seamlessly appear on their monthly bill, indicating the benefits of teamwork to collectively reduce energy use during peak hours.

   Rationale

   Economic drivers have always been recognized as strong motives for consumer decisions in energy flexibility programs. As the study from Denmark [8] stressed that financial motivators by a large margin drove adoption by consumers, it did so in tandem with other additional forcing functions. It delivers on direct monetary discount making it an incentive as consumers can experience and see benefits immediately, achieving maximum participation.
   Additionally, economic stimulus is a simple and effective way for participants to be

engaged. Applying the discount directly to their bill every month makes it easier for them to see and feel how this is saving, which increases the perceived value of what they just participated in. This idea is supported by research that shows potential rewards can override reason in consumers' minds; especially financial gain the researchers suggest, if it comes fast and easy.
Even the fact that people who care less about the environment or feel no non-financial rewards may well be convinced by this incentive as a money prize is universally relatable. This is an attractive incentive for the frugal consumer looking to spend less on their home.

2. **Public Recognition**

   Description: Participants would volunteer their time for public recognition. On the Ministry website, they would be listed as participants and issued a diploma from the Ministry. This public recognition would serve to underline their role supplying the grid with energy flexibility and furnish them an official letter of acknowledgement in a kind way.

   Rationale

   Recognition can be as a powerful motivational factor and is treated equally to economic incentives. I believe that public declaration of your achievement (non-financial) can pave the way to motivate people who value social acknowledgment/ prestige etc. The English study suggested that non-financially incentivized consumers responded better to flexibility programs, and this incentive could boost their sentiment of belonging to the program and even make it a competition with their friends. This is called gamification, and the concept could be further researched in future studies. The public acknowledgment of participants not only shows gratitude for their collaboration, but also raises significant properties important to many people.

   Also, in the last years social media has become a very important part of our lives and I believe that being able to share with the community that you are helping the environment can really be a game changer. Moreover, some companies really value these types of actions and this certificate could be included in the LinkedIn profiles of the participants to even help them have greater chances of getting a new job.

3. **Discount in the bill to the Municipality**

   Description: In return for the participants' contribution, a deduction of 1 to 3 euros per hour of participation will be applied against the energy invoice from the municipality. This way schools, sports centers or street lighting could use less budget on energy costs and allocate more to other important needs in the community.

   Rationale

   This very small push comes from the altruistic principle and communal enhancement, which may be a powerful force among people who care for public welfare. This way, participants can directly link their efforts to benefits for the community's most affected demographics by providing a financial discount coming from those that pollute less than they could. These kinds of incentives promote an ethos of mutual responsibility and collective gain, thereby encouraging greater community involvement.

   As the reviewed studies have shown, the individuals with a social consciousness and those who are environmentally friendly usually respond well to these programs, therefore it makes sense to incorporate an incentive that combines these two matters. Not only they are helping the community by contributing to the grid's stability and the environment, but they are also aiding the most necessitated people in a tangible way.

   In addition, we can frame this benefit as something that will help local public services without raising taxes or fees and-for most residents-that is going to be a good thing. And it uses the visible impact of decreased energy costs in public buildings as a permanent, tangible symbol of what those participants have achieved - constantly reminding them how their engagement adds value.

4. **Tree Plantation**

   Description: A tree will be planted for every hour a participant collaborated. This will lead to a better environment and lowering the carbon footprint. It would allow tree planting projects to support reforestation and sustainability in the community.

Figure 10: The Nature Conservancy tree planting program in Colombia [30]

Rationale

Firstly, I want to state that this type of initiatives have already been done and there are some organizations which have had a lot of success with them, like the one from The Nature Conservancy [30].

They have been working since the 1950's to help conserve the nature and landscapes of the planet by plating trees in places like Colombia, The United States, Colombia and Mexico.

For those inspired by environmental awareness and sustainability goal, these small steps will have a significant influence due to ecological incentivization. A study in Denmark showed the power of financial incentives and documented synergistic effects with environmental motives. By planting trees as a reward for participation, the incentive connects individual efforts to larger environmental outcomes in a symbolic manner.

> This gives environmentally friendly individuals a push to participate and also anyone who wishes to play an active part in the sustainability of the community in the long run. The Japanese study [9] also emphasized how non-financial incentives - in this case, environmental rewards rather than discount codes or free products with purchase - are effective on consumer behavior. Planting trees further gives the volunteers a concrete and enduring reminder of how they have contributed to improving their surroundings, thereby adding value in terms of pride for what has been done as well as commitment to what is yet undone.
>
> Moreover, this motivation aligns with broader eco-friendly program goals, and can easily be packaged as a showcase of team green achievements locally or around the world. Also, being able to see maturing trees in their local area will provide motivation and awareness of what the benefits are.

This mix of incentives—discounts on electricity, public recognition as a green neighbor, discount to the municipality and tree planting—are strategic in targeting a largely different pool of consumers. These initiatives would be able to engage consumers at scale by weaving together financial, social and environmental motivators. Instant receipt of financial benefits (appealing to those with a tight budget) is accompanied by public recognition and communal rewards, elevating the sense of pride and collective responsibility. The tree plantation, meanwhile, plays into minor environmental incentives - for anyone who is committed to sustainability.

In the author's best opinion, these four different incentives really appeal to a wide base of consumers and could be easily implemented in Spain without big investments. Which is a very crucial part when thinking on what to offer to participants if I really want these measures to take place in the real world.

3.2 Research Design

3.2.1 Overview

As discussed before, this study assesses the effect of four unique incentives on intention to participate in an energy reduction initiative, using a between-subject experimental test design. In the following lines I will explain how the experiment was structured in a way to provide good, accurate results, and also which questions were asked to the participants. Also, I conducted a experimental design and not a survey in order to test causal relationships and gain internal validity. Finally, I will also explain the different paths possible for the interviewees to follow and the additional questions (demographic, filtering and control) that they were asked.

3.2.2 Participant Recruitment and Pre-screening

This was a community-recruited sample to ensure good representation of diverse demographics, so results are generalizable. It is important to note that as I had to get 50 interviewees for each of the incentives (200 in total), it was impossible for me to get so many responses. Therefore, I contacted a specialized survey distribution company to help me distribute the form, as I personally believe that this is the main contribution of my thesis. I had to pay a certain amount to this company, however, I finally ended up getting 245 responses and more than 50 for each of the incentives. All in all, the sample is sufficiently powered to detect differences.

It is also important to mention that the responses of those participants who did not pass the manipulation check (explained in the lines below) were discarded (only 75 percent of interviewees passed it), so this further sustains the idea that the information gathered is credible.

One of the first steps in the survey is a brief introductory screening question to assess eligibility by age. The only question participants are asked in this first step is whether they 18 years or older. Participants under 18 are excluded from the survey so as not to bypass ethical standards regarding participation of minors in research studies. This initial screening is essential to maintain the quality of a study and that respondents are within an appropriate respondent pool.

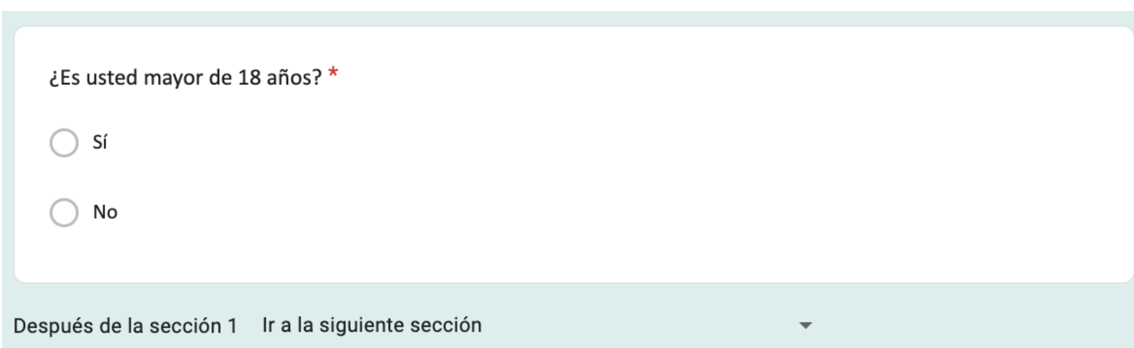


Figure 11: Participants are asked about their age in the first screen

3.2.3 Random Assignment through Birth Date Intervals

Participants are not directly assigned to incentive group in order to preserve the experimental design. Instead, placements are randomized based on the person's date of birth. This approach gives one a way to minimize any possible biases and guarantees the random allocation of participants into different incentive groups. Respondents provide their date of birth (there are four possible options, each of them based on the day of the month each were born in), which funnels them to one of four paths associated with different incentives, as explained before.

Figure 12: Participants are directed to one of four paths depending on their date of birth

3.2.4 Questions related to incentives

Each participant is exposed to only one incentive and then asked a particular set of questions related to that incentive. This way all responses clearly indicate how the incentive being shown affects their decision, so that comparisons can be made without affecting other factors. Experimental designs are the appropriate method for testing causality which is test objective here. Participants are asked to rate in previous questions reactions related to chances of participation, perceived easiness, anxiety level and how pleased the respondent feels with the incentive.

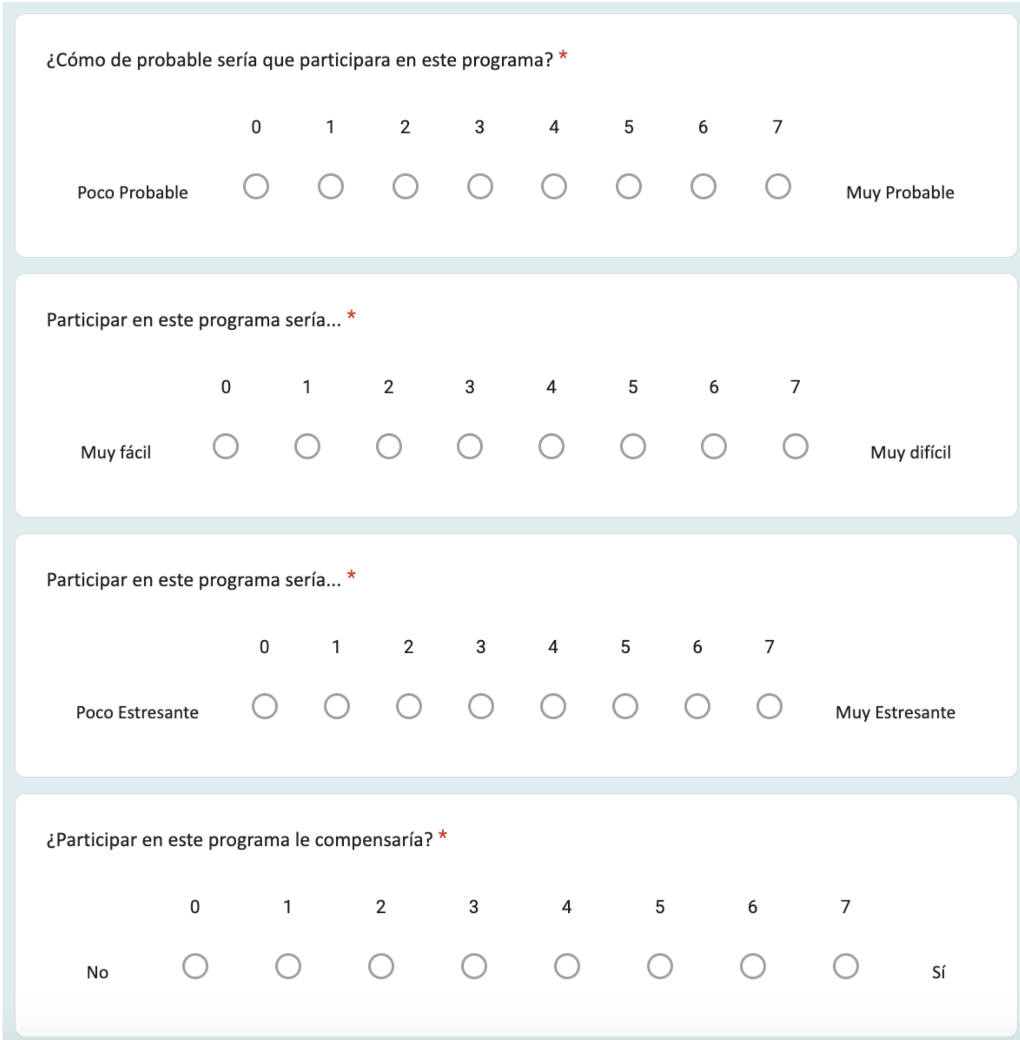


Figure 13: Participants are asked these questions about each incentive

1. **Participation Likelihood:** “How likely would you be to participate in this program? (Scale of 0 to 7). This item assesses in which direction the participant is initially motivated to participate based on the incentive.

