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Tailored Gamification Platform based on Artificial Intelligence. Connected Thermostats as a Case Study for Saving Energy in Connected Homes

A thesis presented by

Juana Isabel Méndez Garduño

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Dedication

To my parents
Gandhi and Isabel, who taught me how to be persistent and for all your unconditional confidence, support, patience, and encouragement. You inspire me to be a better person every day and to not forget the spiritual aspect.

To the love of my life
Ana Victoria, thank you for being by my side at every step. For all your support and love. You inspire me to be a better person every day.

To my spiritual guide
Maestra Ana Victoria, thank you for your spiritual guidance that strengthened me when everything was good and bad. You give me the temperance to not get overwhelmed by my emotions and to act by impulse.

To my sister
Guadalupe, for your support, and for pointing out the importance of being healthy for better performance.

To my dearest friends
Oscar Cuq Martínez Martín (and your family), Adán Medina Rosales, Karla Rivera Vázquez, Iveth Ordoñez Sánchez, and Rocío Hernández Larriba for their encouragement and unconditional support throughout these years.

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Abstract

The product platforms are a set of system components that are interdependent with other system components. Furthermore, platforms are the basis for all technology-based products and allow collaborations for multi-product systems. Traditionally, products were created without third-party collaboration. Thus, the same owner's product upgraded, modified, or updated the product falling in limited customization, lack of integration, and modularity.

Evolving products into product platforms creates value, but it is complex to implement. The relevance of transitioning into product platforms relies on companies entering global markets. Therefore, platforms are cost-effective for global competition. For instance, around 60 % of technological companies value investing in platforms. Furthermore, the tendency shows that companies aspire to turn the business into a fully integrated digital technology company.

On the other hand, customers prefer a tailored service, platform, or product over generic products. Nevertheless, the adoption of these product platforms fails due to usability and behavioral problems. Hence, it is complex to measure individuals' satisfaction because their behavior is related to perception and other context-specific factors, such as age, gender, income, cultural aspects, specific needs, personality traits, and other preferences.

To achieve the adoption of product platforms, this thesis proposes to tailor user solutions by profiling the consumer through personality traits to propose strategies that allow them to adapt more easily to product usage. Thus, appealing ludic interfaces engage end-users to interact better with platforms. Therefore, social interaction (social platform) plays a primary role in understanding and knowing better the users' patterns and profiles them. In addition, it is feasible to understand consumers' habits by sending stimuli through gamification or serious game strategies. Gamification enhances a platform with affordances for gameful experiences to support the user's overall value creation. Besides, Artificial Intelligence decision systems link the type of consumer and gamification for deploying user-oriented product platforms.

Hence, this thesis proposed a four-step methodology for deploying tailored platforms and validating the methodology in a case study. Furthermore, this methodology was used in the context of smart homes, smart communities, and smart cities.

Contents

Chapter 1

Introduction

The platforms are a set of system components that are interdependent with other system components. Furthermore, platforms are the basis for all types of technology-based products and allow collaborations for multi-product systems [8]. Traditionally, products were created without third-party collaboration. Thus, the same owner's product upgraded, modified, or updated the product falling in limited customization, lack of integration, and modularity [5].

However, due to technological advances is achievable to turn products into product platforms [5, 7]. Hence, the more demonstrated value has the platform, the more likely the consumer will use the platform [5]. Deloitte [5] expresses that a product platform must have the following characteristics:

- They are virtual or physical platforms or both.
- They enhance new features.
- They allow functionalities modifications or additions.
- They create products for the Business to Business (B2B) model.
- They create products for the Business to Consumer (B2C) model.

Besides, they suggest categorizing the product platforms into four types [5]:

1. Aggregation platform: This platform eases transactions, connects users to resources, and operates on a hub-and-spoke model.
2. Social platform: This platform eases social interaction, connects individuals to communities [29, 33], and fosters relationships.
3. Mobilization platform: Move users to act together, fosters long-term relationships, and achieves shared goals.
4. Learning or tutored platform: This platform eases learning, brings participants together to share insights, and promotes teamwork. Tutored platforms fall in this category; this platform seeks to teach the users to learn new things with new learning methodologies [32].

Figure 1.1 exemplifies three product variants and the considerations when deploying platforms. Thus, the main goals of the shared elements in the platform are to (a) maximize the number of shared elements and variants; (b) reduce the number of unique elements; (c) use low-cost variant parts. In addition, Nadadur et al. [36] proposed a Venn diagram for the platform considerations. A platform must consider the regulation aspect in order to meet the criteria according to the local normative or international standards. Another element to consider is the business aspect, the product platform must have the capability to scale up and position itself within the global market. Furthermore, the user aspect considers the needs that the product must fulfill to satisfy the conventional consumer. This element considers the customization of the platform based on average demands. Unfortunately, the consumers have seen as a ”service user” that technology improves them and they must learn a set of skills to use the platform [12]. That product-oriented leads to usability and behavioral problems for adopting these new platforms due to the lack of tailored user-oriented platforms.

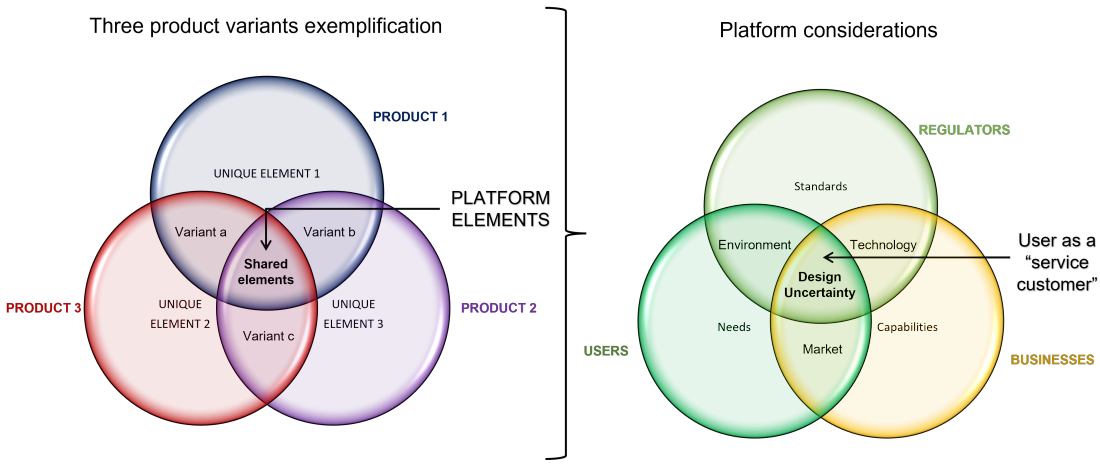

Figure 1.1: Types of Product Platform [5]

Furthermore, figure 1.2 depicts thirteen usability problems. There are eight behavioral problems when using platforms, devices, or products [32, 43]:

1. **Operation**: Consumers operate the platform differently than how the engineers intended or the manual establishes
2. **Ignorance**: Consumers do not understand the functions and feel complicated to use the platform.
3. **Indifference**: Consumers do not know or care about the benefits of the platform.
4. **Environment**: Consumers are not aware of the environmental impact.
5. **Interest**: Consumers' interests are different from the platform goal.
6. **Usage**: Consumers do not know how to use the platform system.
7. **Adaptation**: Consumers have a psychological, physiological, and behavioral adaptation that affects their adaptation

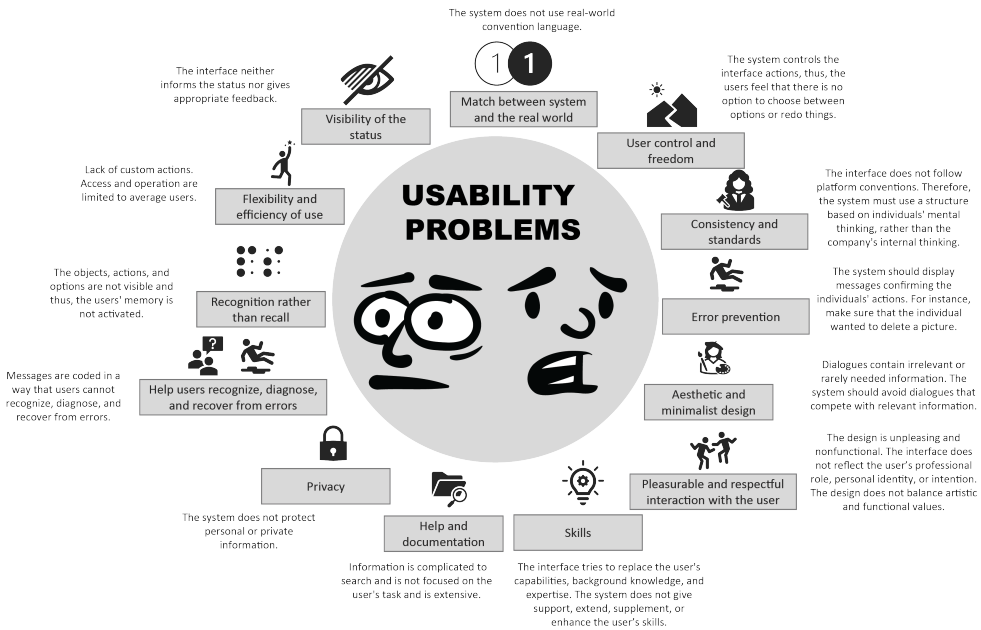

Figure 1.2: Thirteen usability problems when using devices [**?**]

8. **Energy Poverty**: Consumers face energy poverty problems and suppress their requirements to financially meet other basic needs leading to the misuse of platforms.

There are two approaches to learning how to use devices [12]. The banking model considers the consumer as a "service user" and technology improves the system. Hence, the individuals are consumers and not co-creators of services. Therefore, individuals must learn a set of skills that the technology deploys. Thus, consumers are containers waiting to be filled with the technological knowledge and skills to understand and live in the household. The other model is the creative consumer model, which focuses on the individuals. The consumers are active learners and involve a deeper understanding of the individual's current cultural knowledge and experience. Thus, this thesis focuses on the creative model as it focuses on the individuals rather than the service.

In that sense, attractive ludic Human-Machine Interfaces (HMI) engage end-users to better interact with platforms. In consequence, social interaction plays a primary role in understanding and knowing better the users' patterns and profiles them [29, 26, 43]. A manner of understanding better the type of user is through personality traits [11]. In [11, 17], the OCEAN model, or the "Big Five" personality traits, describe five personality traits depending on the perception and attitudes of the individual. The openness personality trait has a positive attitude toward learning new things and an appreciation of divergent thinking where new ideas are explored. The conscientiousness trait is responsible for a rational and clear purpose in life. The extraversion personality is optimistic, assertive, and loves social interactions that allow diverse activities. The agreeableness individual cooperates with sympathy and empathy for others. The neuroticism trait is bad-tempered, impulsive, and experiences negative emotions. [4, 32, 39, 49]. Moreover, each personality learns things and adopts technology differently [39]. Rammstedt and John [48] analyzed and concluded that it was reliable to reduce the 44 questions of the Big Five Inventory (BFI-44) into 10 questions (BFI-10). Thus,

the BFI-10 is a 10-question survey that measures personality traits in a minute using a Likert response scale: (1) Very inaccurate; (2) Moderately inaccurate; (3) Neither accurate nor accurate; (4) Moderately accurate; (5) Very accurate. In addition, there are global online datasets that provide insights about the personality traits around the world [1, 52].

In addition, another way to understand consumers' habits is by sending stimuli through gamification or serious games strategies [43, 32, 29]. Gamification enhances a platform with affordances for gameful experiences to support the user's overall value creation [9]. Furthermore, gamification uses game elements in real context to achieve specific goals, for instance, energy savings [43]. Gamification is a different concept than gaming, gamification uses game technology and elements in real-context environments to achieve goals by learning new concepts, whereas gaming has the only purpose of fun and is not focused on encouraging the users to achieve real-context goals [9]. Bartle [3] described four types of gamers (killer, achiever, explorer, and socializer); whereas Tondello et al. [50] linked those gamers into six gamified user types (disruptor, free spirit, achiever, socializer, philanthropist, achiever, player) and associated them with the personality traits.

Thus, they positively associated openness, conscientiousness, extraversion, and agreeableness traits with the philanthropist. The extraversion and agreeableness traits positively associate with the socializer type. The openness and extraversion traits positively associate with the free spirit type, and this same trait negatively associates with the neuroticism trait. The achiever SGs user type focuses on earning points and levels. The explorer type finds and gathers all the information available on the game and about the players. The main purpose of the socializer user type is to interact with other players. On the contrary, the killer type imposes on others to control them.

Therefore, Tondello et al. [50, 51] related the socializer player with the openness, conscientiousness, extraversion, and agreeableness personality traits. The explorer player relates with the openness, extraversion, and agreeableness traits. The achiever type associates with the conscientiousness trait, whereas the killer type with the neuroticism trait. Hence, the personality traits represent the main core in which each trait is related to a gamified or serious game user, energy end-user segment, and target group. Figure 1.3 shows in the middle part the main axis and the relationship with the gamified/serious game user in the upper part with their associated game design elements and in the lower part the energy target and segment.

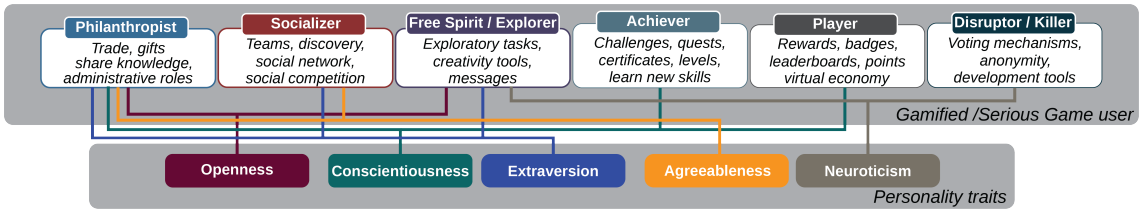

Figure 1.3: Personality traits and their association with the gamified/serious game user

Furthermore, a link between the type of consumer and gamification is required. A solution is through decision systems based on Artificial Intelligence (AI) [43]. Using current technologies in artificial intelligence as an adaptive neuro-fuzzy inference system (ANFIS), fuzzy logic, or neural network decision systems provides outcomes regarding the type of gamification elements required for deploying tailored human-machine interface (HMI).

The relevance of the adaption of these AI decision systems is that they emulate humans making decisions so goals can be achieved. Non-typical users are not considered when the products are designed and deployed [43]. Therefore, it is necessary to understand how the consumer behaves or thinks to propose tailored product platforms for all types of users, typical and non-typical. The following chapters employed three AI techniques: fuzzy logic, two-layer feed-forward artificial neural networks (ANN), and adaptive neuro-fuzzy inference systems (ANFIS).

Fuzzy logic Type-1 was employed to test the most used elements in a gamification application. In 1965, computer scientist Lotfi [53] from the University of California Berkeley proposed fuzzy set theory as a class of sets based on membership grades from 0 to 1 and inference rules that do not require a mathematical model of the real system, but rather, rules generated by experts, polls, or consensus-building [40, 46]. Fuzzy logic models uncertainty based on linguistic words and sentences (linguistic variables) associated with human logic. Thus, numerical and mathematical expressions are not needed.

Artificial Neural Networks (ANN) extract information from experimental data or databases determined by human experts. The most used topologies are the feed-forward or forward propagation network and the recurrent network. The feed-forward network's information flows from inputs to outputs and is exclusively forward. Therefore, it continues through multiple layers of units with no feedback connection. Opposite, the recurrent network has feedback connections derived from a process of evolution towards a stable state with no changes in the activation state of neurons. [40]. In 1943, McCulloch and Pitts [18] introduced the first simple artificial neuron. A Neural Network is characterized by a set of processing units or neurons, an activation state for each unit equivalent to the unit's output, and connections between units.