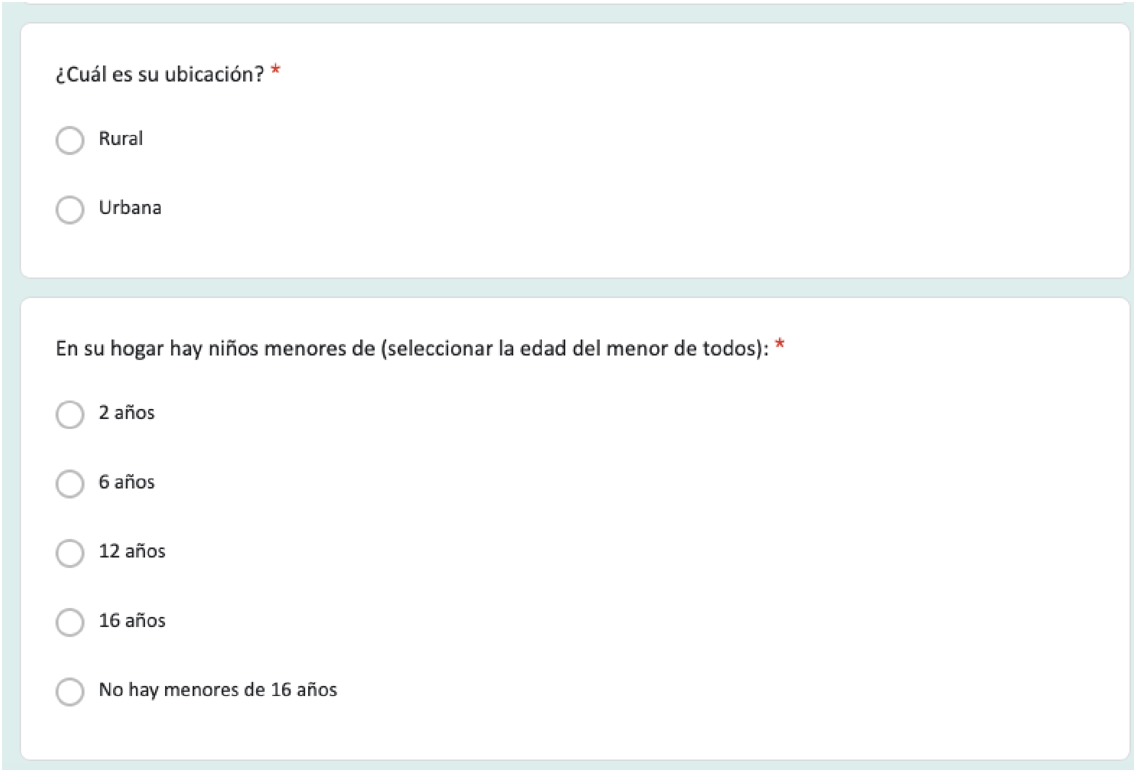
2. **Perceived Ease:** “Taking part in this program would be...to ”(On a Scale of 0 to 7, from very easy, up to and very difficult).” This question checks how doable it is for them to participate in the program and this affects their motivation to involve themselves as a participant.

3. **Actual Stress:** Participating in this program would be... [Scale of 0 to 7, where not at all stressful = 0 & extremely stressful = 7]. This is an important question since the perceived stress has been demonstrated to be a big issue when it comes to engaging.

4. **Perceived Compensation:** “Do you feel like this program is adequate for the value provided to you?” (0-7 scale, no-yes) This question reflects the overall perception of value that a participant has in relation to an incentive, comparing thought effort vs. perceived reward.

3.2.5 Attention Check

Subsequently, following the incentive specific items there is a manipulation check to test whether participants attended to and processed information about the incentive. The manipulation check prompts respondents to designate which incentive they received. This is an important step to eliminate careless responses that can make the data less reliable. Responses from participants who incorrectly identify what the reward is are filtered out, as expressed before, since I only want to get data that actually reflects an engaged and knowledgeable audience.



¿Cuál es su ubicación? *

- Rural
- Urbana

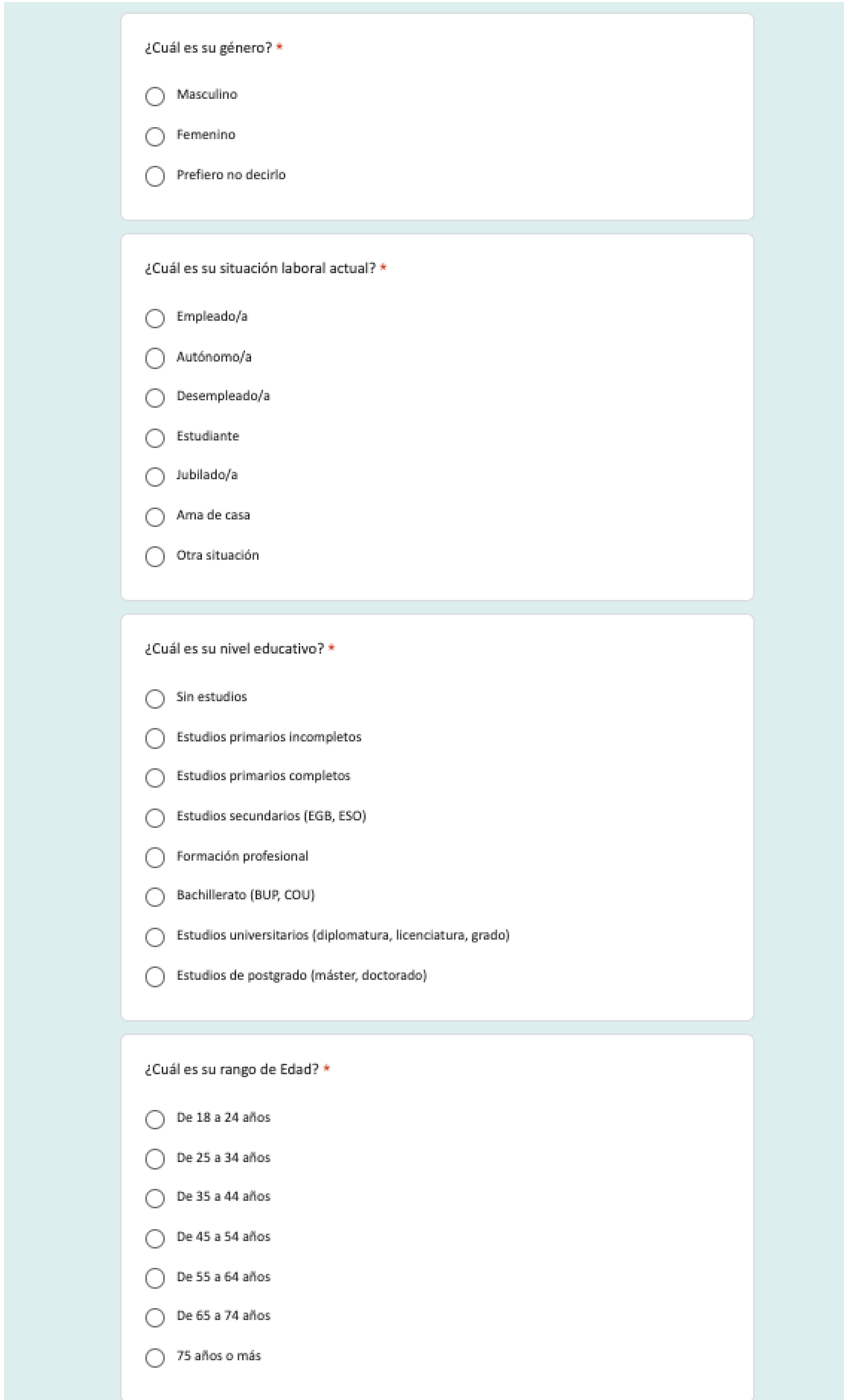
En su hogar hay niños menores de (seleccionar la edad del menor de todos): *

- 2 años
- 6 años
- 12 años
- 16 años
- No hay menores de 16 años

Figure 14: Participants are asked what incentive has been shown to them

3.2.6 Socio-demographic questions

After the manipulation check, interviewees proceed to the main path again (all the paths collide) where they respond a common set of socio-demographic questions. These questions elicit information on the age, gender, etc of participants. The information that is collected enables a full analysis of which demographic factors might impact on responses to the different types of incentives. It is in this wider context of the participants behavior that data about broader profile aspects like gender and age can help identify any demographic trends which could skew how effective these incentives actually are.



¿Cuál es su género? *

- Masculino
- Femenino
- Prefiero no decirlo

¿Cuál es su situación laboral actual? *

- Empleado/a
- Autónomo/a
- Desempleado/a
- Estudiante
- Jubilado/a
- Ama de casa
- Otra situación

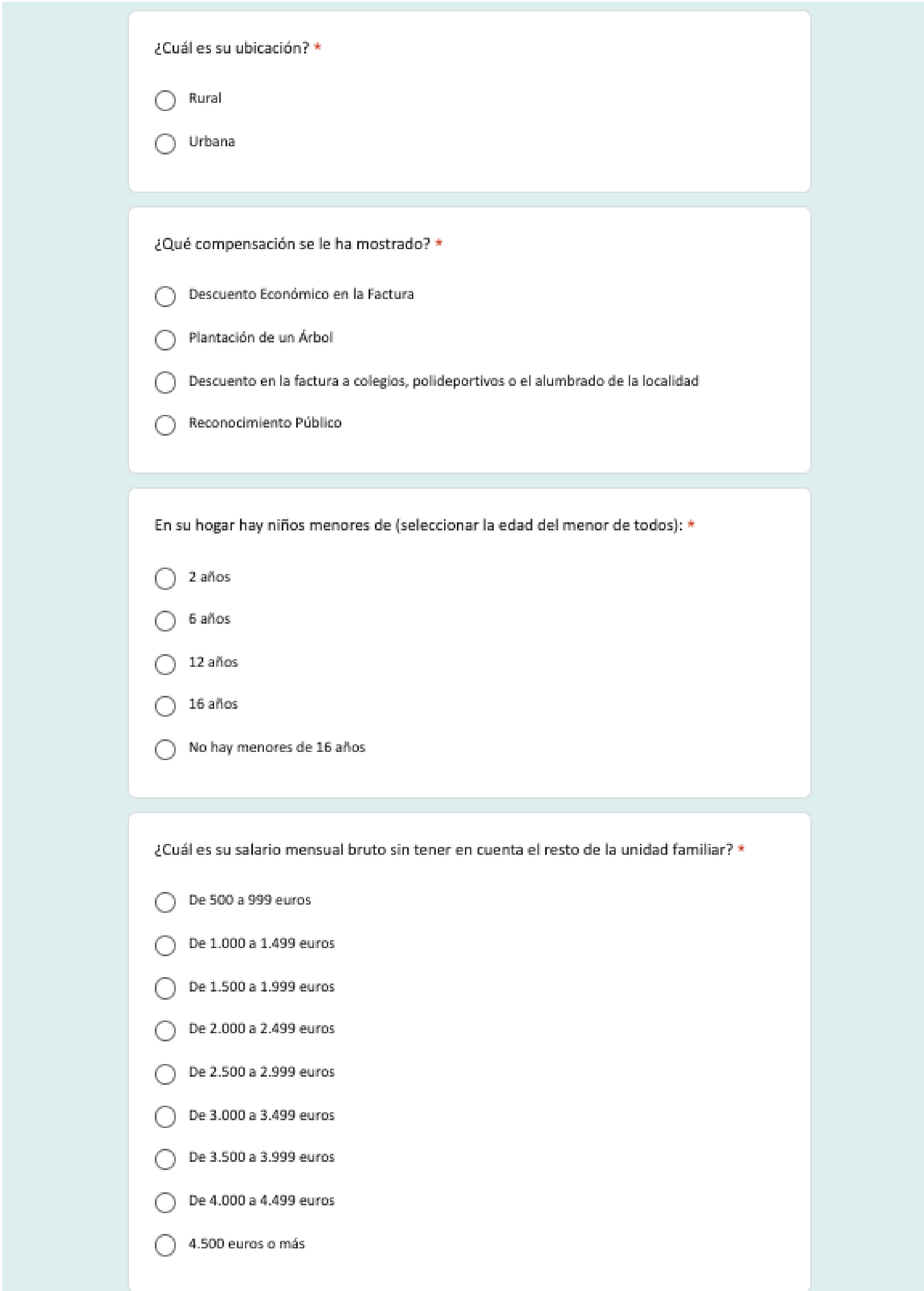
¿Cuál es su nivel educativo? *

- Sin estudios
- Estudios primarios incompletos
- Estudios primarios completos
- Estudios secundarios (EGB, ESO)
- Formación profesional
- Bachillerato (BUP, COU)
- Estudios universitarios (diplomatura, licenciatura, grado)
- Estudios de postgrado (máster, doctorado)

¿Cuál es su rango de Edad? *

- De 18 a 24 años
- De 25 a 34 años
- De 35 a 44 años
- De 45 a 54 años
- De 55 a 64 años
- De 65 a 74 años
- 75 años o más

Figure 15: Participants are asked these questions to further analyze the socio-demographic factors (part 1)



¿Cuál es su ubicación? *

- Rural
- Urbana

¿Qué compensación se le ha mostrado? *

- Descuento Económico en la Factura
- Plantación de un Árbol
- Descuento en la factura a colegios, polideportivos o el alumbrado de la localidad
- Reconocimiento Público

En su hogar hay niños menores de (seleccionar la edad del menor de todos): *

- 2 años
- 6 años
- 12 años
- 16 años
- No hay menores de 16 años

¿Cuál es su salario mensual bruto sin tener en cuenta el resto de la unidad familiar? *

- De 500 a 999 euros
- De 1.000 a 1.499 euros
- De 1.500 a 1.999 euros
- De 2.000 a 2.499 euros
- De 2.500 a 2.999 euros
- De 3.000 a 3.499 euros
- De 3.500 a 3.999 euros
- De 4.000 a 4.499 euros
- 4.500 euros o más

Figure 16: Participants are asked these questions to further analyze the socio-demographic factors (part 2)

3.2.7 Principles of experimental design

1. **Randomization**

   By randomly assigning participants to either of the two incentive conditions, we can be sure that both groups are similar and there is no effect due different make-up of these groups. This technique strengthens the internal validity of your study by reducing selection bias. Randomization guarantees that any detected repercussions can be grounded directly into the incentives without some other potential interfering factors [31].

2. **Single-Blind design**

   This principle is important because it eliminates biases that may have occurred in the responses due to them being able to compare their incentive with others, which they might view as either better or worse. Single-Blind design also allows to maintain the integrity of experimental conditions and ensure that responses by participants are influenced only via the incentive they were exposed.

3. **Control and Reliability**

   The answer to the manipulation check is used so researchers can verify that participants fully understood and took seriously whatever incentive they were promised. That way, for example, I ensure that the data measures real survey engagement instead of estimating responses from people who do not know what was asked. This is really important because it helps ensure the reliability of the results.

This experimental test design structure is effective assessing how well various incentives work for inducing activities in energy end-use. Through the use of randomized assignment, blinding and a robust control measure, the study is intended to generate high-quality generalizable knowledge with relevance for future policy development in energy flexibility. This holistic approach allows to control for gaming strategies that participants may use, hence allowing the merits and success of incentivization in a real environment (among other factors) to be analyzed.

3.3 Justification for Choosing Google Forms

There were a few reason for choosing Google Forms as the primary method of conducting this experimental survey. The ability to create paths is important for my experimental design as it assigns subjects randomly to one of four incentive groups by the year and month they are born. That is where Google Forms comes in, it allows this conditional logic to be set up and directs participants toward different paths seamlessly. This guarantees every participant is configurable to only be considered for one reward, keeping the experiment clean and free from bias.

Besides the path management, what I liked about Google Forms is its UI with respect to its competitors. As the researcher, it was easy for me to set up and deploy this survey since Google Form creation is quick and efficient. With google forms the clean and simple layout makes taking the survey a very pleasant experience for participants, which can increase participant attention engagement potentially translating to more completions and quality of data.

Also, the fact that I am already familiar and comfortable using it is very important. As I have been utilizing Google Forms for awhile, the familiarity reduces the curve and allows me to use them professionally so as to have the survey designed and administered effectively.

Moreover, you can very easily share your survey using Google Forms. The survey is shareable via email, social media and can be embedded on websites. This flexibility makes the survey fast and easy to distribute broadly. Furthermore, the platform allows for anonymity in responses which can lead to frank and honest feedback from co-participant.

Finally, the cost-effectiveness was also a deciding factor. This obviously can save money, which matters a lot in academic or non-profit projects that may be low on funding. For a free tool, Google Forms delivers features as robust and full-featured as many paid survey tools out there, like SurveyMonkey, and the extra money could be used in distributing said survey.

Other major concerns include security and privacy. It lets you know your data is safe with secure transmission and a consolidated environment. Google privacy policies and security hides the answers of participants and their sensible information. This guarantees the privacy and data security, and it's fundamental to generate confidence among participants.

In addition, the great extent of customization you can employ in designing a survey with Google Forms is also a key deciding point. This entails the option to apply cosmetic treatments on form appearance, feature distinct types of questions (multiple-choice, short answer, scale-type and more), opt for using branching logic, or even choosing the background colour. The features are useful as they help in designing a survey which is interactive and also appears to be friendly for participants.

In summary, Google Forms was chosen to conduct this experimental survey mainly because of its ease in handling different paths, cost effectiveness as well as privacy and desing options. In conjunction, the fact that it has a user-friendly interface and can handle data in many ways makes it an ideal program for performing this kind of research.

3.3.1 Data Collection Process

At first, I set out into the world of friends and family for responses, and posted the survey in my social media and also sent it through WhatsApp messages to all my known ones. Implementing such a recruitment strategy led to 33 responses, which while useful was only an insignificant proportion of the desired sample size for rigorous analysis. This was clearly not enough. If I wanted to make an impact with my study something else had to be done. Therefore, I selected, Fiverr.

Fiverr is a digital marketplace that has been innovating the way in which individuals and businesses are able to connect with service vendors who offer not only survey distribution and graphic design (for which Fiverr is most known), but a wide variety of other services as well.

Founded in 2010, Fiverr is arguably the top-of-mind platform for a wide variety of services where freelancers (they are referred to as ”sellers”) provide services with fixed prices and clients, can browse through the list of sellers, contact them, and then purchase a personalized service. I was familiar with Fiverr because I had purchased graphic design services some time ago, and it was an obvious choice.

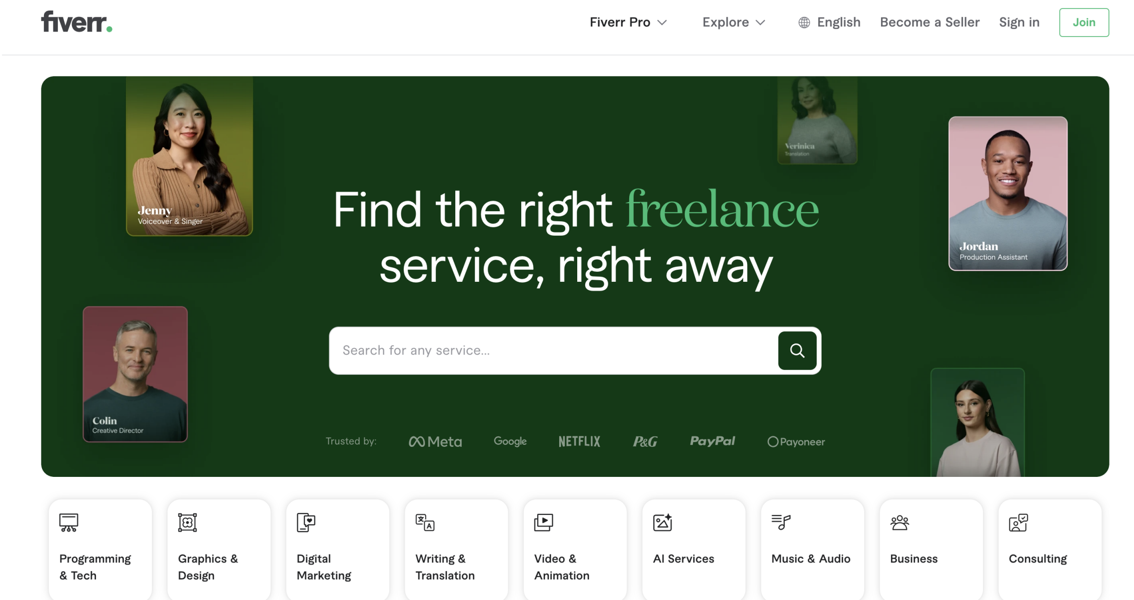


Figure 17: Fiverr's user interface also makes it very easy to use and intuitive [32]

I also explored some other alternatives, like SurveyMonkey, but it costed me four times more and did not allow me to use my Google Forms file, but their own format instead.

Therefore, I got in touch with a survey distribution company through Fiverr. The company in question was large, well-resourced and had the ability to reach a much larger audience. They also committed to deliver X number of responses within Y time frame. This pace helped me accomplish the response objectives, getting over 300 responses within three weeks.