On the other hand, adaptive neuro-fuzzy inference systems (ANFIS) are based on adaptive networks, which are a superset of feedforward artificial neural networks with supervised learning capabilities [40]. Occasionally, conventional mathematical modeling algorithms do not deal with vague or uncertain information. Thus, Fuzzy systems using linguistic rules (IF-THEN) have the strength and ability to reason as humans without employing precise and complete information. However, a problem arises, how to transfer human knowledge to a fuzzy system. Several proposals have been made, such as combining artificial neural networks with fuzzy systems. Artificial neural networks have the ability to learn and adapt from experience, thus complementing fuzzy systems. Among the most important techniques is the ANFIS, an adaptive neuro-fuzzy inference system proposed by Jang [10] in 1993, which generates fuzzy IF-THEN rule bases and fuzzy membership functions automatically. An adaptive network is a structure consisting of nodes and directional links through which the nodes are connected, their outputs depend on the parameters of these nodes, and the learning rule specifies how these parameters should be changed to minimize a prescribed error measure [40].

In 1943, McCulloch and Pitts [81] introduced the first simple artificial neuron. A Neural Network is characterized by a set of processing units or neurons, an activation state for each unit equivalent to the unit's output, and connections between units. These neurons are usually defined by a weight that determines the effect of an input signal on the unit; a propagation rule that determines the effective input of a unit from external inputs; a trigger function that updates the new trigger level based on input effect, and previous action; an external input that is the bias for each unit; a method of gathering information corresponding to the learning rule; and an environment where the system will operate, with input signals and error signals. The

most used topologies are the feed-forward or forward propagation network and the recurrent network [40]. The feed-forward network's information flows from inputs to outputs and is exclusively forward. Therefore, it continues through multiple layers of units with no feedback connection. Opposite, the recurrent network has feedback connections derived from a process of evolution towards a stable state with no changes in the activation state of neurons.

1.1 Motivation

This doctoral research started with the funding project "A Strategy to Increase Energy Savings from Smart Thermostats Based on Gamification and Deep Learning". This project was won in 2019 and funded by the CITRIS-ITESM Seed Funding Program [37]. This program *supports binational collaborations between Tecnologico de Monterrey (ITESM) and CITRIS and the Banatao Institute that further our mutual research interests, strengthen connections among the campuses, and catalyze early-stage research that can lead to external funding.* [37]

Evolving products into product platforms creates value, but it is complex to implement [7]. The relevance of transitioning into product platforms relies on companies entering global markets [6]. Therefore, platforms are cost-effective for global competition. For instance, around 60 % of technological companies value investing in platforms. Furthermore, the tendency shows that companies aspire to turn the business into a fully integrated digital technology company [7].

On the other hand, customers prefer a tailored service, platform, or product rather than generic products [5]. Nevertheless, the adoption of these product platforms fails due to usability and behavioral problems [43]. Hence, it is complex to measure individuals' satisfaction because their behavior is related to perception and other context-specific factors, such as age, gender, income, cultural aspects, specific needs, personality traits, and other preferences [32].

To achieve the adoption of product platforms, tailored user solutions seem feasible as this type of solution focuses on understanding better the consumer to adapt the product to the user's needs instead of expecting that the consumer adapts to the product platform.

Hence, considering the user's personality traits is required so customers can easily adopt those product platforms. Thus, appealing ludic HMI engages end-users to better interact with platforms [43]. Therefore, social interaction (social platform) plays a primary role in understanding and know better the users' patterns and profiles them [26, 29, 43]. In addition, by sending stimuli through gamification or serious game strategies [29, 32, 43], it is feasible to understand customers' habits. Gamification enhances a platform with affordances for gameful experiences to support the user's overall value creation [9]. Besides, AI decision systems link the type of consumer and gamification for deploying user-oriented product platforms.

1.2 Problem Statement

Product platforms orient and improve their solutions based on product needs [5] so that customers adapt to them rather than the product adapts to the customer [12]. Therefore, tailored user solutions are required so that customers can easily adopt those product platforms.

Research suggests that tailoring products are feasible by profiling the consumer through

their personality traits through gamification strategies to teach, engage, and motivate consumers to target specific goals [34, 43]. Moreover, in [43], they proposed to profile end-users to understand their expectations and their usability and behavior problems to propose tailored interfaces. platforms based on their needs. Hence, the combination of gamification and AI techniques allows designers to achieve a dynamic interface that engages end-users to adopt new technologies. Furthermore, dynamic interfaces improve the sustainability of connected devices in smart homes or buildings.

State-of-the-art shows that there does not yet exist a tailored dynamic product platform that uses gamification and SGs through a set of AI decision systems for deploying user-oriented platforms. Hence, this dissertation proposes to bridge the gap between users' expectations and their usability and behavior problems through a platform framework methodology.

This thesis dissertation proposes a methodology for deploying tailored gamified product platforms for user-oriented solutions. Thus, this thesis reviews and studies aspects of personality traits, behavior, adaptation, gamification, serious games, AI techniques to deploy tailored platforms depending on the specific goal to achieve. Therefore, a framework product platform must address strategies to engage consumers in adopting the products or targeting specific goals such as energy reductions without losing thermal comfort by providing step-by-step how to deploy tailored ludic tailored platforms.

1.3 Research question

The main objective of this thesis is to create a framework that supports the development of tailored gamified platforms for deploying tailored user solutions based on artificial intelligence decision systems.

1. What steps should a platform based on artificial intelligence be considered for deploying tailored user-oriented solutions?

This research objective and research question are validated through a case study of a household located in Concord, California. The goal of this case study was to provide a tutored interface platform based on energy simulations of a household located at Concord to analyze energy savings and thermal comfort depending on the setpoint and location.

1.4 Solution Overview

Social products have been proposed for the design process or for developing social products in platforms. An approach to this product platform has been made for smart home applications. There are social products platform that serves and fulfill the occupants' comfort demands [2, 19, 20, 32, 30], for recreation, well-being, and safety [47], for monitoring householders' health through smartphones, wearables, cameras, or voice assistants connected to the home [28, 31]. Other implementations relate to employing socially connected platforms to profile consumers based on their personality traits, type of gamified user, and energy user [29, 32, 43].

It is, therefore, necessary to understand how the user behaves or thinks to propose tailored products for those non-typical users that are not considered when the products are designed and deployed. In this regard, tailored products based on gamification and serious

games structure within AI decision systems are proposed for all types of users (typical users and non-typical users) when the products are designed and deployed.

Thus, this thesis proposes four steps for deploying tailored user-oriented platforms to bridge the gap between the information provided by the platform, the consumer's expectations, and the HMI. Figure 1.4 depicts the platform proposal. First, determine the platform's goal; as this type of platform is focused on users, it is imperative to ensure that the Quality of Life is considered. Then, learn the user characteristics, their associated gamified elements, and the platform usage patterns. Following, perform statistical data analysis to obtain the insights and patterns of the data from the previous steps; during this step, as suggested by [5], consider the national or global regulations. Once determined, employ an AI decision system to consider the strategies based on the goal and the statistical data outcome. Finally, propose a tailored dynamic gamified platform. Once ended, in a period of six months, answer the question, "is the goal achieved" if it was not achieved, then adjust the platform in the first step and provide feedback when needed.

Furthermore, some applications of this platform proposal include education [13]. energy savings [14, 16, 21, 22, 35, 42, 43], thermal comfort [2, 19, 20, 32, 30], rapid prototyping [26, 34], healthcare sector [25, 28, 31, 41]; transition to smart communities or smart cities [15, 23, 24, 27, 29, 33, 44, 45, 47]. Other applications could be oriented to reduce CO_2 emissions during the manufacturing process.

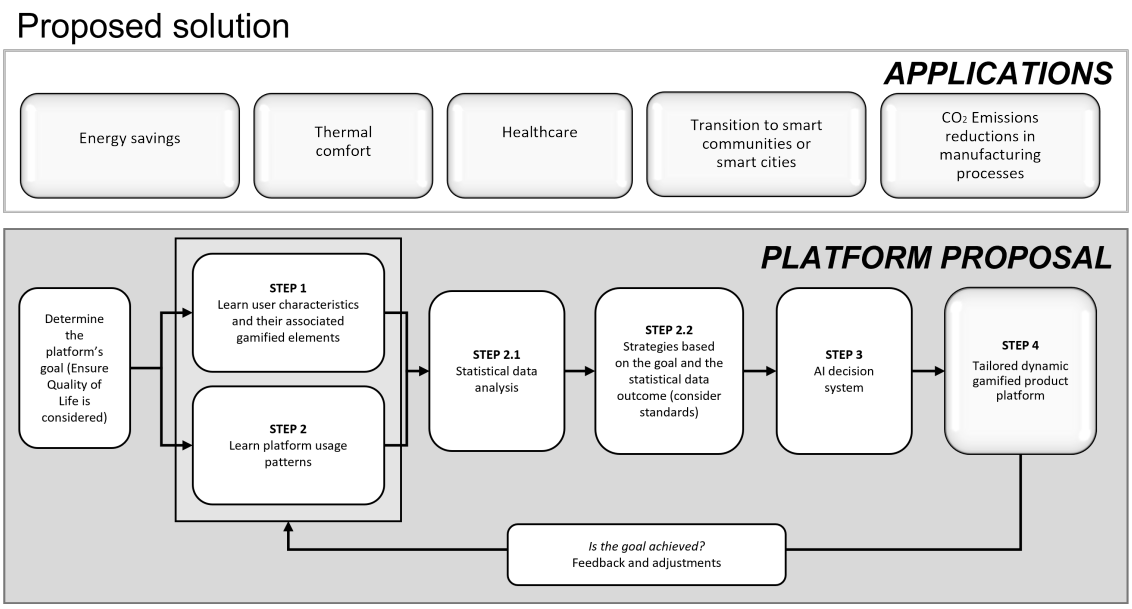

Figure 1.4: Proposed solution

This proposal has the following advantages:

- The decision system is adopted depending on the problem.
- This platform is tailored for user-solution needs.
- Provide a set of needs and preferences.

- Allow modular functionalities and applications

This proposal has the following disadvantages:

- Information about the user type is needed to tailor the interface or assume a generic *persona*.
- This proposal does not consider real-time interaction.
- This proposal, depending on the problem, requires a large amount of data. For example, when predicting energy consumption and thermal comfort. An energy model must be simulated.
- The tailored interface requires to be tested in a real context.

This proposal has the following limitations:

- The proposal is based on simulations. Thus, the interface platform requires real-time implementation.
- This proposal considers three AI decision systems, but it is not limited to these techniques. It can be expanded in the future.
- This proposal considers the Big Five personality traits. However, user profiling can be expanded by including other user characteristics.
- This proposal considers gamification elements associated with personality traits. However, other game techniques can be included.

1.5 Methodology

This proposal suggests a four-step methodology for deploying tailored gamified platforms (See Figure 1.5).

1. Step 1: Learn user and product type.
    - This step collects the information provided by databases, surveys, and literature reviews. During this step, the collected data helps to profile the user type. For instance, profile the householder depending on the type of energy end-user, personality traits, gamified or serious game user [29, 32, 43]. Furthermore, here, the household appliance is analyzed through surveys or simulations. For example, the energy impact of the connected thermostat is analyzed through energy simulations or surveys such as the RECS, RASS, ENCEVI, or similar [32].
2. Step 2: Learn building, process, or service usage pattern

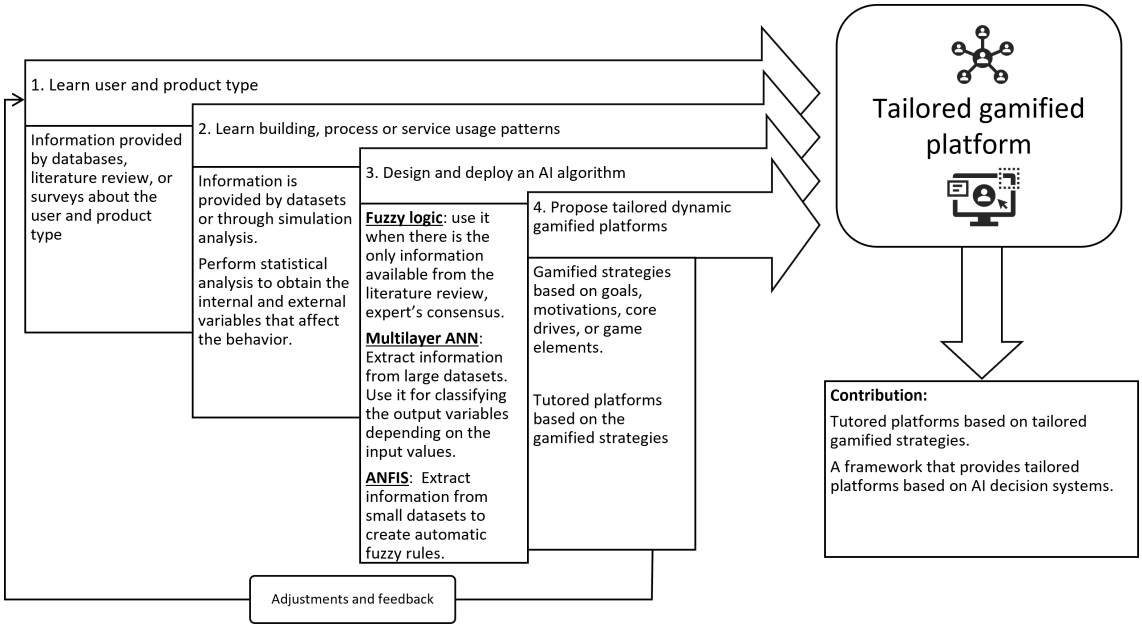

Figure 1.5: Methodology

- This step performs simulations and analyzes the platform product usage pattern, process, or service through statistical analysis to determine the internal and external variables that affect the product behavior associated with the users' characteristics. For instance, in an energy household application, through descriptive statistics, information about the outdoor and indoor temperature, thermostat setpoints, occupant behavior, and adaptive thermal comfort are obtained [2, 19, 20, 30, 32].

3. Step 3: Design and deploy an Artificial Intelligence algorithm

- This step proposes a decision system based on AI. During this research, three types of AI were applied depending on the study's objective and the available information.
  - Fuzzy logic: Gathers the information from the literature review, expert's consensus, or databases to obtain the descriptive statistics for implementing the rules and membership functions [22, 25, 31, 33, 34, 43]. Furthermore, if the dataset contains representative data, it is better to use artificial neural networks.
  - Artificial Neural Network: Extract information from datasets and help classify output variables depending on the input values. The topology used during this research was the feed-forward or forward propagation network to predict energy consumption, cost, thermal comfort, and game elements based on the location, date, and personality traits [26, 27, 32]. If there is not enough information available in the dataset and it is better to implement fuzzy inference rules, it is better to use adaptive neuro-fuzzy inference systems (ANFIS).
  - ANFIS: Extract information from datasets to create fuzzy inference rules. For instance, this decision system was used to create automatic fuzzy rules

to classify the seniors' emotions based on their facial expressions [28] or to suggest game elements based on the energy consumption and thermostat setpoint [2, 35]. During this research, the Neuro-Fuzzy Designer toolbox from MATLAB was employed. The limitation that this toolbox has is that it only allows one output.

4. Step 4: Propose tailored dynamic gamified platforms.

   - This step launches a dynamic interface platform that works as a tutored platform by providing gamified strategies based on goals, motivations, game elements or core drives [29, 32, 33]. The theory of planned behavior suggests evaluating six months prior to the implementation and analyzing if the goals are achieved, and individuals are adopting, for instance, the platform [43].
   - These dynamic gamified platforms can be built into software such as LabVIEW or SIMULINK.

Furthermore, Figure 1.6 exemplifies this proposed methodology employed for the validation of the proposal through Concord's household case study.