However, a closer inspection of those responses revealed that only 25 percent had managed to respond correctly on the manipulation check which aims to test whether participants are reading and adequately following instructions in responding. I removed all the non-suitable responses, and this allowed only quality data to be collected, and respondents who were not paying sufficient attention or clicking away through the survey before it was complete could be automatically weeded out.

I contacted Fiverr again to get the survey distribution company to facilitate a resolution of this issue immediately. Over the next month, they meticulously tested different ways in which to distribute their survey. This extra time required heavier participant selection and more in-depth communication. It worked, and they were able to acquire another 250 responses. This time the rate was far better, with 80 percent of these responses passing the manipulation check– results that certainly indicate much stronger participant engagement and data quality.

In the end, after including all of the valid responses from both phases of data collection I ended up with a final number of 237 participants who passed my manipulation check. This concatenation led to a clean dataset, which served as the final seed for building a solid study that can really contribute to the community.

3.4 Statistical Analysis

3.4.1 Choice of Software

As I was planning and conducting the research for my project, one of those fundamental choices revolved around deciding which software would facilitate our data analysis phase. The most obvious candidates here were Python and Jamovi, each offering unique advantages with objectives that span across different layers of requirements in this project. In the end I decided to begin using Python — not only because of its versatility when it comes to software but also as a strategic move in order improve my technical skills and use these extra resources with regards project for exploiting more quantitative work.

In the domain of data manipulation, Python has unique capability and strength as a programming language that makes it an appropriate choice for project such with nuanced data handling requirements. The data used for my study consisted of a large dataset containing many responses from participants who had been interviewed in Spanish. This required more than just basic data cleaning and analysis but also advanced operations like text translation and creating custom visualizations. Tasks such as data manipulation and visualization could now be done efficiently with the help of libraries like Pandas for data, Matplotlib for plotting etc. This was substantially streamlined by the ability to script these processes in Python compared running more manual operations via other software.

On the other hand, Jamovi - a graphics interface highly liked among nontechnical audiences- is much appealing when it comes to statistical analysis due to its simplicity yet effectiveness for running statistical tests. However, it wasn't enough for me to do only some basic data processing and statistics, as I really had to personalize the data, clean it, and also wanted to perform more than a single ANOVA, which would have meant reordering the data each time. Python's Pandas were simply more convenient.

Therefore, using Python instead of Jamovi came down to a variety of factors both specific to the project and my own ambitions for development. Python being able to manage complex large scale data processing coupled with its much higher flexibility easily made it the best choice for this project. This was not only a decision that suited the immediate requirements of this project, but also because I felt it could be an important feather in my cap as part of building more technical skills and getting to experiment with advanced data analysis techniques.

The exact libraries I used are the following:

1. **Pandas:** Used for data analysis and manipulation, also to read Excel sheets.
2. **Numpy:** Used for logic and mathematic operations on large amounts of data.
3. **Statsmodels.api:** Used to perform statistic analysis on data, including ANOVA analysis.
4. **Matplotlib.pyplot:** Used to create graphs and adjust the visualization to the desired standards.
5. **Seaborn:** Used to enhance the graphs visualization even further and create professional boxplots and barcharts.

3.4.2 Methods of Analysis (ANOVA)

I chose to analyze this data using **ANOVA** (Analysis of Variance) to compare the different incentives and measure if one is more effective than another. An ANOVA is a statistical method that lets you compare the means of three or more groups to see if at least one of those group means is significantly different from the others. I think this works well for this data because I want to know whether individuals respond differently based on the incentives, and whether those differences are statistically significant.

I began my analysis by using an ANOVA in order to compare the incentives against each other. The results of the initial ANOVA allowed to determine whether consumer preferences differed for the four incentives.

Thereafter, to understand the differences in each of demographic attributes I ran separate ANOVAs for all. This allowed me to take a closer look at the relationship between different incentives, and how they work for people who belong in various categories regarding their preferences (as well as whether these differences are significant by gender groups or users of distinct age ranges). I could more specifically isolate trends and preferences within unique segments, which provides more granularity of the incentive dynamics.

I also printed P-values and F-values from each ANOVA ran. The lower the p-value, the more significant, e.g., if it is lower than 0.10 (it normally is lower than 0.05, but it will be lower than 0.10 in this case due to sample size) then whatever result was found in our experiment can typically be attributed to something other than natural random variability of an intact biological process. In contrast, the F-statistic is a measure of among-groups variance to within group variances. An F-value higher than 1 indicates that the significant differences in means between groups are greater than variability within groups, which increases confidence in results.

In summary, the choice of ANOVA allowed a thorough assessment of incentives and in-depth exploration for any demographic confounding influences both guaranteeing statistical significance as well as confidence that those actually represented the underlying data.

4 Results

4.1 Description of the Sample

In total 513 samples were collected, but of those a large number of responses did not pass the manipulation check. Therefore, all of them were removed with a python script and after this process, only 237 responses were gathered. This is the valid sample.

All the participants were 18 years old or older and were Spanish citizens. To sum up the important information of the participants, Google Forms has a tool that creates graphs directly, and the stats are the following[1]:

[1]Some parts of the graph could not be translated due to software limitations, please contact the author for any clarifications

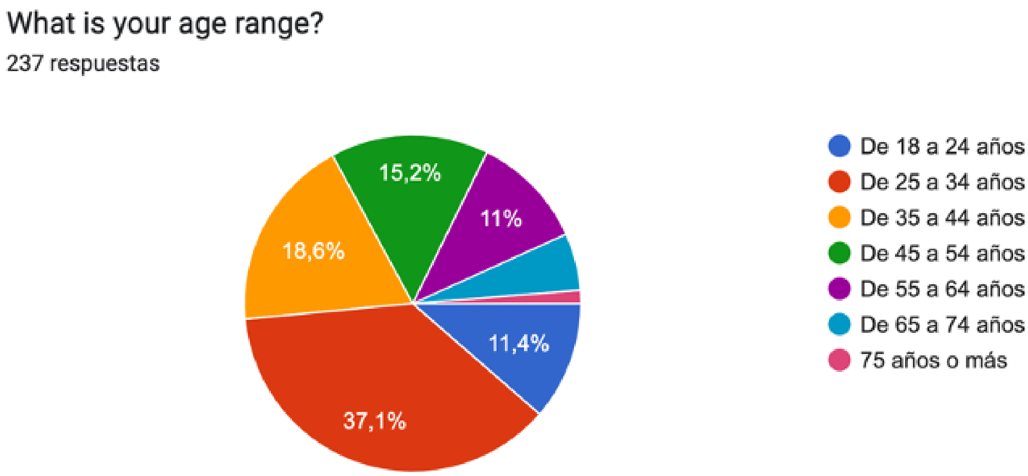


Figure 18: Age distribution of respondents

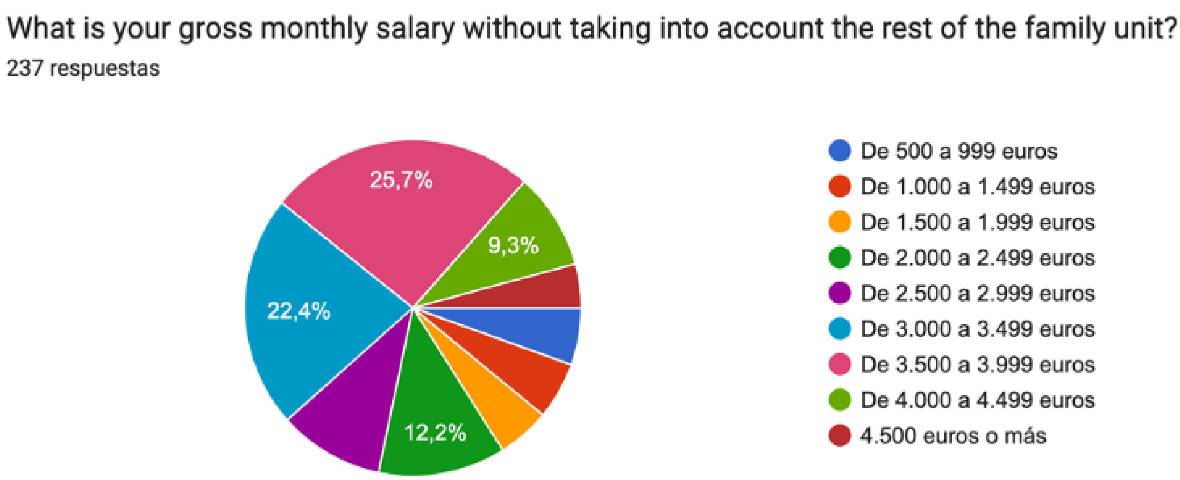


Figure 19: Salary distribution of respondents

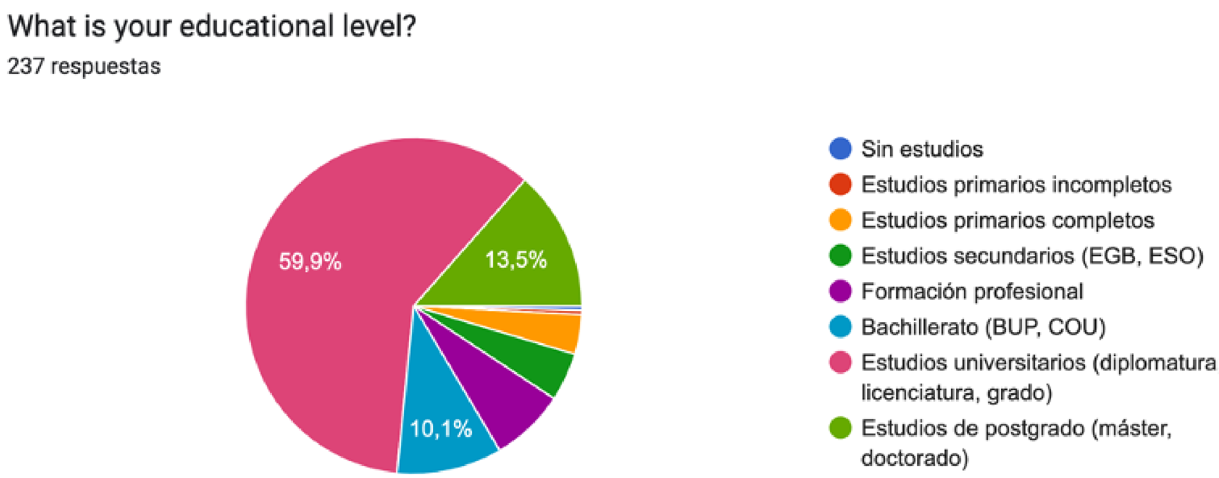


Figure 20: Education distribution of respondents

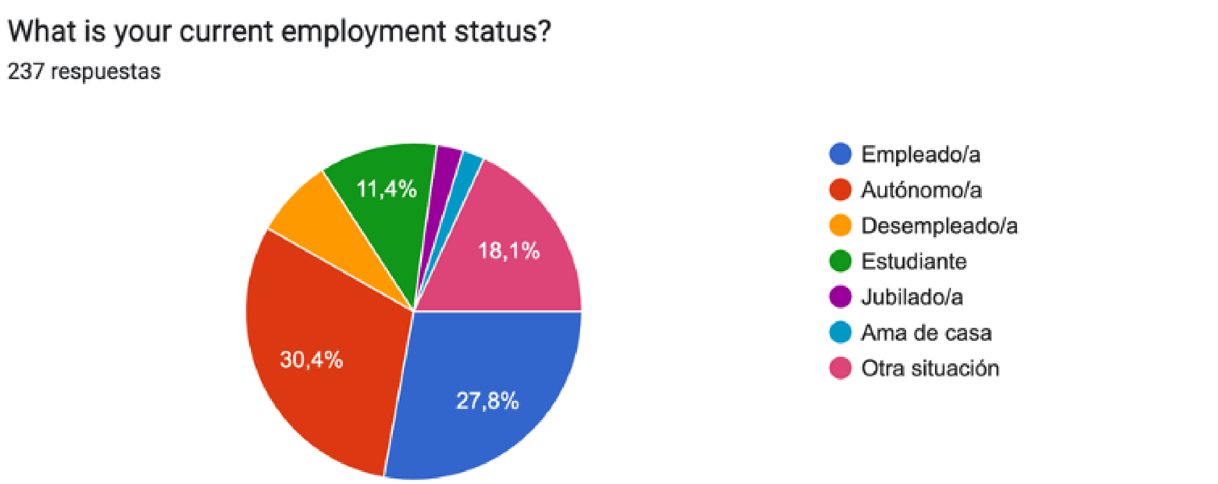


Figure 21: Employment distribution of respondents

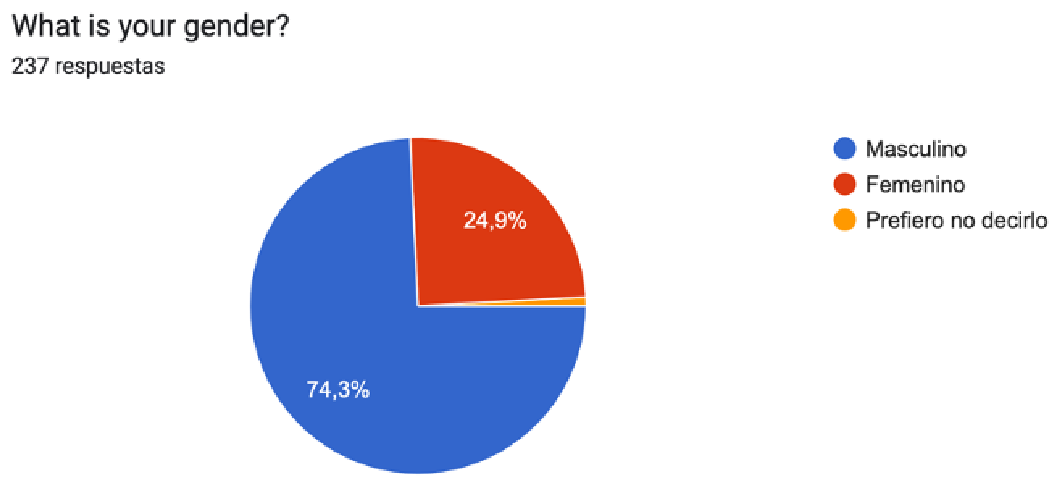


Figure 22: Gender distribution of respondents

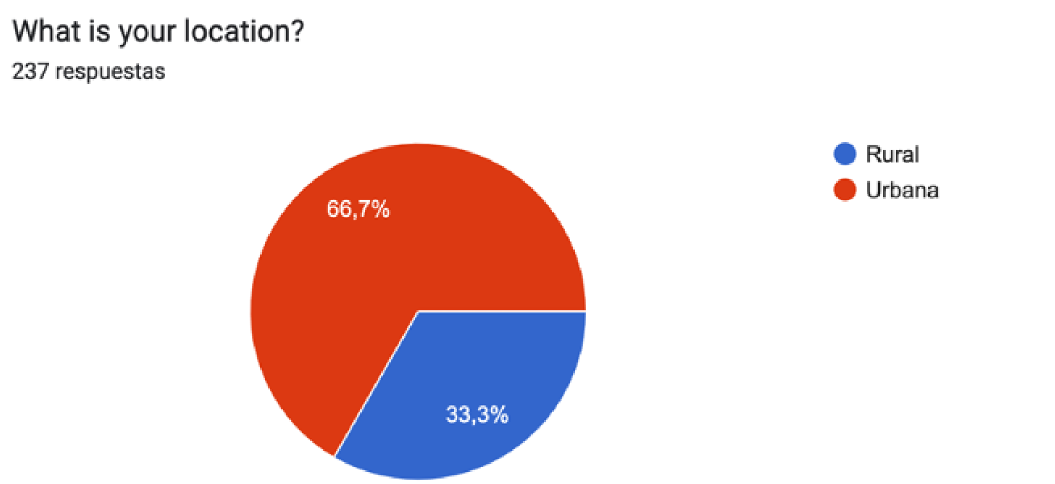


Figure 23: Location distribution of respondents

As we can see in figures 18 to 23, the majority of the respondents were male and had university degrees (which is due to myself having mostly male friends from college or school that shared education with me). However, it is fair to say that the sample is varied and may be representative of a large piece of the Spanish society.

It is also important to mention that the answers with subgroups that did not consolidate a sufficient number where not used in the graphs. [2].

4.2 Comparison between incentives

In this section I will compare the effectiveness of the four incentives through an ANOVA analysis. Before explaining the code, we must get dive into the basics of the analysis. It is important to introduce how the formula for these scores work. The participants were asked to give a score from 0 to 7 for 4 different questions, which were:

1. How likely would you be to participate in this program? (0-7)
2. Participating in this program would be... (0-7 Difficult)[3]
3. Participating in this program would be... (0-7 Stressful) [4]
4. Would participating in this program compensate you? (0-7)

To combine the scores into one single number the following formula was applied:

The formula used to calculate the base score is as follows:

$$\text{ScoreBase} = 0.25\times\text{Participate}+0.25\times\text{Difficulty}+0.25\times\text{Stress}+0.25\times\text{Compensate} \quad (1)$$

To make sure that the score is on a fixed scale from 0 to 50, we scale the ScoreBase. Firstly, we must calculate the maximum value of ScoreBase, given that all scores range from 0 to 7:

$$\text{MaxScoreBase} = 0.25 \times 7 + 0.25 \times 7 + 0.25 \times 7 + 0.25 \times 7 = 7 \quad (2)$$

Afterwards, we scale the score to a scale of 0 to 50 to make it more easy to understand:

[2] E.g. 'I prefer not to say' answers where not included as the sample was to small for statistic study

[3] The scores in this section were swapped around for the analysis making the scale from 0-7 (Easy)

[4] The same method as in question 2 was applied

$$\text{Score} = \text{ScoreBase} \times \left(\frac{50}{7}\right) \tag{3}$$

In the beginning one of the options I thought of was giving weights to each of the sections, but after some thoughtful consideration it was decided to use a simple mean method to not introduce unnecessary bias.

Also, in some further treatment of the data had to be done. In order to perform a simple mean all the variables had to go in a positive scale. Therefore, the Difficulty and Stressful scales were all swapped around, meaning for instance that if a participant had given a 7 score in stressful the final score would reflect a 0, and if it gave a 1 the final score would be a 6 and so on. This is important because without this data treatment some negative coefficients would have been necessary in the formula.

Here is a snippet of the code, with everything explained in detail. I will be including the code for the following ANOVAs in the Appendix, not in the main body of the study. This is the Python code used for this analysis:

```python

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns
# Load the Excel file
file_path = '/path.xlsx'
df = pd.read_excel(file_path)
# Rename columns for easier analysis
df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

# Calculate weighted score
df['ScoreBase'] = 0.25 * df['Probability'] \
                        - 0.25 * df['Difficult'] \
                        - 0.25 * df['Stressing'] \
```

```
                        + 0.25 * df['Compensate']

# Make sure the score is not negative
df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))
# Scale the score to the range of 0 to 50
df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())
# ANOVA analysis to see which incentives work best
model = ols('Score ~ C(Incentive)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
# Show ANOVA results
print("ANOVA Results for Incentives:\n")
print(anova_table)
# Get the p-value of the ANOVA
p_value = anova_table["PR(>F)"][0]
print(f"\nP-value: {p_value}")
# Style settings for professional graphics
plt.style.use('seaborn-whitegrid')
# Create a color palette from green to blue
palette = sns.color_palette("GnBu_d")
# Viewing ANOVA results with an improved box plot
plt.figure(figsize=(12, 8))
# Set the default font to Calibri
plt.rcParams['font.family'] = 'Calibri'
plt.rcParams['font.size'] = 12
plt.rcParams['font.weight'] = 'bold'

boxplot = sns.boxplot(x='Incentive', y='Score', data=df,
                      palette=palette)

# Add the mean in each box of the graph
means = df.groupby('Incentive')['Score'].mean()
for tick, label in zip(range(len(means)), boxplot.get_xticklabels()):
    boxplot.text(tick, means[label.get_text()] + 1,
                 f'{means[label.get_text()]:.2f}',
                 horizontalalignment='center', size='x-small',
                 color='black', weight='semibold')

plt.title('Average Score by Type of Incentive', fontsize=16,
```

```
            fontweight='bold')
plt.xlabel('')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=0, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('professional_boxplot_with_means.png', dpi=300)
plt.show()
```

The code is executed in the Python 3.7 Terminal and Mac OS X Sonoma 14.0 operating system. These are the results of the statistical analysis:

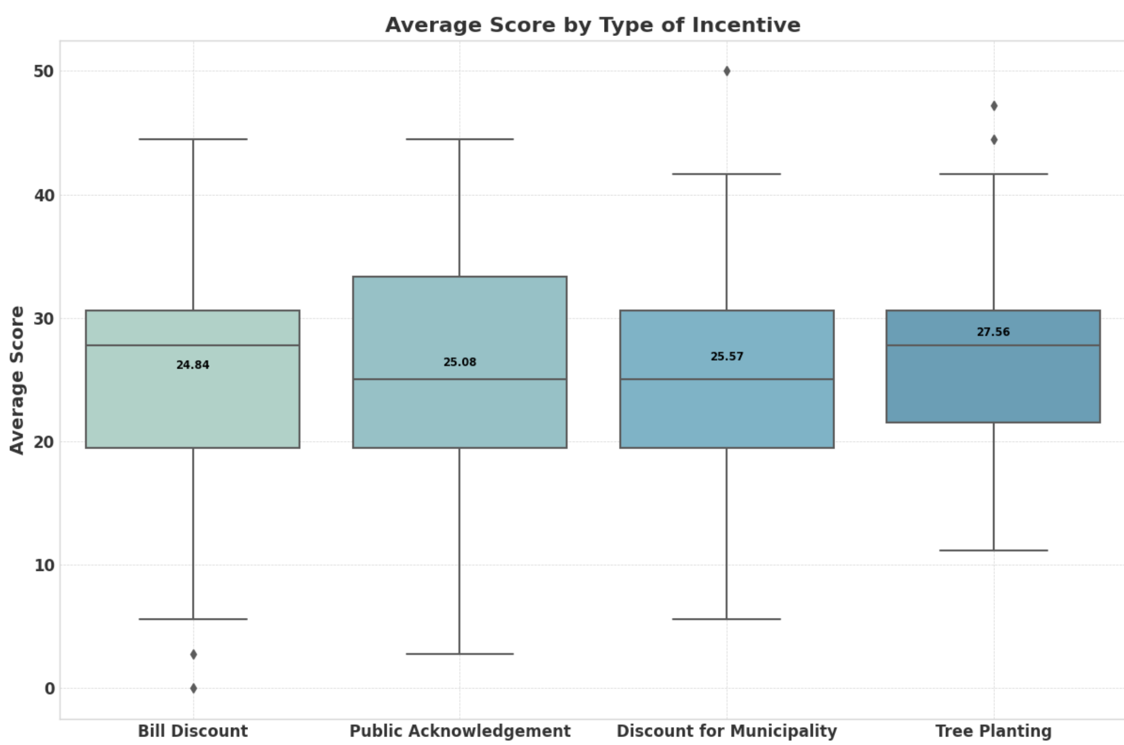


Figure 24: Comparison between incentives

In addition, the results for the P-value and F-value are the following:

```
P-value: 0.364223244772745
F-value: 1.0658673865379482
```

The ANOVA results of the analysis to compare between the various incentive mechanisms show no statistical difference between groups. This is inferred from the P-value and F-Value. In this particular comparison, the P-value is high (0.36) and well above our common significance threshold of 0.1, indicating that differences between groups could have happened by chance.