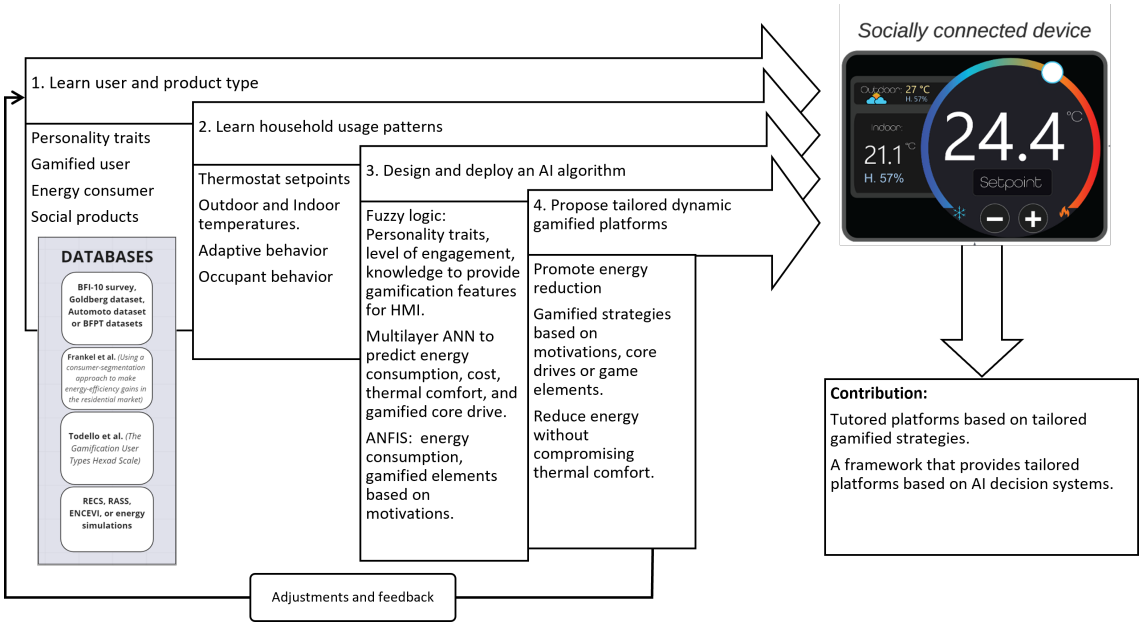

Figure 1.6: Case study validation methodology

Another application of this methodology was used for deploying a tailored platform based on personality traits and electricity bills in Mexico [29] (See Figure 1.7).

Moreover, this methodology is not only limited to product platforms such as connected thermostats or connected interfaces. Figure 1.8 shows the methodology applied for educational purposes for engaging the students in solving mathematical problems [13].

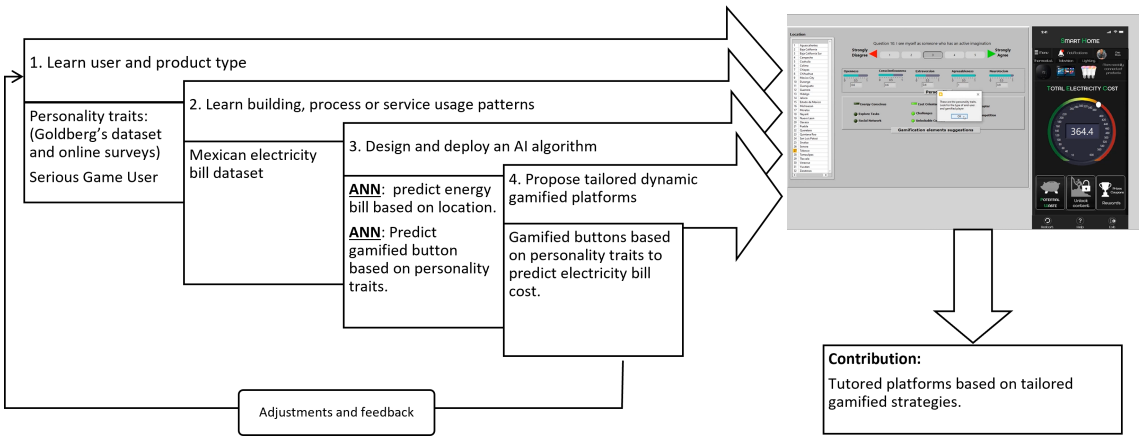

Figure 1.7: Methodology employed for the tailored platform in the Mexican context.

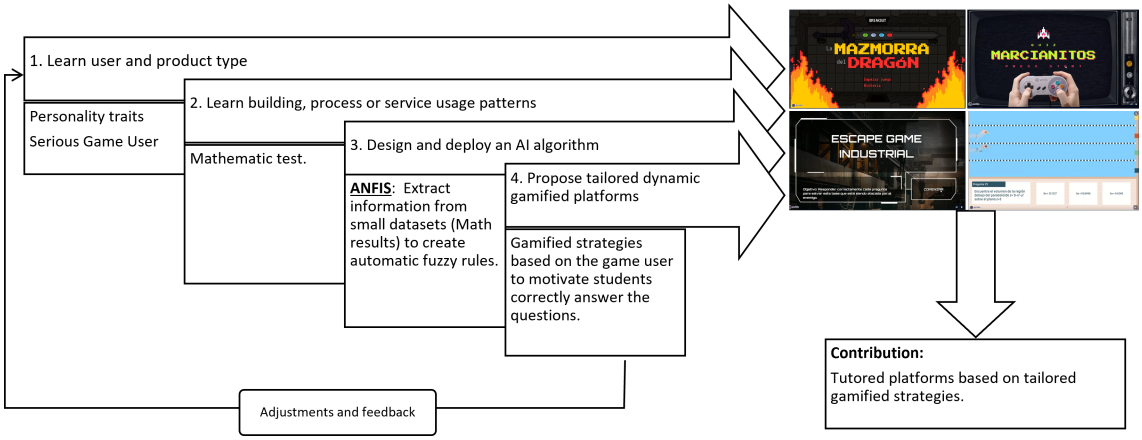

Figure 1.8: Methodology employed for solving mathematical problems.

1.6 Outline

This thesis is structured as follows:

- **Chapter 2** belongs to the publication [32]. This chapter presents step-by-step how two deploy interactive and tutored platforms for a connected thermostat in a home. This research details how to save energy without losing thermal comfort and describes the limitations and implications of reducing energy and preserving thermal comfort.
- **Chapter 3** refers to this paper [31]. This chapter presents how to deploy interactive healthcare monitoring for pre-diagnosis symptoms through an interface platform. This research works as an ally for the healthcare expert by providing information about the consumer and their mental behavior within a smart home environment.
- **Chapter 4** corresponds to this research paper [29]. It develops step by-step the implementation of a tailored gamified platform for smart communities with the objective of teaching residential consumers how the electricity bill affects depending on the location.
- **Chapter 5** presents a two-part publications [20, 30]. It exemplifies the energy consumption and thermal comfort differences in three communities with different environmental conditions to address strategies that help in the reduction of energy consumption without losing thermal comfort.
- **Chapter 6** belongs to this research [23] and exemplifies how to transition from smart homes to smart communities and smart communities to cities. Furthermore, this chapter evaluates the level of energy consumption in households to classify them into three types of environmental homes.
- **Chapter 7** depicts the paper [43] by detailing how to deploy a product platform. It reviews the aspects behind successful gamification strategies related to the users' expectations, personality traits, behavioral theories, and various game elements applied for gamification.
- **Chapter 8** presents the final remarks of this thesis and discusses the two types of interactions explored throughout the chapters and their limitations. Provide conclusions, the main contributions, and future work.

Chapter 2

Empowering saving energy at home through serious games on thermostat interfaces

2.1 Summary of the Chapter

This chapter presents a research journal paper on two types of tutored platforms. Thus, an interactive interface and a predicted interface are proposed. The main contribution of this research relies on proposing tailored dynamic interfaces focused on the user and their thermal comfort. Thus, this paper employed the methodology presented in 1.5.

This proposal is focused on the residential sector. Hence. the residential Heating Ventilation and Air-Conditioning (HVAC) system use around 3/5 of the total energy consumption. Connected thermostats optimize the HVAC operation; however, householders have personality traits that lead to behavioral and usability problems with the thermostat's interface usage. Thus, a serious game applied in the thermostat interface can balance entertainment and education. Therefore, thermostat interfaces must address strategies that reduce energy without losing thermal comfort.

This research proposed an interactive interface type and a predicted interface type based on an HVAC strategy and a Natural Ventilation strategy. These strategies measured the impact of adaptive thermal comfort, energy consumption, and costs. Hence, twelve energy models located in California (Concord, Riverside, Los Angeles, and San Diego) were simulated using EnergyPlus™ through LadybugTools. The first interactive interface included Serious Game elements, so the householder interacted with the date, location, and setpoint. The second interface predicted the energy consumption and thermal comfort during winter and summer in Concord by a two-layer feed-forward Artificial Neural Network structure. The proposed structure decreases energy consumption by at least 62% without losing thermal comfort.

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Empowering saving energy at home through serious games on thermostat interfaces

Juana Isabel Méndez [a,*], Therese Peffer [b], Pedro Ponce [a], Alan Meier [c], Arturo Molina [a]

[a] School of Engineering and Sciences, Tecnologico de Monterrey, Mexico
[b] California Institute for Energy and Environment, University of Berkeley, United States
[c] Energy and Efficiency Institute, University of California, Davis, United States

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ABSTRACT

The residential Heating Ventilation and Air-Conditioning (HVAC) system use around 3/5 of the total energy consumption. Connected thermostats optimize the HVAC operation; however, householders have personality traits that lead into behavioral and usability problems toward the thermostat's interface usage. Thus, a serious game applied in the thermostat interface can balance entertainment and education. Therefore, thermostat interfaces must address strategies that reduce energy without losing thermal comfort. This paper proposed an interactive interface type and a predicted interface type based on an HVAC strategy and a Natural Ventilation strategy. These strategies measured the impact of adaptive thermal comfort, energy consumption, and costs. Hence, twelve energy models located in California (Concord, Riverside, Los Angeles, and San Diego) were simulated using EnergyPlus™ through LadybugTools. The first interactive interface included Serious Game elements, so the householder interacted with the date, location, and setpoint. The second interface predicted the energy consumption and thermal comfort during winter and summer in Concord by a two-layer feed-forward Artificial Neural Network structure. The proposed structure decreases the energy consumption by at least 62% without losing thermal comfort.

1. Introduction

In 2020, the US electricity consumption was about 3.6 trillion kW; the residential sector contributed 40% to the electricity consumption and 22% to the energy consumption [1]. The Heating Ventilation and Air-Conditioning (HVAC) system is the greatest energy consumer in this sector, with about 40% to 60% [2–5]. Existing technologies can reduce envelope losses, increase the efficiency of HVAC systems, or control the HVAC operation [6]. Thermostats control the HVAC systems, and more than 86% of the residential buildings have one, representing an opportunity area to optimize HVAC usage [2]. Householders set their thermostats based on their behavioral adaptation, garments, and activities [7–9] affecting the impact on energy use [2–5,10]. Connected thermostats can reduce energy consumption from 10% to 35% of the peak load and 5% of occupant energy efficiency due to behavioral change [11,12]. Nevertheless, Fanghella and Della Valle [13] suggested that end-user behavioral factors explain up to 50% of the variance of overall cooling and heating consumption.

In that sense, attractive gamified Human–Machine Interfaces can engage end-users to better interact with the thermostat [14–16]. Moreover, Ponce et al. [14] suggest using Serious Games (SGs) within the thermostat interfaces as they balance entertainment and education to teach, engage, and motivate householders reduce energy consumption. SGs focus their efforts on teaching end-users specific topics such as energy reduction to improve their skills, acquire knowledge, and get more experience. Thus, SGs consider experience, multimedia, and entertainment elements to teach, engage, and motivate individuals to achieve specific targets like energy savings. Some SGs applied to the energy topic include end-users interacting with household appliances to see how their actions, either by a single user or by all family members, affect the energy consumption [14,17–19].

Thus, changing user behavior through real-time feedback, historical feedback, financial information, social influences, gamification, and goal-setting strategies can decrease energy consumption by 18% [20]. However, to succeed in those reductions, it is relevant to focus on the end-users' behavior and usability problems, for instance, when using a thermostat [14,21–26]. Hence, Ponce et al. [14,27] classified the householders based on their personality traits Ponce et al. [14,27,28], SG user [14,29–31], and energy end-

* Corresponding author at: CDMX, Calle del Puente 222 Col. Ejidos de Huipulco, Tlalpan C.P. 14380, Mexico.
E-mail address: A01165549@tec.mx (J.I. Méndez).

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user segment [14,24,27,32,33] when socially connected devices are deployed [16,34].

Additionally, Ponce et al. [14] described six behavioral problems that avoid energy savings through thermostats: (1) Users operate the thermostat differently than how the engineers intended or the manual establishes [22]. (2) Users do not understand the functions and feel complicated to use the thermostat. (3) Users do not know or care about the benefits of thermostats. (4) Users are not aware of the environmental impact. (5) Users' interests are different from energy saving. (6) Users do not know how to use the HVAC system. Nevertheless, two additional behavioral problems must be added: (7) Users have a psychological, physiological, and behavioral adaptation that affects their thermal comfort [7,9], preventing the reduction in energy consumption. (8) Users face energy poverty problems [35,13,36,37] and suppress their energy requirements to financially meet other basic needs avoiding energy-saving behavior and leading to the misuse of thermostats.

The psychological dimension derives from the perception and reaction to past experiences and expectations [7,9]. The physiological adaptation relates the body reaction based on genetic adaption and acclimatization with the exposure to thermal factors [7,9]. The behavioral adjustment considers the personal, technological, and cultural responses that an individual perform to adapt to their environment [7,9].

The thermal comfort concept gained attention since the 1920s as it became possible to control indoor temperatures [38]; however, it was until the 1970s that Fanger [39] proposed the Predicted Mean Vote/Predicted Percentage of Dissatisfied (PMV/PPD) method. This method considers six mandatory parameters [40]: metabolic rate, clothing insulation, air temperature, air speed, and humidity. In 1998, de Dear and Brager [7] proposed the adaptive method based on human behavior through three categories of thermal adaptation (behavior, clothing, and air temperature). In 2002, Nicol and Humphreys [9] included the outdoor temperature to calculate the range of thermal comfort temperatures at indoors. The occupants feel free to adjust the clothing insulation and accept wider ranges of indoor temperatures during swing seasons that fall outside the conventional adaptive comfort zone [41].

Adaptive behavior requires considering the conditions to which an individual is exposed. The behavior includes adaptive and non-adaptive actions [35]. The adaptive actions occur when the individual opens or closes windows, adjusts thermostat setpoints, uses heaters or coolers, or adapts through a set of actions as a response to warm or cool environments [35,42]. The non-adaptive actions rely on reporting discomfort, occupant presence, or data gathering from sensors [35]. Therefore, Humphreys et al. [43] outlined how householders use strategies to achieve thermal comfort, such as selecting areas shaded by trees or sheltered from the wind, occupying rooms based on the season, selecting the type of HVAC system, thermostat, ceiling fans, or another type of control to increase the air movement inside a room to cool the occupants and become comfortable [44]. Other strategies include selecting the garments and activities based on the climate, season, indoor temperature, or fashion style. Thus, they pointed out that householders have attitudes toward the indoor operative temperature because users accept wider ranges of indoor temperature to save or spend money.

By considering the outdoor temperature, it is unnecessary to think about other factors such as humidity or air movement because thermal comfort can be achieved by clothing insulation or even by metabolic rates [9]. Besides, adaptive thermal comfort provides opportunities to reduce costs and become energy efficient, and an example is by changing clothes with few to little cost or adjusting setpoints [8,21]. During cooling periods, increasing the setpoint by 1.8 °F (1 °C) can save 6% of electricity [15]. In [45], they used the adaptive comfort model in Europe, and depending on the location, they found an energy saving of 35% compared with a static setpoint.