This is substantiated with an F-value of 1.065. In the context of ANOVA, you use F-value to compare how well a variance between your groups explains variances within those same groupings. A larger F-value usually means that, relative to the within-group variance, there is a lot of between-group variance and therefore the independent variable (type of incentive) has an effect. However, this low F-value of 1.065 indicates that most of it is within-groups variation so not massively greater variance between groups than within them.

Visualizing the averages by incentive type in a boxplot, it becomes more obvious that average scores do not vary too much between different types of incentives, although it seems interesting to me the fact that the economic incentive is the one with the lowest mean score. As said above, these results must be taken with a grain of salt due to the F-Value and P-Value, but there is some consistency with the existing literature, such as the study conducted by Anca-Elena Mihalache and Sam Hampton [10], in which also the conclusion was that the people with a greater environmental concern where the most likely to participate actively in the DR initiaves.

The boxplot also includes the interquartile ranges (IQR) and the whiskers. IQR for different types of incentives are all quite wide, implying that scores within each type can also vary substantially. The non-significant ANOVA result may be due to this variability within each group, since high amount of the within-group variability could reduce the statistical power for detecting significant between-group differences.

Also, the extremely high outliers are clear from the boxplot, especially for example at tree planting incentive. Outliers are figures that mostly fall away from the regular data range and can mislead significance results of statistical tests. Yet the outliers don't seem to be problematic with respect to the main conclusion in this particular case.

4.3 ANOVA Results by Demographic Groups

After the analysis of the differences between incentives, I have dived further into the demographic groups that are part of this study. Therefore, I have prepared six analysis by demographic characteristics that are the following:

1. Age
2. Salary
3. Education
4. Employment Status
5. Gender
6. Location
7. Presence of Kids in the familiar unit

Some of the characteristics mentioned above were included due to some previous literature pointing towards this direction, such as the gender and employment status, both of which the a study in Denmark [8] found to be significant contributors to the participation in DR programs.

The scores follow the same logic and formulas in all the following parts as in the previous analysis. Please refer to equations [1],[2] and [3]. Moreover, only the graph and the P-Value and F-Value will be shown in the following sections. The complete Python code can be found in the Appendix.

4.3.1 Age

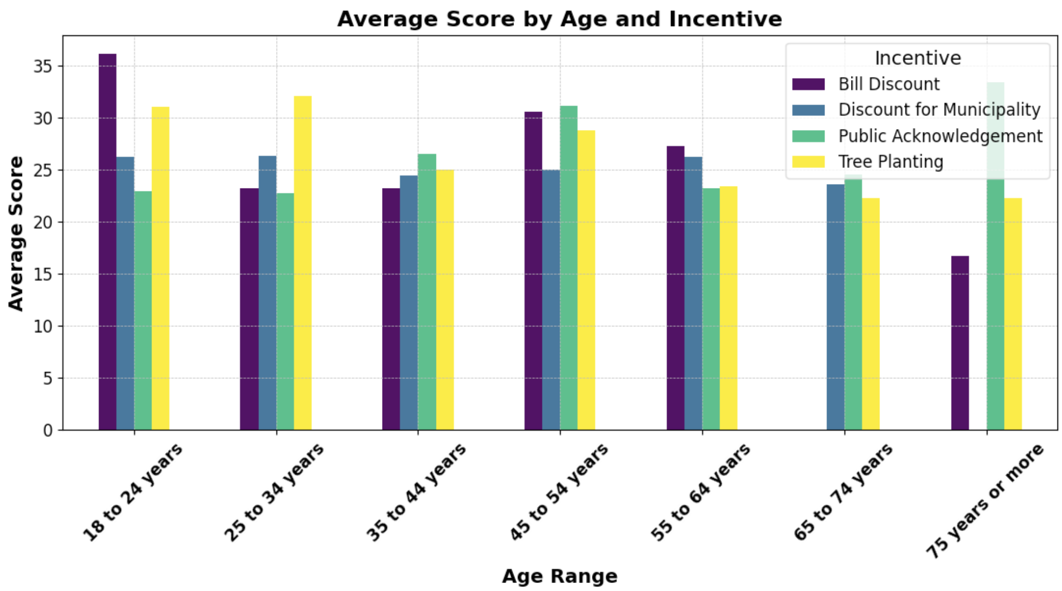


Figure 25: Average Score by Age and Incentive

```
P-value: 0.17809796976922118
F-value: 1.7396081025454806
```

The results obtained are quite interesting. As we can see in the graph, there is quite relevant differences between the preferences between age groups. Tree planting seems to be the most preferred amongst people from 25 to 34 years old, and a relatively close second in the 18 to 24 years range. As a very big percentage of the people were youngsters, this may explain why the tree planting initiative was the one with the highest score overall.

In the next age range there is very little difference, and in the 45 to 54 years age range public acknowledgement is slightly preferred. In the 55 to 64 age range the discount for municipality and the public acknowledgement are the most liked, and amongst the elder people the most preferred are also the non-economic ones.

The P-Value is low but not lower than 0.10, so the null hypothesis cannot be ruled out. Also, the F-Value even though being higher is not high enough to sustain that there are significant differences.

Therefore, it is fair to say that, even though we these results with are not final, young people are more seduced by economic incentives and as people grow older they tend to prefer the non-economic ones either related to helping others or gaining public acknowledgement from their community.

4.3.2 Salary

Figure 26: Average Score by Salary and Incentive

```
P-value: 0.308894833470704457
F-value: 1.2052803071863303
```

I had expected that the Bill Discount incentive, for instance, would be preferred by those of lesser means. In return, the Bill Discount is least favored for those earning between 500 to 999 euros, which caught me in great surprise. This phenomenon is explained because, after crossing the data with the ages of the respondents, those with lower income are in the most cases young individuals who do not pay the bills in the household.

There seems to be either no correlation or a positive correlation between the income level and the likeliness to prefer the bill discount. I would likely suggest that another sample is taken with a bigger pool of people, as I really believe this is a sample error. It is important to take into account that some people do not feel comfortable in saying their salary and sometimes tend to put themselves in a higher bracket, and that could maybe explain partly these results.

On another note, these apparently contradictory findings are reinforced by a statistical analysis. The non-significant P-value of 0.30 and F-statistic value of 1.21 suggest that the average scores are similar across salary ranges and that differences may have occurred by chance. Moreover, these values are worse than observed in the prior analysis so it appears that any differences we have seen were probably due to chance rather real variation. Additional research with larger samples will be necessary in the future to extract further conclusions.

4.3.3 Education

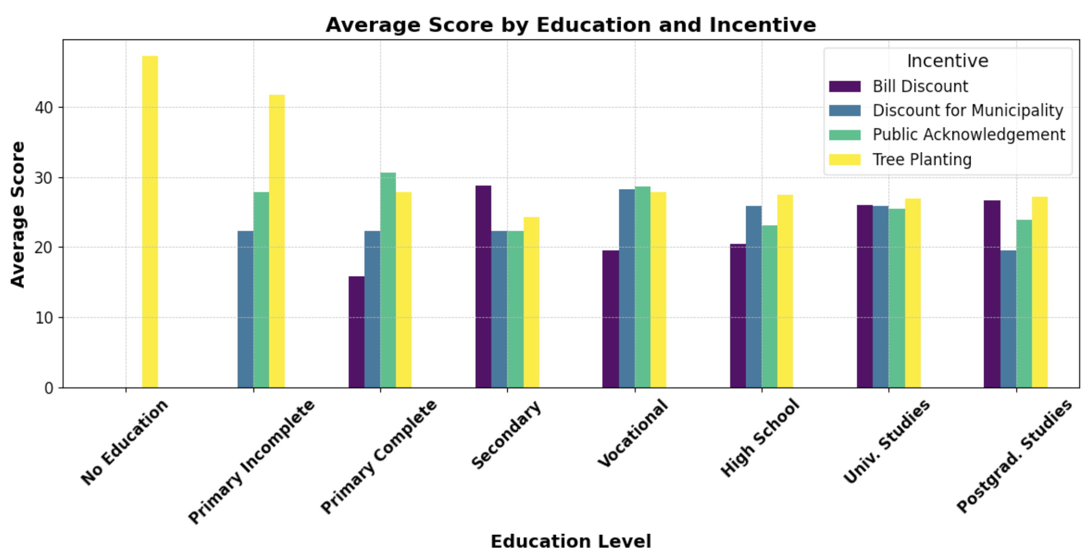


Figure 27: Average Score by Education Level and Incentive

```
P-value: 0.27507148255873504
F-value: 1.3008073883242366
```

We can also observe some interesting patterns in the analysis of average score by education level and incentive. More preference was shown to the Tree Planting incentive by those who have lower levels of Education. This fact is well reflected in the graph as for each of the first two educational levels, Tree Planting has a much higher score compared to other incentives.

No overall pattern emerges, and it is difficult to visualize any overall trend in this graph. Although the picture is more mixed for individuals with secondary and vocational education, those who reach only high school largely express consistent preferences for Tree Planting over all incentives. However, graduates and postgraduates prefer economic incentives in a higher rate than other groups . Higher-educated individuals seem to be more price responsive, but they still prefer Tree Planting amongst all options.

Nevertheless, the P-value of 0.275 and F-value of 1.301 illustrate that these differences in average scores across education level by incentive are likely to not be statistically significant. Such values raise doubts that observed differences might be due to random causes, rather than reflecting a real variation in preference. Based on these facts, it would simply be premature to comment anything definitive. Although there is some suggestion in the data that those with higher education may prefer economic incentives, it seems adventurous to conclude this based on current evidence.