It is complex to measure the satisfaction of householders because their comfort is related to perception and other context-specific factors, such as age, gender, income, cultural aspects, specific needs, or any possible disability or long-term illness beyond climate zones [3,37,38,42–44]. Unfortunately, the income aspect may affect the thermal comfort perception because although users would prefer to be comfortable, a lack of income or inadequate levels of essential energy services in the household lead to domestic energy deprivation or better known as energy poverty condition [13,35–37]. Low-income homes spend less or around 2/3 of their income on fuel conducting to a lack of thermal comfort [36].

Furthermore, the authors of this research had proposed gamified strategies that reduced energy through tailored interfaces [14,15,34,46–51]. Nevertheless, until this paper, they simulated the thermal comfort and energy consumption in different locations to be added within the thermostats' interfaces.

Existing energy building simulators such as EnergyPlus™ can predict the overall energy consumption and the two thermal comfort models, the adaptive and the PMV/PDD model [4,52–56]. This software bases its features and capabilities on BLAST and DOE-2, two different software tools that were in development in 1996 by the Department of Energy [52]. Honeybee Energy from Ladybug Tools (LT) uses EnergyPlus™ for the simulation. LT from Grasshopper visual programming language is a graphical interface that runs within the Rhinoceros software [57]. Examples of applying these tools include:

- The analysis of thermal mitigation potential of façades in Copenhagen, Madrid, Brindisi, and Abu Dhabi [58];
- the modeling of outdoor thermal comfort to get the UTCI values and energy demand in urban canyons [59];
- an algorithm proposal that finds the optimal skylight design while saving energy by considering the impacts of daylight [60];
- the energy performance analysis of a building that integrates photovoltaic panels on façades for power generation [61–63].

Fig. 1 shows the two types of approaches used for thermal comfort and the thermal scales; Fig. 1(a) depicts the building or group approach that considers the six parameters proposed by Fanger [39] and considered in the ASHRAE 55 Standard [40]. Fig. 1(b) shows the human-centered approach or the adaptive thermal comfort [8]. This paper focuses on adaptive thermal comfort as it is demonstrated that it fits better in the residential sector [3]. Fig. 1 (c) shows three types of scales used to measure thermal comfort: the thermal sensation, the thermal preference, and the thermal stress.

The thermal sensation is often known as the predicted mean vote (PMV) index. The ideal scale is the 4 where the individual feels comfortable, or no changes are required in the indoor room [8]. The thermal preference vote is a sensation scale that map the individual's preference when operating HVAC systems or performing activities [64]. Additionally, to avoid local thermal discomfort due to cold feet when the individual prefers warmer temperature or has hot head but prefers cooler temperatures, the body requires to stay in heat balance and adaptive strategies can be addressed as turning on electric fans or put the feet on cold water or cover their feet with warmer socks. The Universal Thermal Climate Index (UTCI) reflects the human physiological reaction to the actual thermal condition and is categorized as thermal stress [65]. Therefore, an individual can have no thermal stress within an air temperature range from 48.2 °F to 78.8 °F (9 °C to 26 °C).

Artificial Intelligence (AI) can classify clothes and predict thermal comfort [21], energy consumption [34], or propose rules to

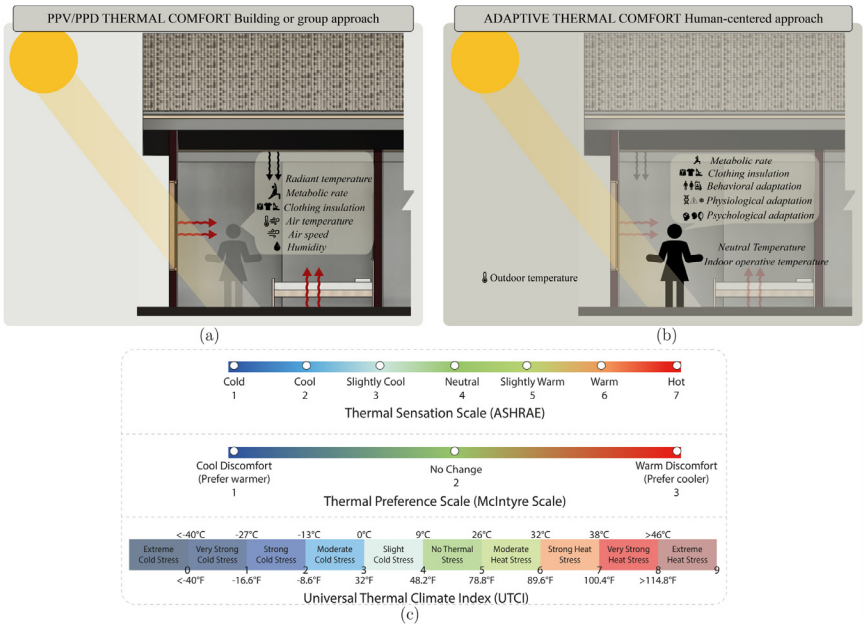


Fig. 1. Thermal comfort approaches: (a) Building or group approach, (b) human-centered approach, and (c) thermal scales.

classify the type of end-user and propose game elements that teaches, engages, and motivates householders in reducing energy even if they are not interested [14,24,27,46].

Hong et al. [66] employed the thermal sensation scale to predict energy savings in a fifteen-floors residential apartment. Ngarambe et al. [67] suggested using AI methodologies to predict thermal comfort. Alamin et al. [68] proposed an Artificial Neural Network (ANN) to predict the energy consumption of the fan-coil by considering as the input variables the energy consumption of the fan-coil for one sample delay and two sample delays, the impulse air velocity, and the indoor air temperature. Zhang et al. [69] used the six factors of the PMV/PPD model to predict if the space was comfortable. Another proposal analyzed occupied periods in a residential building to include a temperature control algorithm to predict setback temperature for the cooling system [70]. Other predictions included the use of input variables as outdoor temperature, outdoor relative humidity, Indoor temperature, cooling load, air handling unit supply air temperature, condenser fluid temperature setpoint, and condenser fluid pressure setpoint to predict the total amount of cooling energy consumption for the next hour [71].

However, none of these proposals included the adaptive theory comfort applied on the thermostat usage as setpoint, date, and location to link those parameters into an SG interface. Thus, the end-user could learn in a ludic manner without being intrusive about the implications of changing those parameters with the thermal comfort, energy usage, and bill costs. Hence, the research question that this paper focuses on addressing is as follows:

- What requirements does a Serious Game interface need to teach the end user the benefits of using an adaptive strategy to promote energy and money savings without losing thermal comfort?

The remainder of this paper is as follows. Section 2 provides a reference framework for tailoring SGs interfaces. Section 3 describes the methodology used in each step of the framework to simulate the energy models and strategies for predicting thermal comfort and energy usage. As a result, Section 4 deploys two types of interactive interfaces for a connected thermostat. Section 5 describes the scope of the research and discusses the advantages and disadvantages of the study. Finally, conclusions and suggestions for future work are presented in Section 6.

2. Proposed framework

Fig. 2 describes the five steps required to deploy a custom SG interface. This reference framework allows for a continuous adjustment and feedback environment that analyzes the end-user engagement and energy or monetary savings. Hence, the platform can update the SGs design elements to continue engaging the occupant. Ponce et al. [14] showed that occupants must play an active role in the energy platforms to give them the desire to control their energy behavior.

2.1. Step 1: User and product type identification

Fig. 3 depicts the relationship between the personality traits, SGs player type, and energy end-user segment. During this step The personality trait type, energy end-user type, SG player type, SGs design elements, and product type for energy-saving platforms are identified (see Fig. 3).

2.1.1. Personality traits

Oliver and Srivastava [28] defined the OCEAN model with particularities in each trait. The openness personality trait appreciates divergent thinking and novel ideas with a curious and imaginative attitude. The conscientiousness trait is a rule-follower with clear goals in life. This user type is self-discipline, competitive, and responsible. Both openness and conscientiousness traits are positive to learn new things through the internet while saving energy. Extroversion traits prefer social interaction, exciting and varied activities, and have a confident and optimistic attitude; the higher level of extroversion, the more inclined to save energy. The agreeableness trait has a modest, cooperative, and altruistic nature with a sympathetic and tolerant attitude to others, and with inclinations to save energy. On the contrary, the neuroticism trait experiences negative emotions leading to an impulsive, stressful, and bad-tempered attitude. Higher neuroticism levels indicate a positive energy-saving attitude.

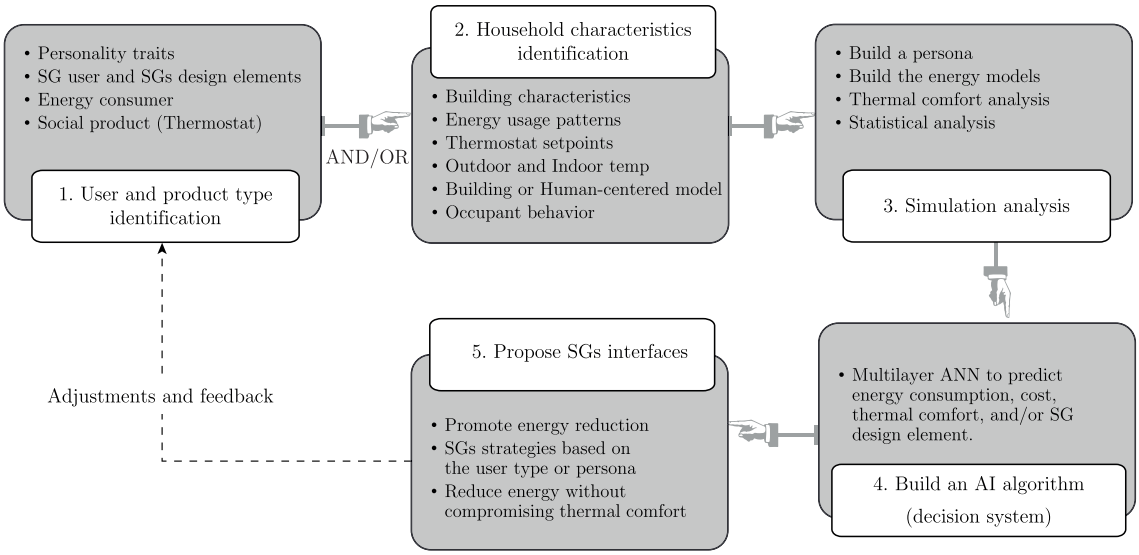


Fig. 2. Conceptual steps of the proposed framework for SGs energy applications.

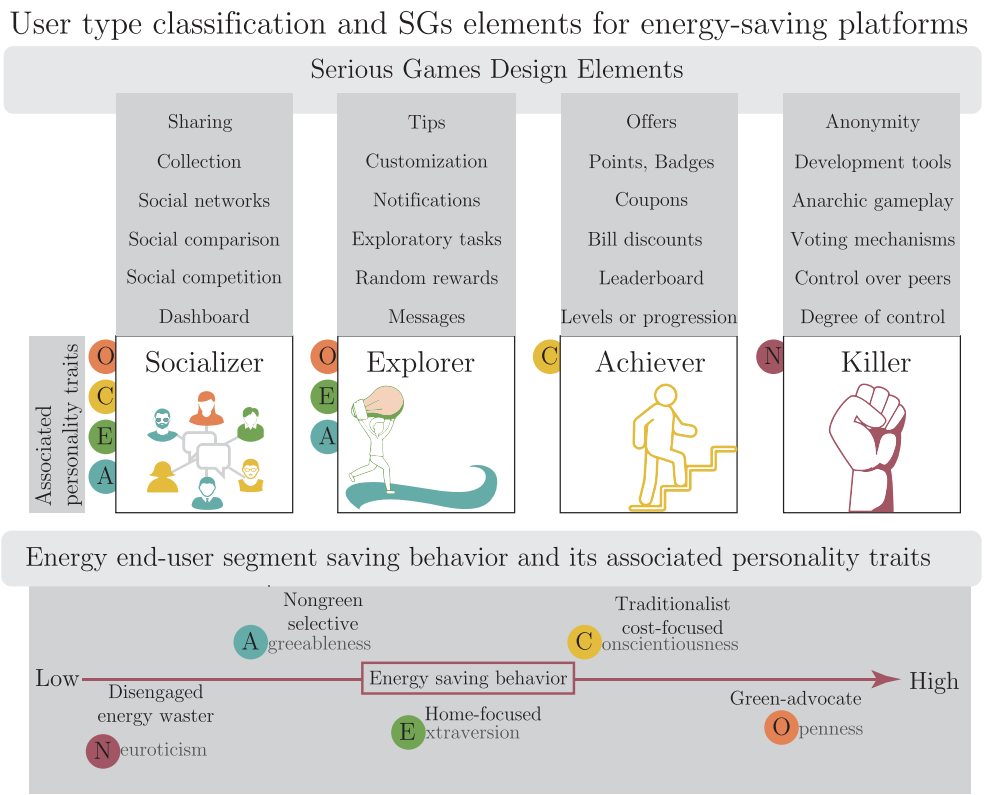


Fig. 3. User type classification and SGs elements for energy-saving platforms.

2.1.2. Serious games user type

Bartle [29] described four types of gamers and Tondello et al. [30] linked those gamers into SGs user types and associated them with the personality traits. The achiever SGs user type focuses on earning points and levels. The explorer type finds and gathers all the information available on the game and about the players. The main purpose of the socializer user type is to interact with other players. On the contrary, the killer type imposes on others to control them. Therefore, Tondello et al. [30,31] related the socializer player with the openness, conscientiousness, extraversion, and agreeableness personality traits. The explorer player relates with the openness, extraversion, and agreeableness traits. The achiever type associates with the conscientiousness trait; whereas the killer type with the neuroticism trait.

2.1.3. Energy end-user segment

Frankel et al. [33] found out and classified five types of residential energy end-user segments. The green advocate energy end-user segment prefers new technologies to continue being energy-aware. The traditionalist cost-focused segment has little to no

interest in new technologies, and cost-saving is their motivation with an extensive overall energy-saving behavior. The home-focused group looks for household improvements while saving energy and money. The non-green selective segment is a not energy-aware type and selects energy savings through set-and-forget inventions. The disengaged energy waster segment's motivation relies on saving money through energy savings.

Ponce et al. [27] exemplified the relationship between the energy end-user segment and the personality traits. Therefore, the disengaged energy waster is related to the neuroticism user type, the non-green selective with the agreeableness, the home-focused with the extraversion, the traditionalist cost-focused with the conscientiousness, and the green-advocate with the openness.

2.1.4. Social products

Ponce et al. [72] detailed that the socially connected products observe, register, analyze, and change consumer behavior by adapting their characteristics to improve their performance and acceptability in the market. These products use sensors to detect events, collect data, and measure changes in the environment. Additionally, they integrate their physical and smart components, as well as their interconnectivity, to make products smart and accessible to other interfaces. Furthermore, they combine social, environmental, and economic factors to produce balanced and optimized performance.

Hence, these social products can be upgraded by knowing the type of behavior and usability problems in the connected devices. For instance, the household appliance communicates between the householder and the product and between products to propose a tailored service for the connected thermostat [14,16,34].

2.2. Step 2: Household characteristics identification

In this step, the design parameters and characteristics that the energy model will have must be established. It is important to collect information on the type of building to be analyzed, its thermal properties, consumption patterns of household appliances, and thermostat setpoints. Another essential element to consider during this stage is the location of the building to obtain the indoor and outdoor temperatures metrics, and other climatological data that the model will need. At this step, it is necessary to define the type of comfort model used for the energy simulations, whether the adaptive model or the Fanger's model. In this case, we will use the adaptive. Besides, this step identifies the adaptive and non-adaptive behaviors and the occupant behavior.

2.3. Step 3: Simulation analysis

This step builds a persona, a calibrated energy model, and performs the thermal comfort and statistical analysis. The first step can be omitted and start with the second step. Thus, acknowledging that there is not a defined user type, Ponce et al. [27] described a *persona* as a fictitious individual that represents the characteristics of a consumer group. During this research, the *persona* has the five personality traits, the four SG player types, and the five energy end-user described in the first step. Having this type of person serves as the basis to display the game elements on the platform and thus obtain a generic interface. This interface type helps as a guideline to analyze the householders' interaction.

2.4. Step 4: Build an AI algorithm

This step establishes the decision system, the data from the previous step that will fed the AI algorithm, such as indoor temperature, date, location or adaptive strategy. In this research, a multilayer ANN was considered; however, other AI algorithms can be deployed. For example, fuzzy logic can profile the type of user and level of engagement [14,16,24], ANFIS can gather the information from sensors and classify the type of home and its energy consumption [34,48].

2.5. Step 5: Propose SGs interfaces

This step analyzes the results and plots them into a tailored SG interface or platform. The interface considers the SGs design element depicted in Fig. 3. A generic interface works in case of not knowing the user type. This generic interface must consider the *persona* described in step 3.

3. Methodology

This section presents the five steps of the proposed Framework and the required tools to propose SGs interactive interfaces.

3.1. Step 1 and Step 2: Householder and Home Characteristics

This research considers a generic *persona* that gathers the five personality traits, the SGs player type and do not know if they prefer to save energy or money. The social product considered is the connected thermostats. Fig. 4(a) shows the east façade of the home and Fig. 4(b) the 3D Energy Model that was created and simulated in Rhinoceros + Grasshopper and LT. Fig. 4(c) depicts the floor plan; its distribution had three bedrooms, one bathroom, one kitchen, dining and living room, dining, and a one-level home with an attic. Bedroom 2 and the Dining and Living Room have two room air conditioners and two wall furnaces. For this paper, all the units were in kWh to better dimension the energy savings impacts.

The software used during this research were:

- Rhinoceros Version 7 SR10 and Grasshopper 3D version 1.0.0007
- Ladybug Tools Version 1.2.1.
- Excel from Microsoft 365
- RStudio Version 1.4.1106 and RPubs
- Neural Network toolbox from MATLAB Version R2021a
- MATLAB/Simulink Model Version 1.36 and Simulink Version R2021a

The adaptive thermal comfort considers the metabolic rate and the clothing insulation as they are related to the occupant. An acceptable range of clothing insulation is 0.5 clo for typical summer season and 1.0 clo for winter season [73]. The metabolic rates considered for the simulation [74] were:

- Activity: Sleeping
  - Activity level: 72 W/person
  - Metabolic rate = 0.7 met
- Activity: Seated or writing
  - Activity level: 108 W/person
  - Metabolic rate = 1 met
- Activity: Standing
  - Activity level: 126 W/person
  - Metabolic rate = 1.2 met
- Activity: Typing
  - Activity level: 117 W/person
  - Metabolic rate = 1.1 met
- Activity: Cooking
  - Activity level: 190 W/person
  - Metabolic rate = 1.8 met

Fig. 4. (a) East Façade, (b) 3D Energy Model, and (c) Home Zones (Floor plan distribution).

The energy model required of the weather file in EnergyPlus™ Weather Format (EPW). Thus, the climate data were from the Climate One Building repository; this meteorological database derived weather data hourly from 2004 to 2018.

Five Californian locations were selected: Concord [75], Riverside [76], Los Angeles [77], and San Diego [78]. All the locations belonged to the IECC Climate Code 3B (warm, marine). Moreover, whereas the IECC Climate Zone 3B covers the four locations, the California Climate Zone (CaCtZ) considers three different zones. Hence, the selection of these places relied on considering the north part and the south part of Zone 3B to measure the HVAC kWh consumption compared to the three different CaCTz.

The kWh costs were calculated using the current Electricity time-of-use C (E-TOU-C) [79] rate from the Pacific Gas and Electric Company (PGE) for all the locations to uniform the results and value the costs' impacts.

3.2. Step 3: Simulation analysis

This subsection describes the energy model characteristics and the parameters needed to perform and analyze the energy simulations.

3.2.1. Energy model calibration

The ASHRAE Guideline 14 was followed to calibrate the building model and achieve Normalized Mean Bias Error (NMBE) values within ±5% and Cumulative Variation of Root Mean Square Error (CV(RMSE)) values below 15% [80–82]. The NMBE and CV(RMSE) were calculated using Eqs. (1) and (2).

$$NMBE = \frac{1}{\bar{m}} \bullet \frac{\sum_{i=1}^{n}(m_i - s_i)}{n - p} \tag{1}$$

Where $\bar{m}$ is the mean of measured values, p is the number of adjustable model parameters and is suggested to be one for calibration purposes. m_i is the measured values and s_i is the simulated values, n is the number of sample.

$$CV(RMSE) = \frac{1}{\bar{m}} \sqrt{\frac{\sum_{i=1}^{n}(m_i - s_i)^2}{n - p}} \tag{2}$$

The measured data came from the PGE utility bill and consumed 2,113.7 kWh. The calibrated model had an annual energy consumption of 2,052.1 kWh. The NMBE was 3.18%, and the CV(RMSE) was 10.55%. After this calibration, six cases were analyzed.

3.2.2. Energy model cases

The energy model required the HVAC setpoints; thus, in addition to the owner HVAC schedule, two additional HVAC schedules were included. Fig. 5 (a) displays the HVAC setpoints from the owner's home; during heating periods, the setpoint was set to 68°F at 7 a.m. as it was the hour where all the householders were awake, interacting, for instance, at the dining and living room zone. Woods [10] collected, from 96 houses with a total of 783,459 observations, the monthly cooling and heating setpoints; hence, Fig. 5 (b) displays the monthly cooling and heating setpoints proposed by Woods [10]. The 2019 Residential Appliance Saturation Study (RASS) metered 69,682 householders and 303 households to provide information on appliances, equipment, and general consumption [83]. Fig. 5 (c) displays the cooling and heating setpoint based on the utility that belonged to Concord, Riverside, Los Angeles, and San Diego were used to feed the energy model.

Therefore, twelve energy models were developed to compare the differences between HVAC strategy and natural ventilation strategy. These models gave as a result the indoor temperatures, electrical consumption, billing costs, and thermal scales (thermal

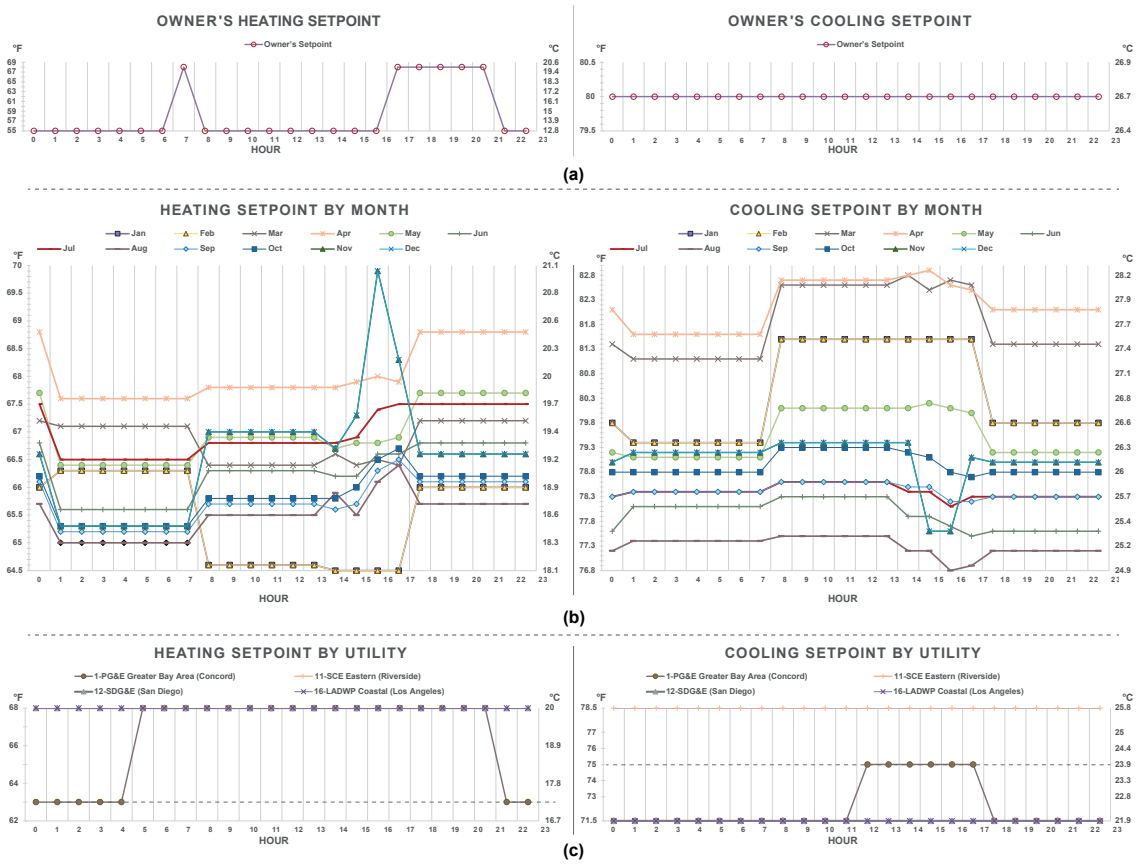


Fig. 5. Heating and Cooling Setpoint by month: (a) Current heating and cooling setpoint; (b) Thermostat setpoints analyzed by Woods [10]; (c) RASS setpoints by Utility [83];.

sensation, thermal preference, and UTCI). The selection of these locations relied on the importance that each location belongs to the ASHRAE Climate Zone 3B; however the California Climate Zone is different, Concord belongs to the California Climate Zone 12, Riverside to the California Climate Zone 10, Los Angeles to the California Climate Zone 9, and San Diego to the California Climate Zone 10. Therefore, the selection of the thermostat setpoints were based on Fig. 5. The twelve models were divided into six cases:

- Case 1: Owner's heating and cooling setpoint (See Fig. 5 (a)). Energy model 1 was the HVAC simulation and Energy model 2 was the Natural Ventilation simulation.

Table 1
Characteristics fed into the residential energy simulator.

Characteristics	Description
Location Case 1 to 3	Concord (IECC 3B; CaCtZ 12 [75]). *Utility: PGE.*
Location Case 4	Riverside (IECC 3B; CaCtZ 10 [76]). *Utility: SCE.*
Location Case 5	Los Angeles (IECC 3B; CaCtZ 9 [77]). *Utility: LADWP.*
Location Case 6	San Diego (IECC 3B; CaCtZ 10 [78]). *Utility: SDG&E.*
Non occupied HVAC schedules	8 am to 3 pm (Monday to Friday) Heating: November to March Cooling: April to October
Occupants	4 family members (mother, father, two children)
Equipment	Appliances: gas water heater, stove, oven, and two wall-furnaces. Electric: refrigerator (100 W), microwave (500 W), instant pot (900 W), electric kettle (1000 W), toaster (600 W), two room air conditioners (840 W, 1100 W), computer/monitor (120 W), laptops (60 W), LED lights (10 W).
	Construction set
External wood wall (R11): 2 × 4 @ 16″ (40.6 cm) O.C.	Wood Siding, Wall insulation R10, 1/2″ (1.27 cm) Gypsum Board
External window: Single pane wood framed windows.	U 0.20, SHGC 0.22, Simple Glazing
Ceiling (R22)	Wood Siding, 5/8″ (1.6 cm) Plywood, Insulation R20, 5/8″ (1.6 cm) Plywood
Exterior Roof (R25)2x6 @ 24″ (61 cm) O.C.	Asphalt Shingles, Insulation R24, 5/8″ (1.6 cm) Plywood.
Floor (R22): Under floor crawl spaces; 2x8 @ 24″ (61 cm) O.C.	5/8″ (1.6 cm) Plywood, Insulation R20, 5/8″ (1.6 cm) Plywood, Wood Siding

- Case 2: James Wood's heating and cooling setpoint (See Fig. 5 (b)). Energy model 3 was the HVAC simulation and Energy model 4 was the Natural Ventilation simulation.
- Case 3: RASS's heating and cooling setpoint from Concord, CA (See Fig. 5 (c)). Energy model 5 was the HVAC simulation and Energy model 6 was the Natural Ventilation simulation.
- Case 4: RASS's heating and cooling setpoint from Riverside, CA (See Fig. 5 (c)). Energy model 7 was the HVAC simulation and Energy model 8 was the Natural Ventilation simulation.
- Case 5: RASS's heating and cooling setpoint from Los Angeles, CA (See Fig. 5 (c)). Energy model 9 was the HVAC simulation and Energy model 10 was the Natural Ventilation simulation.
- Case 6: RASS's heating and cooling setpoint from San Diego, CA (See Fig. 5 (c)). Energy model 11 was the HVAC simulation and Energy model 12 was the Natural Ventilation simulation.

Table 1 describes the location, occupancy hours, HVAC schedules, number of family members, equipment, and shows the building materials characteristics used to feed the 3D energy model simulator. The 1000 square foot household is located at in Concord, CA. Besides, for the cost calculation the rate was considering using the electricity time-of-use C (E-TOU-C) [79] with these characteristics:

- Summer: From June 01 to September 30
  - Peak: 0.34229 $/kWh
  - Off-peak: 0.27885 $/kWh
- Winter: From October 01 to May 31
  - Peak: 0.2452 $/kWh
  - Off-peak: 0.22788 $/kWh

An adaptive strategy was added by first considering opening the windows to ventilate the indoors and then closing the window when the indoor temperature was higher than the HVAC setpoints to turn on the system. Therefore, this research analyzed twenty-four strategies; twelve were for HVAC usage, and the other twelve were for Natural Ventilation (NV).

Fig. 6 depicts the nine steps used to build and run the energy model simulations and the block generated using the LT.

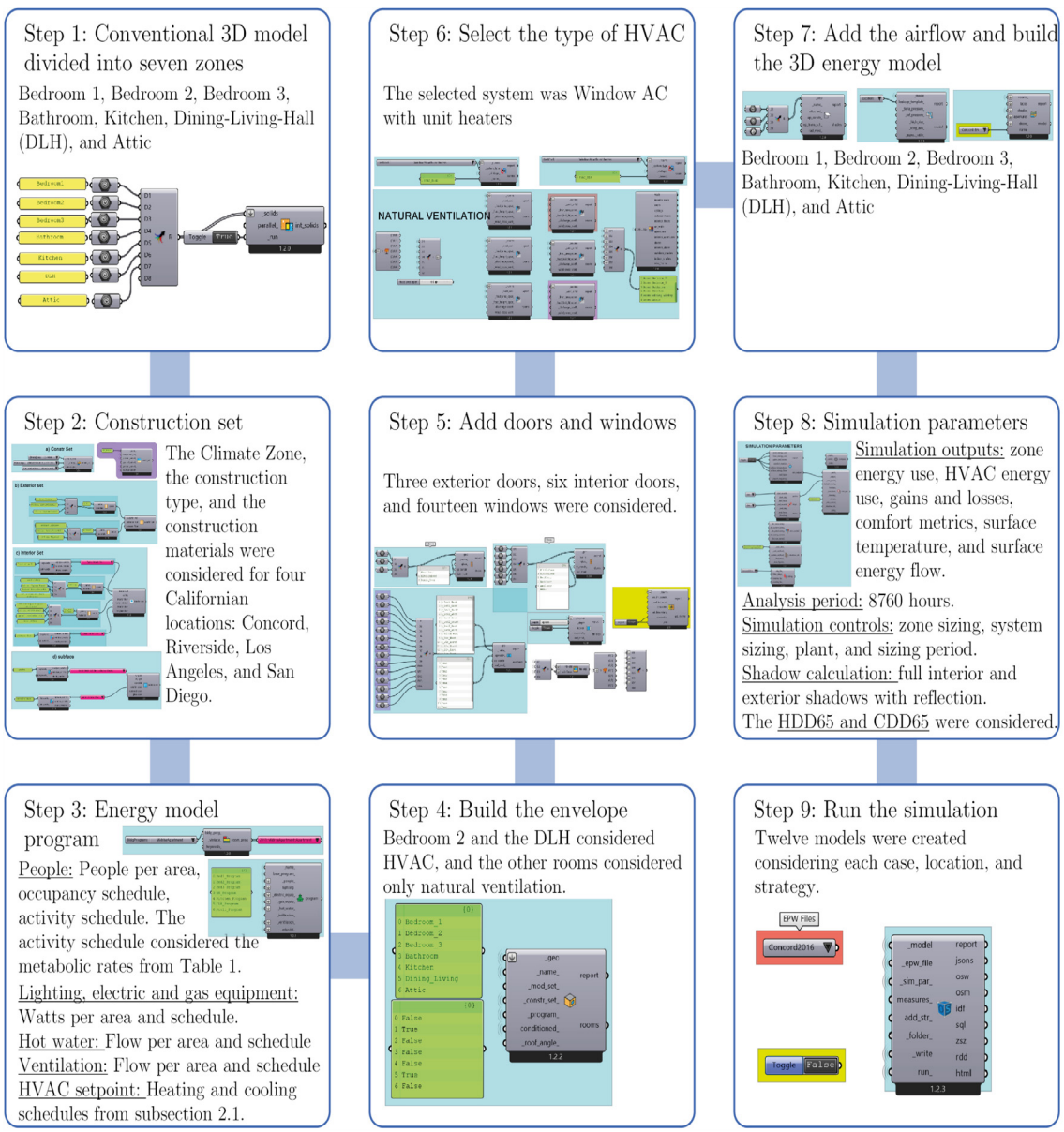


Fig. 6. Energy model diagram of each step of the simulation.