4.3.4 Employment Status

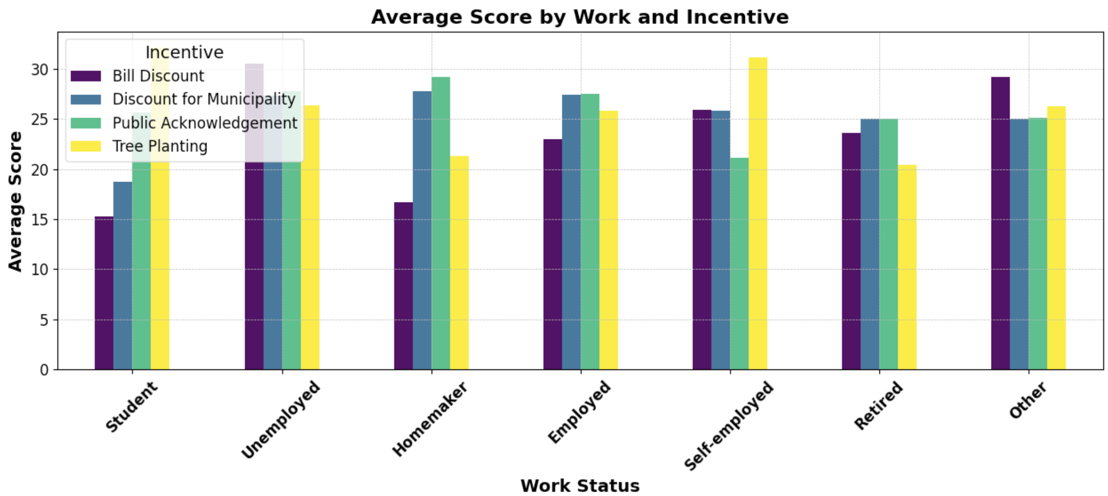


Figure 28: Average Score by Employment Status and Incentive

```
P-value: 0.27507148255873504
F-value: 1.3008073883242366
```

The results obtained in this section are quite interesting. Firstly, we can see in the figure above that the students prefer tree planting, showing that younger generations have a stronger environmental consciousness, as also do self-employed individuals.

On the other hand, homemakers prefer social incentives and giving back to the community, while retired people tend to prefer public acknowledgment. It is quite surprising however that retired people have shown an overall lower score, which means they would be less likely to engage in these initiatives. This may be because older people are afraid to take part in them. Also, this contrasts with the study conducted by Dr. Moller [8], in which one of the conclusions where that retired people were more likely to engage in these programs, as well as homemakers.

It is also interesting to note that unemployed people have a good acceptation for the economic benefits, and this makes a lot of sense, as they are a group of people, as well as students, which have lower means and are in necessity of financial aid.

All in all, the P-value and F-value are better than in the last sections, but they are still not enough to discard the null hypothesis. However, it is important to note that some of the conclusions extracted are logic and point in the same direction as some previous studies.

4.3.5 Gender

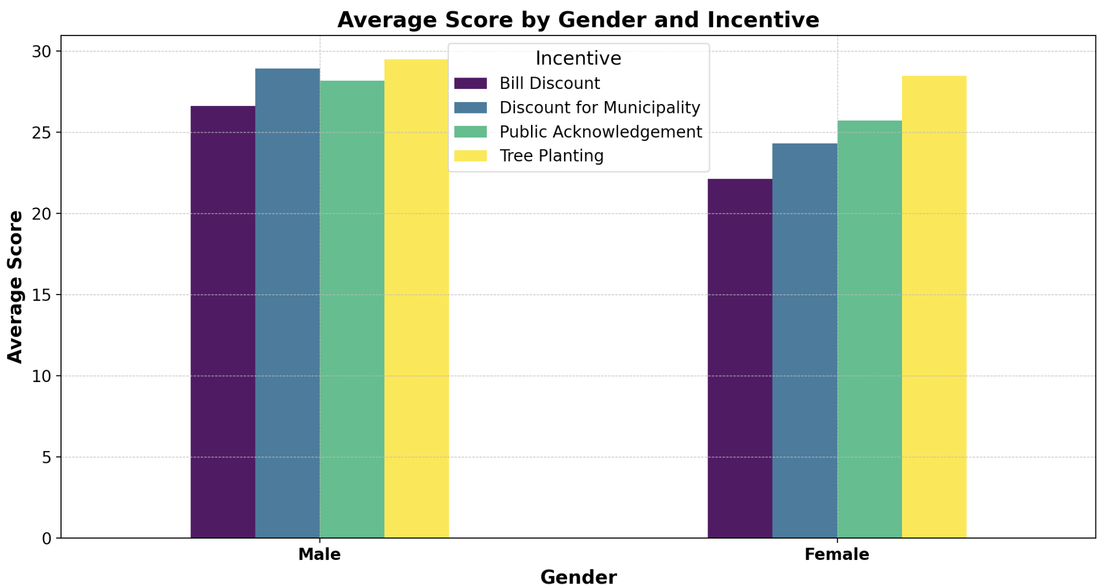


Figure 29: Average Score by Gender and Incentive

```
P-value: 0.2935644951530121
F-value: 1.2467266750365333
```

The results seen in the figure above indicate that males have a stronger preference towards economic incentives than women do, and also that women prefer environmental incentives in the first place and economic in the last, which shows their high environmental consciousness. Also it is clear that men prefer public distinction.

Overall, males have given higher scores in all incentives in general, which means that they would be more likely to engage in Demand Response programs. This contrasts with the existing literature, as previous studies [8, 10] showed that it was the other way round, but maybe in the case of Spain it's different.

The P-value and F-value are better overall than in the previous sections, but they still aren't good enough to discard the null hypothesis and to rule out randomness.

4.3.6 Location

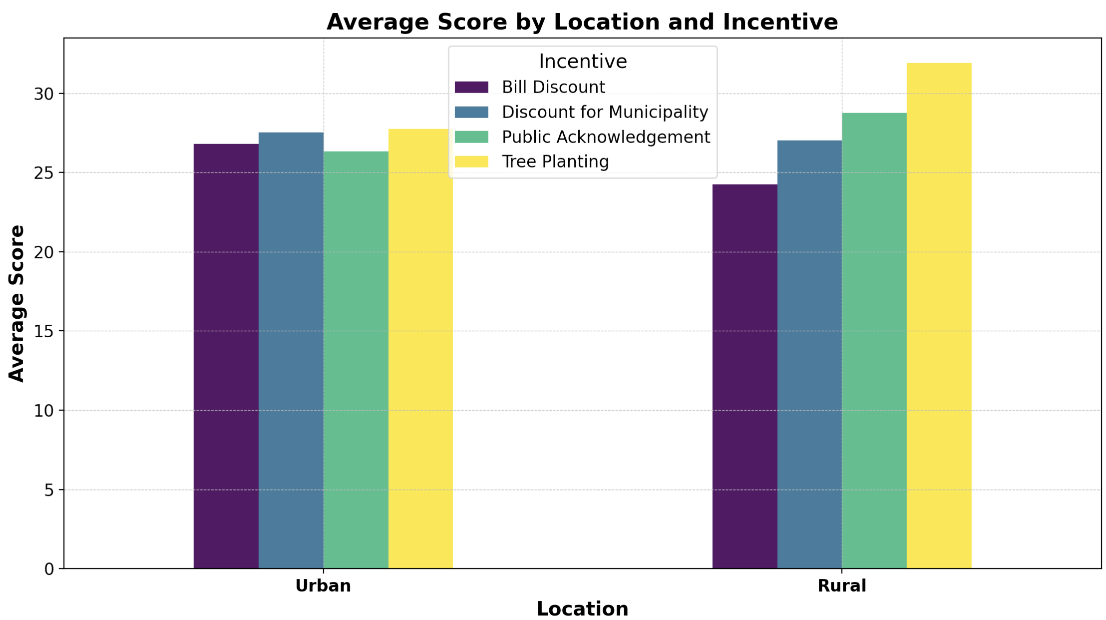


Figure 30: Average Score by Location and Incentive

```
P-value: 0.35019121555381033
F-value: 1.0991518864274794
```

It seems that there is a clear tendency regarding to preferences based on location. Individuals who live in the countryside prefer the environmental initiatives and are overall more likely to involve in DR programs. This could be because as they are more in contact with nature their environmental consciousness is higher (this latter being a fact confirmed by crossing data), so it could be wise to target this part of population when establishing a trial in Spain.

Also economic incentives seem to be more effective in the cities, maybe because of the higher costs of living. As in all previous sections, the F-Value and P-Value are not good enough to state that these results have scientific evidence, but they may point towards the direction in which the trials should go.

4.3.7 Presence of Kids in the familiar unit

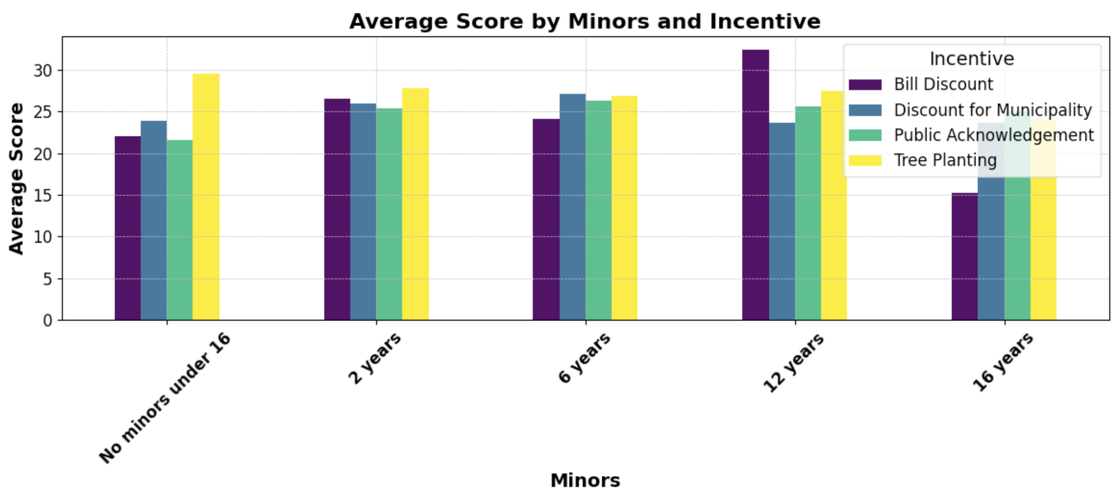


Figure 31: Average Score by Minors in the Familiar Unit and Incentive

```
P-value: 0.31314835289871545
F-value: 1.193153327357721
```

This section was included because some existing literature [8, 10] pointed out that families which had little kids in their family unit were less likely to involve in DR programs. However, these results do not indicate that the overall scores were higher in families without small children.

The only interesting finding we can extract is that families without children seem to have a higher environmental consciousness, so maybe offering environmental incentives to them in the case that a trial was established in Spain could be a good idea.

Finally, as in the last sections, the P-value and F-value are not low and high enough respectively to rule out the null hypothesis and chance out of the equation, so we have to take these results with a grain of salt.

5 Conclusions

5.1 Summary of Key Findings

In order to make it easier for the reader to understand the key findings of this study, I have elaborated a bullet list with the most important conclusions. These are the following:

1. Non-Economic incentives seem to be more appealing to the Spanish population, specifically those based on direct environmental actions (Tree Planting)
2. There seems to be slight to no difference between Public Acknowledgment and Discount for Municipality in general terms although there are some differences in terms of the total sample.
3. Young people prefer either Bill Discount and Tree Planting, which indicates that youngsters value financial aid but also have a great environmental consciousness.
4. The results of the analysis relating to the salary are non-conclusive.
5. More preference was shown to the Tree Planting incentive by those who have lower levels of Education. Graduates and postgraduates prefer economic incentives.
6. Homemakers prefer social incentives and giving back to the community, while retired people tend to prefer public acknowledgment. Also, unemployed people have a good acceptation for the economic benefits.
7. Spanish men seem to be more likely than women to engage in DR programs.
8. Individuals who live in the countryside prefer the environmental initiatives and are overall more likely to involve in DR programs. Also economic incentives seem to be more effective in the cities.
9. Families without children seem preffer environmental incentives.