3.2.3. Adaptive thermal comfort analysis

The mean outdoor temperature estimated the exponentially weighted running mean outdoor temperature with an α = 0.7 (Eq. (3)). Research indicates that mid-latitude climates have alpha values lower than 0.9, such as 0.7 because people are used to weather variability [84]. This formula means that today's prevailing mean outdoor temperature would be 30% of yesterday's mean daily outdoor temperature in addition to 70% of yesterday's running mean outdoor value. This equation advances the value of the running mean from one day to the next and is convenient for computer algorithms and manual calculations. However, a value for running mean temperature has to be assumed for day one to seed the sequence. Besides, the running mean needs to be initiated seven days before the start of the period of interest. Therefore, the first day of January seeded the sequence, and the last week of December initiated the period.

Eq. (4) describes the adaptive thermal comfort formula for the acceptable operative temperature used in this paper for a time-interval of seven days.

$$\overline{tpma(out)} = (1-\alpha) \times \left[t_{e(d-1)} + \alpha t_{e(d-2)} + \alpha^2 t_{e(d-3)} + \alpha^3 t_{e(d-4)} + \alpha^4 t_{e(d-5)} \ldots\right] \quad (3)$$

Where $\overline{tpma(out)}$ is the prevailing mean outdoor temperature, the α is equal to 0.7, and $t_{e(d-n)}$ is the mean daily outdoor temperature for the day before the day in question.

$$80\%\ Acceptability\ limit = \left(0.31 * \overline{tpma(out)}\right) + (54.2^{\circ}F \pm 6.3^{\circ}F) \quad (4)$$

In °C the Eq. (4) should be changed from 54.2 ±6.3 to 17.8 ±3.5.

The operative temperatures for the HVAC Zones (Bedroom 2 and Dining and Living Room) considering the upper and lower 80% acceptability limits of Eq. 4 were plotted to visualize the adaptive thermal comfort from each case using the HVAC and the NV strategy.

Table 2 shows the thermal sensation values considered for each case. The shaded row means the Neutral thermal sensation scale and the No Change thermal preference scale.

3.2.4. Statistical analysis

As a result of the energy model, a new database was created with thirty-two variables for the thermal comfort and the statistical analysis. Table 3 depicts those variables.The statistical analysis data was performed using RStudio Version 1.4.1106.

The descriptive analysis was conducted for the outdoor temperatures and indoor variables of subSection 3.2.2:

Table 3
Variables created from the energy model to analyze the HVAC usage in Bedroom 2 and the Dining and Living Room zones.

Outdoor variables	Indoor variables	Indoor variables by HVAC zone (Bedroom 2 & DLH)
Outdoor Temperature	Heating Setpoint	Operative Temperature
α = 0.7	Cooling Setpoint	UTCI
Upper limit (80%)	HDD65	Thermal sensation
Lower limit (80%)	CDD65	Thermal Preference
Month	Total Heating kWh	Heating kWh
Day	Total Cooling kWh	Cooling kWh
Hour	Total Heating Cost	Heating Cost
Date (mm.dd.hr)	Total Cooling Cost	Cooling Cost

- For the outdoor temperatures, the boxplot summarized Concord, Riverside, Los Angeles, and San Diego's monthly mean temperatures; and the bar chart depicted the frequencies of the heating degree days (HDD65) and cooling degree days (CDD65) with a baseline of 65 °F (18.3 °C).
- For the indoor variables, the shape statistics, the histogram, and the Kolmogorov–Smirnov test determined the kWh and costs' normality. The objective was to decide the appropriate central tendency and dispersion measures to describe the variables, select which test best fit both strategies' comparison, and analyze if there was a statistically significant change. Furthermore, a table summarized the characteristics of operative temperature and thermal sensation scales.

The comparative analysis for the kWh and the costs between the HVAC strategy and the NV strategy of each case were performed using the Wilcoxon signed-rank test; this test is a non-parametric alternative to paired t-test.

- The null hypothesis was that the differences of medians of the kWh and costs between both strategies are equal.
  - *H0: Median* $kWh_{Natural\ Ventilation}$ *- Median* kWh_{HVAC} *= 0*

The paired samples were dependent and continuous variables; the 8760 observations yielded the annual data. Consequently, the pair had those hours for each strategy. Besides, both groups were pairs as they were measured for two occasions, for the HVAC strategy (before) and the NV strategy (after).

3.3. Step 4: AI decision system

Four ANN models were developed, two for the summer and winter period of the HVAC strategy and two for both seasons of the NV strategy. Summer periods were from June to September and Winter periods were from October to May. Each ANN model

Table 2
Thermal Sensation Scale values considered for each case (See Fig. 1(c)).

Cases		1		2	3	4	5 and 6
		Summer	Winter	Summer and Winter			
ASHRAE Scale (°F)	1	[35,46]	[32,41]	[32,41]	[32,41]	[32,41]	[32,41]
	2	(46,55]	(41,50]	(41,50]	(41,50]	(41,50]	(41,50]
	3	(55,64.4)	(50,55)	(50, Htg.Stpt-3)	(50,60)	(50,65)	(50,65)
	4	*[64.4,80]*	*[55,78]*	*[Htg.Stpt-3, Clg.Stpt + 3]*	*[60,78]*	*[65,80]*	*[65,74.5]*
	5	(80,90]	(78,85]	(Clg.Stpt + 3, 90]	(78,90]	(80,90]	(74.5,90]
	6	(90,114]	(85,114]	(90,114]	(90,114]	(90,114]	(90,114]
	7	(114,inf)	(114,inf)	(114,inf)	(114,inf)	(114,inf)	(114,inf)
ASHRAE Scale °C)	1	[1.7,7.8]	[0,5]	[0,5]	[0,5]	[0,5]	[0,5]
	2	(7.8,12.8]	(5,10]	(5,10]	(5,10]	(5,10]	(5,10]
	3	(12.8,18)	(10,12.8)	(10, Htg.Stpt-1.7)	(10,15.6)	(10,18.3)	(10,18.3)
	4	*[18,26.7]*	*[12.8,25.6]*	*[Htg.Stpt-1.7, Clg.Stpt + 1.7]*	*[15.6,25.6]*	*[18.3,26.7]*	*[18.3,23.6]*
	5	(26.7,32.2]	(25.6,29.4]	(Clg.Stpt + 1.7, 32.2]	(25.6,32.2]	(26.7,32.2]	(23.6,32.2]
	6	(32.2,45.6]	(29.4,45.6]	(32.2,45.6]	(32.2,45.6]	(32.2,45.6]	(32.2,45.6]
	7	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)	(45.6,inf)

considered a two-layer feed-forward network with 100 neurons in the hidden layer and a hyperbolic tangent sigmoid transfer function [85].

The Neural Network Tool (nntool) is a graphical user interface that opens the Network/Data Manager window to create an ANN [85]. The network type used in this paper was the Feed-forward backpropagation, with a network training function that uses the Levenberg–Marquardt optimization method to update the weight and bias values. In addition, it employed the gradient descent with momentum weight and bias learning function and a mean squared error performance function.

Once obtained the database from the energy model, the Concord strategies were selected (Case 1 to 3), due to they had more information to feed the ANN model in terms of a broader range of heating and cooling setpoints leading into a wider range of energy consumption. Hence, eight matrices considering Bedroom 2 divided into winter and summer periods were created in MATLAB to feed the ANN models.

3.4. Step 5: thermostat interactive dashboards

Two types of interfaces were proposed using the premise of teaching the end-users how to save energy and money through a set of SGs design elements. The first interface based their displayed information using the database variables described at the beginning of subSection 3.2.4. Thus Fig. 7(a) displays the interface layout of the Dining and Living Room and Fig. 7(b) for Bedroom 2. The numbering represents the input variables that the end-user needs to select. In contrast, the letters display the third column values of Table: Indoor variables by HVAC zone (Bedroom & DLH).

- Input variables: (1) Month, (2) day, (3) hour, (4) strategy.
- Output variables: (A) Outdoor temperature, (B) HVAC setpoint, (C) Operative temperature, (D) kWh, (E) Cost, (F) thermal sensation.

This interface aims to teach the end-user the differences in cost, energy, and thermal sensation between strategies and the impact benefits of the NV strategy.

The second type of interface were divided into summer (Fig. 7)) and winter period (Fig. 7(d)). These interfaces were the result of the ANN models generated in the previous subSection 3.3. The numbering represents the input variables that the end-user needs to select, whereas the letters display the result.

- Input variables: (1) Month, (2) day, (3) hour, (4) setpoint, (5) Strategy, (6) Outdoor temperature.
- Output variables: (A) Indoor temperature, (B) kWh, (C) thermal sensation.

Furthermore, the number six is blue because the outdoor temperature is an input value needed to predict the output values; however, the temperature was linked into a matrix with the dry-bulb temperature values from the EPW file. Thus, the end-user did not need to plug hypothetical outdoor temperatures. As a result, it was easier for the end-user to test each strategy to analyze the changes depending on the selected strategy without worrying about outdoor temperatures. In both types of interfaces, the thermal sensation scale was shown using the values in Table 2 so that people could visualize in which comfort range they could find themselves.

3.4.1. SG design elements

Fig. 8 diplays a generic SG interface that considers the *persona* described in subSection 2.3. Therefore, this generic interface considers all the personality traits, energy end-user segment and SGs player type. Besides, the energy end-user segment is shaded with different boxes colors because they are related to each specific personality trait depicted in Fig. 3.

4. Results

Fig. 9(a) shows the boxplot for the monthly outdoor temperature for Concord, Riverside, Los Angeles, and San Diego and their statistics. Figs. 9(b) and (c) represent the heating and cooling degree-days of those locations considering 65 °F (18.3 °C) as a baseline.

During the summer periods, Riverside required more cooling than other places. Furthermore, Los Angeles and San Diego required lesser cooling compared to the other places. During winter periods, Concord needed more heating than the other locations. Los Angeles required the least heat of all the places. Another relevant aspect to consider was that Riverside and Concord had the highest standard deviation compared to the other locations; for

Fig. 7. Interactive Dashboard Elements for a Thermostat within a Serious Game context: (a) Dining, Living room, and hall zone; and (b) Bedroom 2 zone. ANN Interactive Dashboard Elements: (c) Summer period; and (d) Winter period.

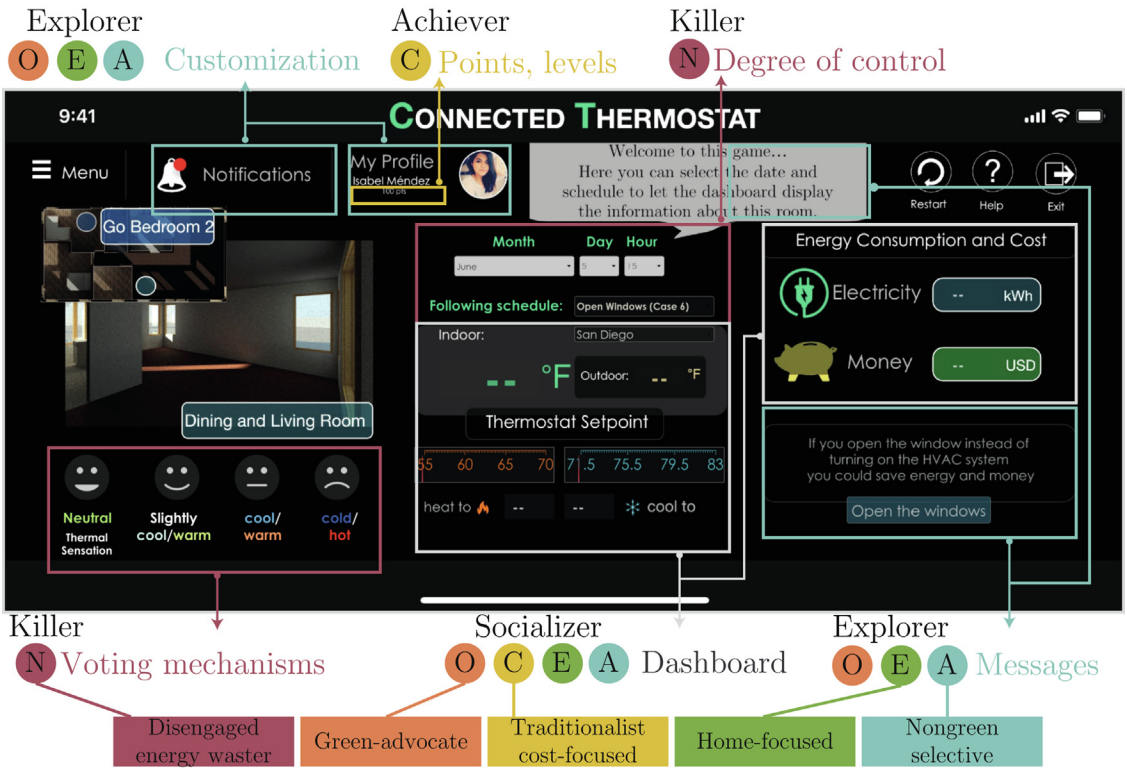
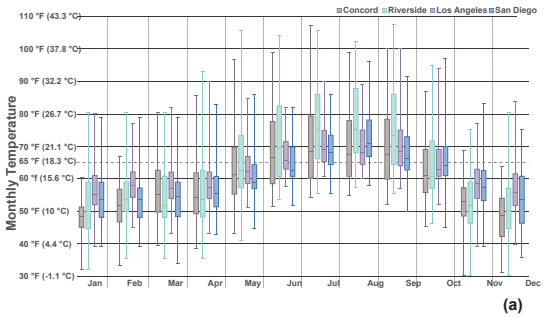
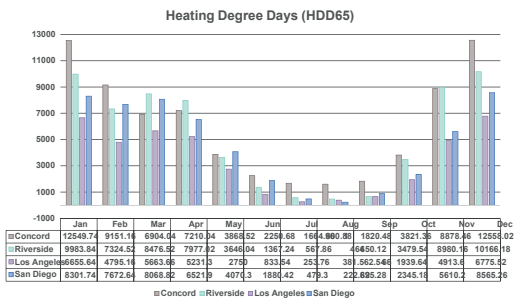


Fig. 8. Generic SG interface prototype based on a *persona*.

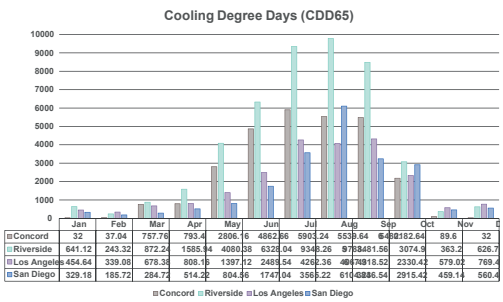


(a)

Statistics	Concord	Riverside	Los Angeles	San Diego
Mean	59.9	62.9	62.8	61.1
St. Dev.	12.7	14.8	8.7	9.8
Min	30.2	30.2	39.0	33.8
25%	51.3	51.8	56.8	53.6
Median	57.7	60.8	62.2	60.8
75%	66.6	71.6	68.0	66.9
Max	107.1	107.6	100.0	97.0



(b)



(c)

Fig. 9. Concord, Riverside, Los Angeles, and San Diego: (a) Monthly Outdoor Temperature; (b) Heating Degree Days considering 65 °F (18.3 °C) as a baseline; (c) Cooling Degree Days considering 65 °F (18.3 °C) as a baseline.

example, those broader ranges were noticeable from June to September.

Moreover, according to the UTCI scale, there was no thermal stress up to 78.8 °F (26 °C), and the neutral thermal sensation scale limits were up to 80 °F (26.7 °C) for Cases 1 and 4 (See Table 2). Therefore, it was possible to infer that there was a chance of reducing energy consumption by initially opening windows before turning on the HVAC system.

4.1. Operative temperatures and thermal sensation scales by case and strategy

Fig. 10(a) depicts the monthly boxplot for Bedroom 2 and Fig. 10(b) for the Dining and Living Room Zone. Furthermore, each image displays the summary statistics of each strategy by case. The maximum temperature decreased when the windows were open; the minimum temperature increased for the NV strategy. From

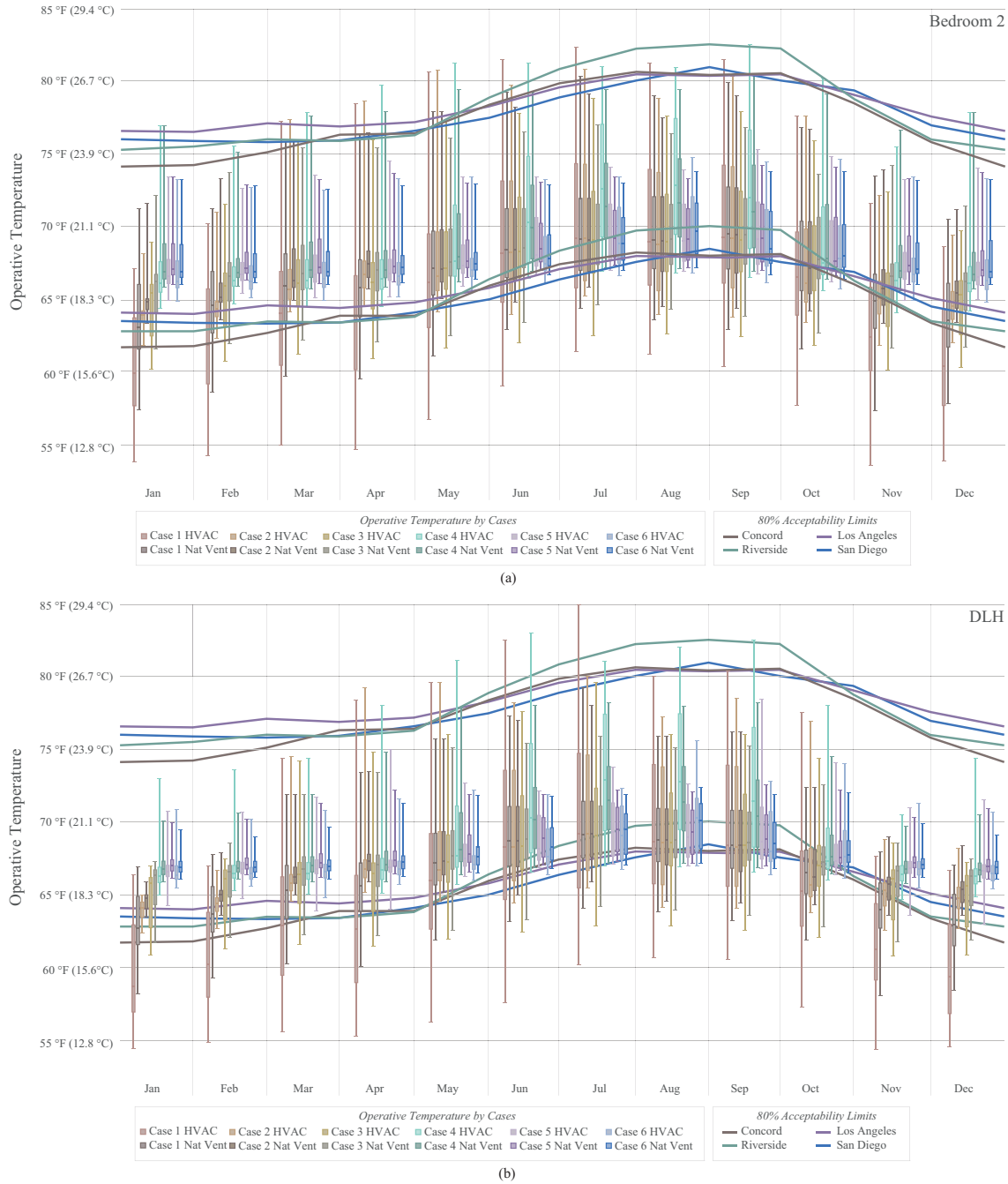


Fig. 10. Monthly Operative Temperature boxplots and their summary statistics for each case: (a) Bedroom 2 and (b) Dining and Living Room.

the boxplot, it was interesting that the temperatures varied due to the cooling and heating setpoint for the Concord location (Cases 1 to 3). In contrast, Riverside, Los Angeles, and San Diego remained with similar temperatures. The drastic changes between seasons were presented in the first case, due to during heating periods, the thermostat setpoint is 55 °F to 68 °F (12.8 °C to 20 °C). The summer season did not present dramatic changes between cases as the cooling setpoint was under 80 °F (26.7 °C).

Cases 5 and 6 for the Bedroom presented changes in the thermal sensation scales. For the NV strategy, the maximum values were a neutral thermal sensation for the ASHRAE scale and no change for the thermal preference scale. For the DLH, the maximum values decreased with the NV strategy from Cases 3 to 6 for the ASHRAE scale and thermal preference. In general, the thermal scales were within the slightly cool to slightly warm spectrum in all the strategies. Case 1 presented wider sensation scales because the householders were habituated to that thermal sensation, although their thermal sensation falls out of the common thermal sensation. In the case of the UTCI scale, most of the cases had no thermal stress, and cases 1, 2, and 4 presented moderate heat stress.

4.2. Adaptive thermal comfort results

The full plotted interactive graphs of each case and strategy were uploaded to the RPubs webpage [86–91]. Thus, the reader can interact with each case and view the hours of occupancy, not occupancy, and sleeping activity and the 80% acceptability limits to review if, in that specific time or hour, the individual was comfortable. The relevance of presenting the graphs with references is

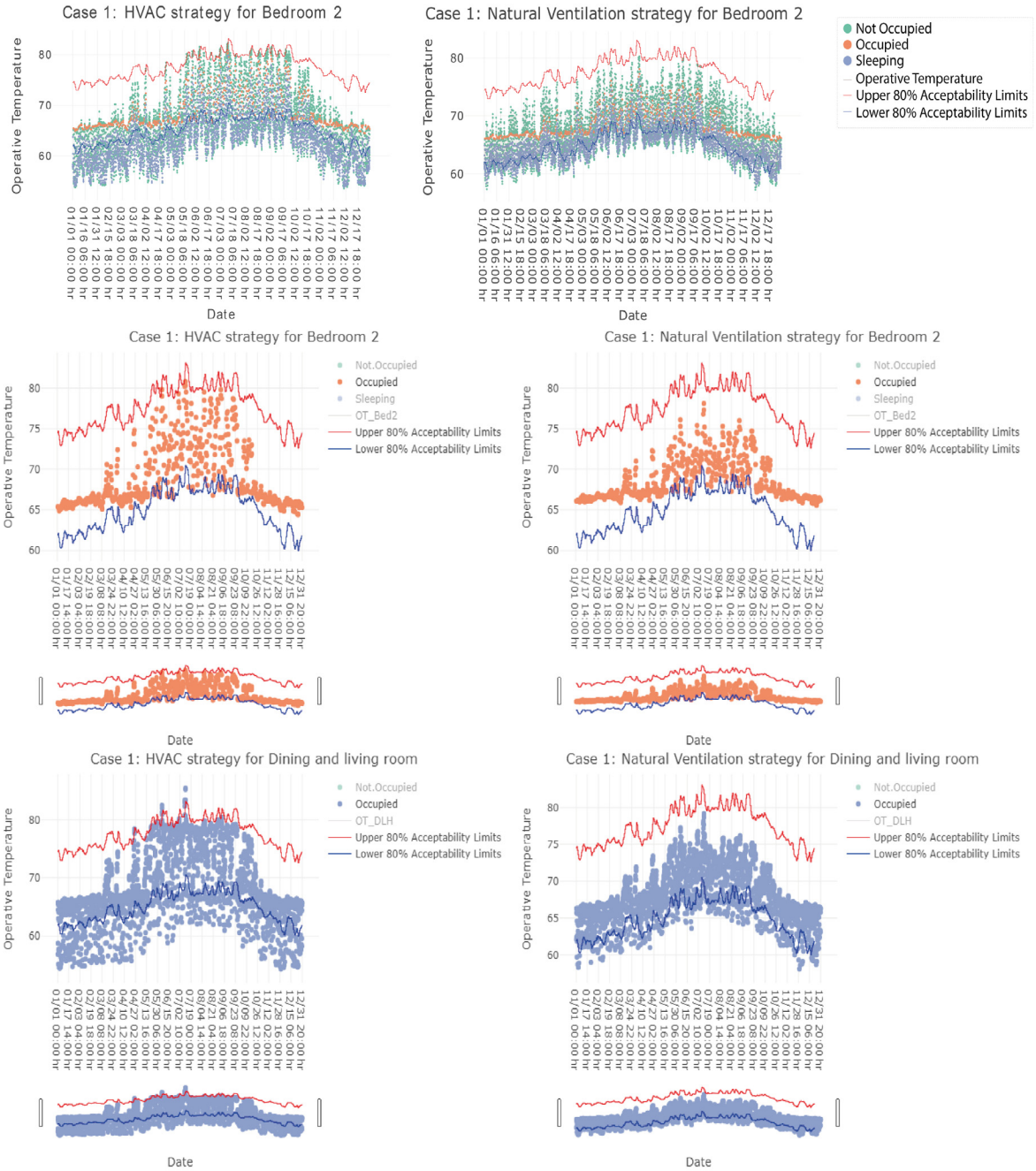


Fig. 11. Case 1: Annual operative temperature with occupancy hours of both strategies.

because it was complicated to show the differences between strategies in a single picture.

Fig. 11 displays the annual operative temperature and with the 80% acceptability limits for the first case. This figure shows the strategies with the occupied, not occupied, and sleeping activities. Then, the next graphs show the information filtered by occupied activity to indicate that the end-user is within the adaptive thermal comfort range during the occupancy. For the specific case of bedroom 2, the sleeping activity fell below the acceptability limit; however, a blanket covers the householder, then there is an acceptance of those ranges.

Although by following the Eq. (4), Case 1 had no thermal comfort during half the year, the actual occupied hours fell within the acceptability range making the place comfortable for the inhabitants. Moreover, if the natural ventilation strategy was added, the thermal comfort increased and continued relying on the acceptability range, and the costs savings increased by 78%.

For instance, in Case 1 Bedroom, the NV strategy raised the thermal comfort within the range; for the case of the DLH zone, it also improved; moreover, there were hours in which the occupied activities in the HVAC case were outside the upper limits of acceptability. Case 2 had an hour in which both cases were outside the comfort range; however, for the NV, this hour increased the comfort. The hour was 08/20 21:00 h from 65.2 °F to 66.4 °F (18.4 °C to 19.1 °C).

Regarding the DLH zone, cases two and four had hours during summer when the temperature range went below the acceptability

limit; however, the temperature increased due to activities and equipment usage.

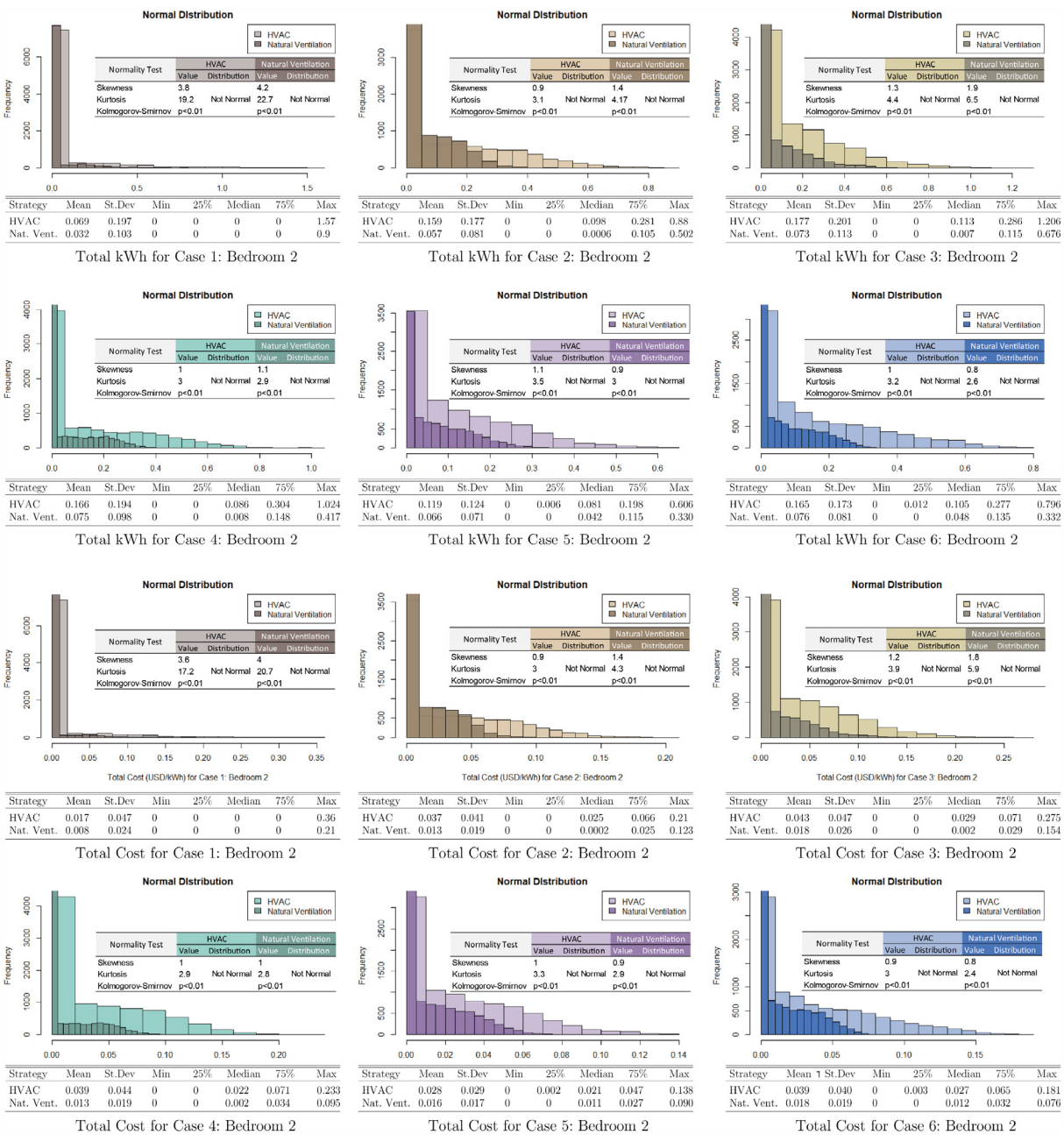
In both strategies for the bedroom zone, from cases 3 to 6, the thermal comfort ranges were within the range most of the time. However, by opening the windows, there was more energy reduction, and the thermal comfort increased. For the case of the DLH, the thermal comfort increased and remained within the range of the acceptability limits. Case 5 and 6 in the DLH zone were within the acceptability limits of thermal comfort.