It is very important to note, as I said before and I will say later, that these results must be taken with a grain of salt. More about this will be talked about in the following section.

5.2 Study Limitations

A key limitation of this study is the possibility for an insufficient sample size and representativeness. This relatively small, and potentially homogeneous sample might not be a full spectrum of the opinions and actions exhibited by the population. This is seen in the P-values and F- values that have been obtained, that don not make it possible to arrive at statistically significant conclusions. As such, the results need to be taken with a grain of salt even as they offer valuable hints.

Furthermore, the way in which data was gathered could be another factor to account for. While online surveys are convenient and cheaper, they face the issue of participants not putting in as much effort on many occasions. This could result in less informed, and thus inaccurate responses which would reduce the reliability or validity of data, although I tried to mitigate this issue implementing a manipulation check. This can be overlooked by conducting the survey in person or implementing a trial. There is usually much more engaged and serious participants there, as they are aware that their responses have a direct relevance to the matters of importance. The results would be a closer representation of the general population's real opinions and activities.

As well, a bigger budget could have been invested in this study, which would enhance its range greatly. More resources would grant me the possibility of including a larger sample, gaining a more robust and heterogeneous set of respondents. It would also enable a far more extensive data to be collected, but I would mainly suggest to implement field trials, such as in the UK [10], given the gap between self-declared preferences and actual preferences, which could compromise validity. While these limitations are present, this study provides a core starting point for further investigations in the area.

Although these findings are preliminary, the trends and preferences identified in this study provide valuable information for future research. This will provide an open door for the researchers to work on it more thoroughly, target its limitations and apply stronger methodologies.

5.3 Suggestions for Future Research

A larger, more diverse sample is necessary in future research so that the results are considered to be better representative and reproducible. As mentioned above, conducting face-to-face surveys or trials could offer more accurate insights into how participants may respond to these methods as compared with online option. In addition, future research should investigate the effect of a wider range of incentives on other demographic populations further and over time. The increase in budget would be beneficial to reach a bigger audience and refine the overall quality of the research. While this article provides groundwork, more research is required in order to realize the full potential of incentives.

5.4 Contribution

With this study I intend to put my grain of sand towards a better understanding of how to incentivize the consumers in Spain to be part od DR programs. This study can have a relatively important implication in the field, aiding other future researchers in narrowing their analysis and knowing better the difficulties I faced, and how to overcome them.

It also serves to gather the most important literature on Demand Flexibility in one place, which could help new researchers reduce the required time to get into the subject, and also get to know some other papers they may otherwise have missed.

Finally, I wanted to address the fact that this work can serve in the design of the energy aggregator business models and also in the regulation of energy flexibility markets. These two final uses are needed in order to establish DR programs and this work should be useful to provide some insights on how these issues should be treated.

All in all I feel like the future of energy in Spain must include DR programs, and this study has great potential to make a difference and aid the future regulations, researchers and companies in the difficult task to shape the future of a basic need such as the access to affordable, clean and reliable energy.

5.5 Final thoughts

Firstly, let me thank you for reaching this point in the text. I really appreciate that you read my research and I really hope you enjoyed it and took something valuable out of it.

I personally believe that there is a lot of work to be done in the Energy Flexibility department, and this work may not be conclusive but it shows the way for future researchers on where and on what to put their efforts and also shows all the difficulties I have faced.

Throughout the elaboration of this project I have learnt so many important lessons and I can confidently say that my environmental consciousness has increased significantly. I have also learnt how to conduct experimental research and how to summarize key findings from existing literature.

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Appendix

Google Forms File & Responses Links

- Google Forms
- Responses

Age ANOVA code

```

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns


file_path = '\path.xlsx'
df = pd.read_excel(file_path)
df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

df['Age'] = df['Age'].map({
    '75 años o más': '75 years or more',
    'De 18 a 24 años': '18 to 24 years',
    'De 25 a 34 años': '25 to 34 years',
    'De 35 a 44 años': '35 to 44 years',
    'De 45 a 54 años': '45 to 54 years',
    'De 55 a 64 años': '55 to 64 years',
    'De 65 a 74 años': '65 to 74 years'
})

df['ScoreBase'] = 0.25 * df['Probability'] \
                       + 0.25 * df['Difficult'] \
                       + 0.25 * df['Stressing'] \
```

```
                       + 0.25 * df['Compensate']


df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Age\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Age)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Age',
                          'Incentive'])['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Age and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Age Range', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Age.png', dpi=300)
plt.show()

```

Salary ANOVA code

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns

file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

df['Salary'] = df['Salary'].map({
    'Menos de 1000 €': 'Less than 1000 €',
    'De 1000 a 1999 euros': '1000 to 1999 euros',
    'De 1.000 a 1.499 euros': '1000 to 1499 euros',
    'De 1.500 a 1.999 euros': '1500 to 1999 euros',
    'De 2000 a 2999 euros': '2000 to 2999 euros',
    'De 2.000 a 2.499 euros': '2000 to 2499 euros',
    'De 2.500 a 2.999 euros': '2500 to 2999 euros',
    'De 3.000 a 3.499 euros': '3000 to 3499 euros',
    'De 3.500 a 3.999 euros': '3500 to 3999 euros',
    'De 4.000 a 4.499 euros': '4000 to 4499 euros',
    'De 4.500 euros o más': '4500 euros or more',
    'De 500 a 999 euros': '500 to 999 euros'
})

df['ScoreBase'] = 0.25 * df['Probability'] \
                       + 0.25 * df['Difficult'] \
                       + 0.25 * df['Stressing'] \
                       + 0.25 * df['Compensate']

df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))
```

```python

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Salary\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Salary)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Salary', 'Incentive'])['Score'
                                                  ].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Salary and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Salary Range', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Salary.png', dpi=300)
plt.show()

```

Education ANOVA code

```

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns

file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

education_order = {
    'Sin estudios': 'No Education',
    'Estudios primarios incompletos': 'Primary Incomplete',
    'Estudios primarios completos': 'Primary Complete',
    'Estudios secundarios (EGB, ESO)': 'Secondary',
    'Formación profesional': 'Vocational',
    'Bachillerato (BUP, COU)': 'High School',
    'Estudios universitarios (diplomatura, licenciatura, grado)':
    'Univ. Studies',
    'Estudios de postgrado (máster, doctorado)': 'Postgrad. Studies'
}
df['Education'] = df['Education'].map(education_order)

df['Education'] = pd.Categorical(df['Education'], categories=
                                 education_order.values(),
                                 ordered=True)

df['ScoreBase'] = 0.25 * df['Probability'] \
                    + 0.25 * df['Difficult'] \
                    + 0.25 * df['Stressing'] \
                    + 0.25 * df['Compensate']
```

```
df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Education\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Education)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Education', 'Incentive'])
['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False, colormap='viridis',
                      rot=0)

plt.title('Average Score by Education and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Education Level', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Education.png', dpi=300)
plt.show()
```

Employment Status ANOVA code

```python

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns


file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

work_order = {
    'Estudiante': 'Student',
    'Desempleado/a': 'Unemployed',
    'Ama de casa': 'Homemaker',
    'Empleado/a': 'Employed',
    'Autónomo/a': 'Self-employed',
    'Jubilado/a': 'Retired',
    'Otra situación': 'Other'
}
df['Work'] = df['Work'].map(work_order)

df['Work'] = pd.Categorical(df['Work'],
                            categories=work_order.values(), ordered=True)

df['ScoreBase'] = 0.25 * df['Probability'] \
                       + 0.25 * df['Difficult'] \
                       + 0.25 * df['Stressing'] \
                       + 0.25 * df['Compensate']

df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))
```

```
df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Work\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Work)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Work', 'Incentive'])
['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Work and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Work Status', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Work.png', dpi=300)
plt.show()
```

Gender ANOVA code

```
import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns

file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

gender_order = {
    'Masculino': 'Male',
    'Femenino': 'Female',
}
df['Gender'] = df['Gender'].map(gender_order)

df['Gender'] = pd.Categorical(df['Gender'],
                              categories=gender_order.values())

df['ScoreBase'] = 0.25 * df['Probability'] \
                + 0.25 * df['Difficult'] \
                + 0.25 * df['Stressing'] \
                + 0.25 * df['Compensate']

df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Gender\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Gender)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
```

```
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Gender', 'Incentive'])
['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Gender and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Gender', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=0, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Gender.png', dpi=300)
plt.show()
```

Location ANOVA code

```python

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns

file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

location_order = {
    'Urbana': 'Urban',
    'Rural': 'Rural'
}
df['Location'] = df['Location'].map(location_order)

df['Location'] = pd.Categorical(df['Location'],
                                categories=location_order.values(),
                                ordered=True)

df['ScoreBase'] = 0.25 * df['Probability'] \
                + 0.25 * df['Difficult'] \
                + 0.25 * df['Stressing'] \
                + 0.25 * df['Compensate']

df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())

print(f"\n{'='*40}\nANOVA for Location\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Location)', data=df).fit()
```

```python
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Location', 'Incentive'])
['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Location and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Location', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=0, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Location.png', dpi=300)
plt.show()

```

Presence of Kids in the familiar unit ANOVA code

```python

import pandas as pd
import numpy as np
import statsmodels.api as sm
from statsmodels.formula.api import ols
import matplotlib.pyplot as plt
import seaborn as sns

file_path = '/path.xlsx'
df = pd.read_excel(file_path)

df.columns = ['Hour', 'Over18', 'BornDate', 'Probability', 'Difficult',
              'Stressing', 'Compensate', 'Incentive', 'Age', 'Salary',
              'Education', 'Work', 'Gender', 'Location', 'Minors']

minors_order = {
    'No hay menores de 16 años': 'No minors under 16',
    '2 años': '2 years',
    '6 años': '6 years',
    '12 años': '12 years',
    '16 años': '16 years'
}
df['Minors'] = df['Minors'].map(minors_order)

df['Minors'] = pd.Categorical(df['Minors'],
                              categories=minors_order.values(),
                              ordered=True)

df['ScoreBase'] = 0.25 * df['Probability'] \
                + 0.25 * df['Difficult'] \
                + 0.25 * df['Stressing'] \
                + 0.25 * df['Compensate']

df['ScoreBase'] = df['ScoreBase'].apply(lambda x: max(x, 0))

df['Score'] = df['ScoreBase'] * (50 / df['ScoreBase'].max())
```

```python

print(f"\n{'='*40}\nANOVA for Minors\n{'='*40}")
model = ols('Score ~ C(Incentive) * C(Minors)', data=df).fit()
anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)

p_value = anova_table["PR(>F)"].iloc[0]
f_value = anova_table["F"].iloc[0]
print(f"\nF-value: {f_value}\nP-value: {p_value}")

plt.figure(figsize=(14, 10))

mean_scores = df.groupby(['Minors', 'Incentive'])
['Score'].mean().unstack()

ax = mean_scores.plot(kind='bar', stacked=False,
                      colormap='viridis', rot=0)

plt.title('Average Score by Minors and Incentive',
          fontsize=16, fontweight='bold')
plt.xlabel('Minors', fontsize=14, fontweight='bold')
plt.ylabel('Average Score', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, fontsize=12, fontweight='bold')
plt.yticks(fontsize=12)
plt.legend(title='Incentive', fontsize=12, title_fontsize=14)
plt.grid(True, which='both', linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.savefig('barplot_incentive_Minors.png', dpi=300)
plt.show()
```