4.3. Statistical analysis

The six cases succeeded in terms of thermal comfort; however, the major differences were in kWh usage and their costs. Thus, satistical analysis was performed to analyze if there were significant changes between strategies; the first step was to evaluate the normality of the data. Therefore, Figs. 12 and 13 exhibit the shape statistics, histogram, and Kolmogorov–Smirnov tests for each case; none of the cases were normal. Besides, below each histogram, the summary statistics of kWh and costs of each zone were displayed.

Thus, the next step was to deploy the comparative analysis between cases and strategies using the Wilcoxon signed-rank test. Table 4 showed the paired sample Wilcoxon test based on the positive ranks. In all of the cases, the null hypothesis were rejected as the medians were not equal. Moreover, the p-values were statistically significant and were based on positive ranks, meaning that there were changes between the NV with the HVAC strategy.

The statistical analysis demonstrated that there were statistically significant changes by allowing NV. Thus, major savings were achieved. Furthermore, the plotted thermal comfort charts available on the RPubs [86–91] and exemplified on Fig. 11 showed that



Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	3.8		4.2	
Kurtosis	19.2	Not Normal	22.7	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.069	0.197	0	0	0	0	1.57
Nat. Vent.	0.032	0.103	0	0	0	0	0.9

Total kWh for Case 1: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	0.9		1.4	
Kurtosis	3.1	Not Normal	4.17	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.159	0.177	0	0	0.098	0.281	0.88
Nat. Vent.	0.057	0.081	0	0	0.0006	0.105	0.502

Total kWh for Case 2: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1.3		1.9	
Kurtosis	4.4	Not Normal	6.5	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.177	0.201	0	0	0.113	0.286	1.206
Nat. Vent.	0.073	0.113	0	0	0.007	0.115	0.676

Total kWh for Case 3: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1		1.1	
Kurtosis	3	Not Normal	2.9	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.166	0.194	0	0	0.086	0.304	1.024
Nat. Vent.	0.075	0.098	0	0	0.008	0.148	0.417

Total kWh for Case 4: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1.1		0.9	
Kurtosis	3.5	Not Normal	3	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.119	0.124	0	0.006	0.081	0.198	0.606
Nat. Vent.	0.066	0.071	0	0	0.042	0.115	0.330

Total kWh for Case 5: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1		0.8	
Kurtosis	3.2	Not Normal	2.6	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.165	0.173	0	0.012	0.105	0.277	0.796
Nat. Vent.	0.076	0.081	0	0	0.048	0.135	0.332

Total kWh for Case 6: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	3.6		4	
Kurtosis	17.2	Not Normal	20.7	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.017	0.047	0	0	0	0	0.36
Nat. Vent.	0.008	0.024	0	0	0	0	0.21

Total Cost for Case 1: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	0.9		1.4	
Kurtosis	3	Not Normal	4.3	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.037	0.041	0	0	0.025	0.066	0.21
Nat. Vent.	0.013	0.019	0	0	0.0002	0.025	0.123

Total Cost for Case 2: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1.2		1.8	
Kurtosis	3.9	Not Normal	5.9	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.043	0.047	0	0	0.029	0.071	0.275
Nat. Vent.	0.018	0.026	0	0	0.002	0.029	0.154

Total Cost for Case 3: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1		1	
Kurtosis	2.9	Not Normal	2.8	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.039	0.044	0	0	0.022	0.071	0.233
Nat. Vent.	0.013	0.019	0	0	0.002	0.034	0.095

Total Cost for Case 4: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	1		0.9	
Kurtosis	3.3	Not Normal	2.9	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.028	0.029	0	0.002	0.021	0.047	0.138
Nat. Vent.	0.016	0.017	0	0	0.011	0.027	0.090

Total Cost for Case 5: Bedroom 2

Normality Test	HVAC Value	HVAC Distribution	Natural Ventilation Value	Natural Ventilation Distribution
Skewness	0.9		0.8	
Kurtosis	3	Not Normal	2.4	Not Normal
Kolmogorov-Smirnov	p<0.01		p<0.01	

Strategy	Mean	St.Dev	Min	25%	Median	75%	Max
HVAC	0.039	0.040	0	0.003	0.027	0.065	0.181
Nat. Vent.	0.018	0.019	0	0	0.012	0.032	0.076

Total Cost for Case 6: Bedroom 2

Fig. 12. Normality Tests for Bedroom 2.

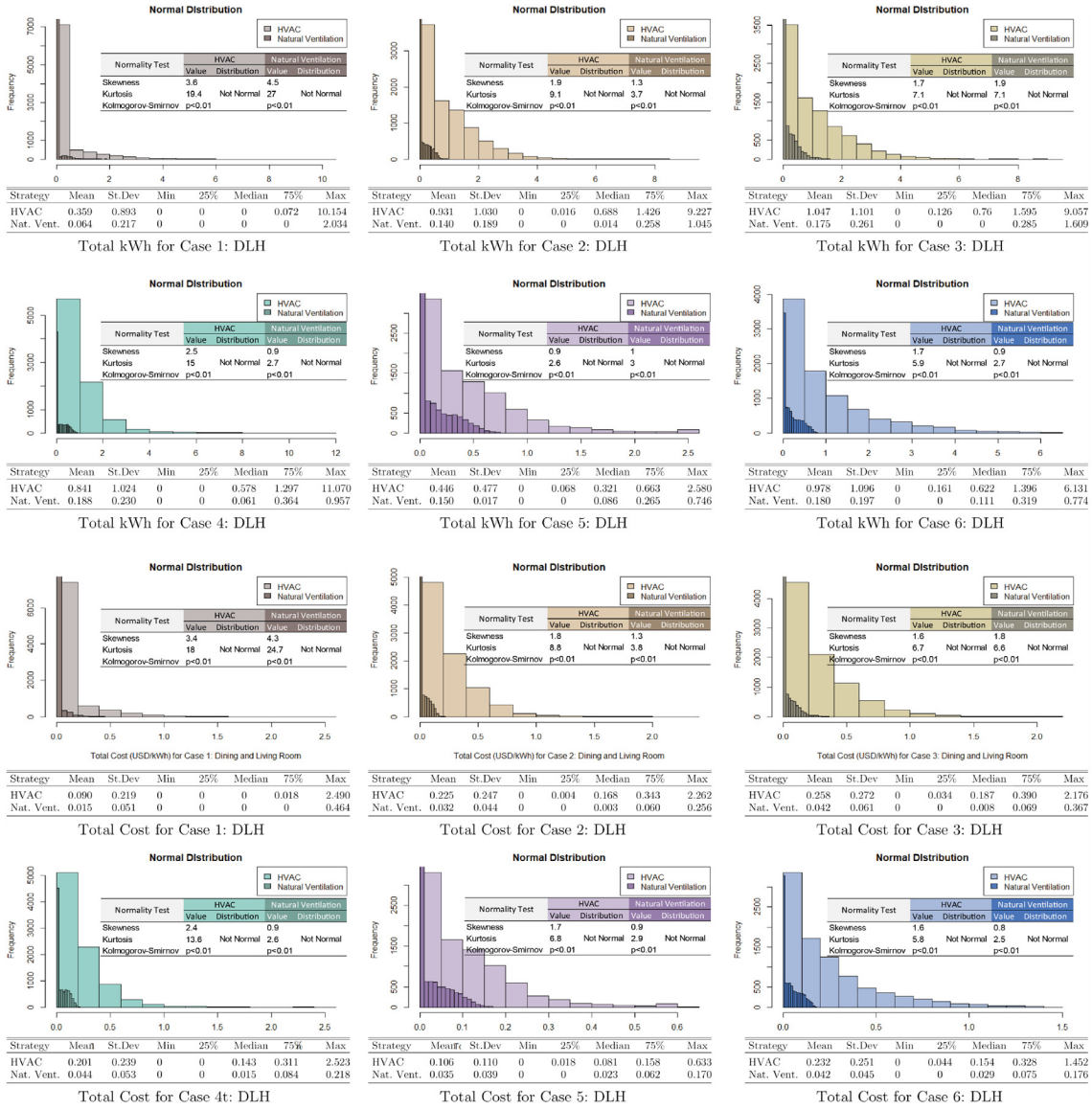


Fig. 13. Normality Tests for Dining and Living Room.

the thermal comfort increased or remained within the acceptability ranges of comfort in all the cases. Hence, by just doing minor changes in routines and activities as opening the windows instead of turning on the HVAC, money savings were achieved without losing thermal comfort.

Therefore, Fig. 14(a) and (b) display the total heating and cooling electricity energy consumption and electricity cost for each case. By choosing the opening windows strategy reflected in changes in energy consumption or potential money savings. Besides, Fig. 14(c) shows the total HVAC energy consumption by case and strategy and the percentage of reduction by first opening the windows. Fig. 14(d) shows the electricity cost and the percentage of reductions. Case 2 was the strategy that had more drastic changes than Case 5. Those variations involved the setpoint ranges described in Fig. 5.

4.4. Simulink models

Fig. 15(a) shows the Simulink code for the first type of interactive interface. The input values required were the month, day, hour, strategy, and case. Thus, 105,120 observations were needed. Each group of observations contained 8760 variables. As a result, the MATLAB function depicted 17 variables. The dashboard enabled the end-user to interact with possible scenarios to value the differences and rate the variations between using HVAC or opening the windows. Besides, this dashboard reflected that either the thermal comfort could be achieved by opening the windows or negatively affecting the thermal sensation scale.

Fig. 15(b) shows the Simulink diagram for the second type of interactive interface and the regression plot of each ANN model during the summer period and Fig. 15(c) for the winter period. The diagrams also showed the calculations performed to get the costs based on the energy consumption. These costs were calculated with the E-TOU-C rates PGE [79].

4.5. Thermostat HMIs: interactive dashboards

Fig. 16 shows twelve interfaces considering SGs environment; the left side shows six cases for the HVAC strategy, and the right

Table 4
The Paired Samples Wilcoxon Test for Bedroom 2 and DLH.

	Positive ranks			Test statistics		
	n	Mean rank	Sum of ranks	Ties	Z	p
			Bedroom 2 ($kWh_{Natural\ Ventilation} - kWh_{HVAC}$)			
Case 1	*2*	103.50	207	6959	−36.740	*<.001**
Case 2	*0*	0	0	2777	−66.990	*<.001**
Case 3	*43*	242.69	10,436	2178	−70.195	*<.001**
Case 4	*4*	115.75	3,007	3007	−65.686	*<.001**
Case 5	*628*	1,425.61	895,285	1510	−68.719	*<.001**
Case 6	*531*	1,160.12	616,026	1343	−71.246	*<.001**
			DLH ($kWh_{Natural\ Ventilation}$ - kWh_{HVAC})			
Case 1	*1*	132.00	132	6303	−42.928	*<.001**
Case 2	*5*	50.80	254	2030	−71.047	*<.001**
Case 3	*16*	161.19	2,579.0	1410	−74.235	*<.001**
Case 4	*59*	165.81	9,783	2217	−69.990	*<.001**
Case 5	*101*	385.45	38,931	1267	−74.760	*<.001**
Case 6	*219*	392.56	85,972	896	−76.374	*<.001**
			Bedroom 2 ($Cost_{Natural\ Ventilation}$ - $Cost_{HVAC}$)			
Case 1	*2*	103.50	207	6959	−36.746	*<.001**
Case 2	*0*	0.00	0	2777	−66.990	*<.001**
Case 3	*43*	235.43	10,436	2178	−70.197	*<.001**
Case 4	*4*	111.25	3,007	3007	−65.686	*<.001**
Case 5	*628*	1,297.41	895,285	1510	−69.170	*<.001**
Case 6	*531*	1,051.11	616,026	1343	−71.560	*<.001**
			DLH ($Cost_{Natural\ Ventilation}$ - $Cost_{HVAC}$)			
Case 1	*1*	129.00	129	6303	−42.928	*<.001**
Case 2	*5*	45.00	225	2030	−71.047	*<.001**
Case 3	*16*	159.19	2,547.0	1410	−74.235	*<.001**
Case 4	*59*	160.47	9,468	2217	−69.992	*<.001**
Case 5	*101*	406.33	41,040	1267	−74.748	*<.001**
Case 6	*219*	399.57	87,506	896	−76.366	*<.001**

* Indicates statistically significant change.

side compares the differences if the NV strategy is selected. These interfaces belonged to the Bedroom 2 zone.

The interface revealed a message indicating to the end-users how they can interact with the interface by selecting the date and the schedule to see how their decisions affect the consumption and the thermal sensation scale. There were cases where the end-user could feel slightly warm with the HVAC strategy, and when the windows were open, the ventilation allowed the end-user to feel neutral. Cases as 4 show that although the outside temperature is warmer than the inside, the indoor temperature decreases by opening windows. This happened because NV allows airflow and removes indoor heat. On the other hand, during these hours this room was not occupied. Thus, strategies as opening windows can be selected. This repository's file titled *InteractiveDashboardDB_ComplementaryData.mat* located the database used to build this interactive dashboard [92].

Fig. 17 shows the second type of interactive dashboard. This dashboard used a two-layer feed-forward ANN to predict energy consumption, indoor temperature, and thermal sensation at Concord, California. Although the energy consumption values displayed in this type of dashboard were lower than the energy model results, the differences between opening windows versus using HVAC existed and impacted the indoor temperature, energy consumption, and thermal sensation. For instance, The left side displays the interface with more energy consumption than the right side. This interactive dashboard aims to teach the end-user how interacting directly with the setpoint affects the energy consumption and the thermal sensation scale. In this interface type, the end-user needed to select the month, day, hour, and setpoint to predict the energy consumption, indoor temperatures, and thermal scales for the Bedroom 2 zone. This repository's file titled *InteractiveANNDashboardDB_ComplementaryData.mat* locateed the databases' matrix used to build this interactive dashboard [92].

In both cases, SGs were created to teach the end-user how to manage their thermostat and how their actions directly affected the energy consumption, indoor temperature, and thermal sensation. In addition, the thermal sensation offered an interesting manner to show the end-user how the setpoint and daily occupancy were affected by their usual ranges of thermostat setpoints. Full occupancy hours can be found at this repository's file titled *EnergyModelResults_ComplementaryData.csv* [92].

5. Discussion

A reference framework that includes connected thermostat interfaces is proposed. This framework integrates the user type, the SGs design element and the thermal comfort within a connected thermostat interface. The user type is a *persona* with all the personality traits and their relationship with the energy-end user segment and SG player type (Fig. 3). Four locations in California are analyzed to gather information regarding thermal comfort and four locations to analyze six cases. Thermal comfort is directly related to the thermostat setpoint and the adaptive strategy used. Woods [10] analyzed householders' thermostat setpoint usages to understand end-user behavior and, hence, he suggested that energy models and policies should consider different ranges of setpoints. Besides, Fig. 14 supported that energy reductions are achieved by providing different ranges of setpoints even by just considering the HVAC strategy. Case 3 considers the Greater Bay Area setpoints collected by the RASS survey, whereas Case 2 considers the setpoints of Woods [10]. Although Case 2 has wider setpoints values, Case 3 had more energy and money usage than Case 2. This means that Case 2 strategy is more appropriate for savings.

Moreover, Case 1 has less energy consumption of all the cases; however, this is atypical. It can be considered a non-typical user and a green-advocate end-user as these household members are aware of the environmental impact of their actions. On the other hand, case 2 can be considered a traditionalist home-focused end-user type [34], and Case 3 is another type of user that does not change the values from default or a disengaged energy waser

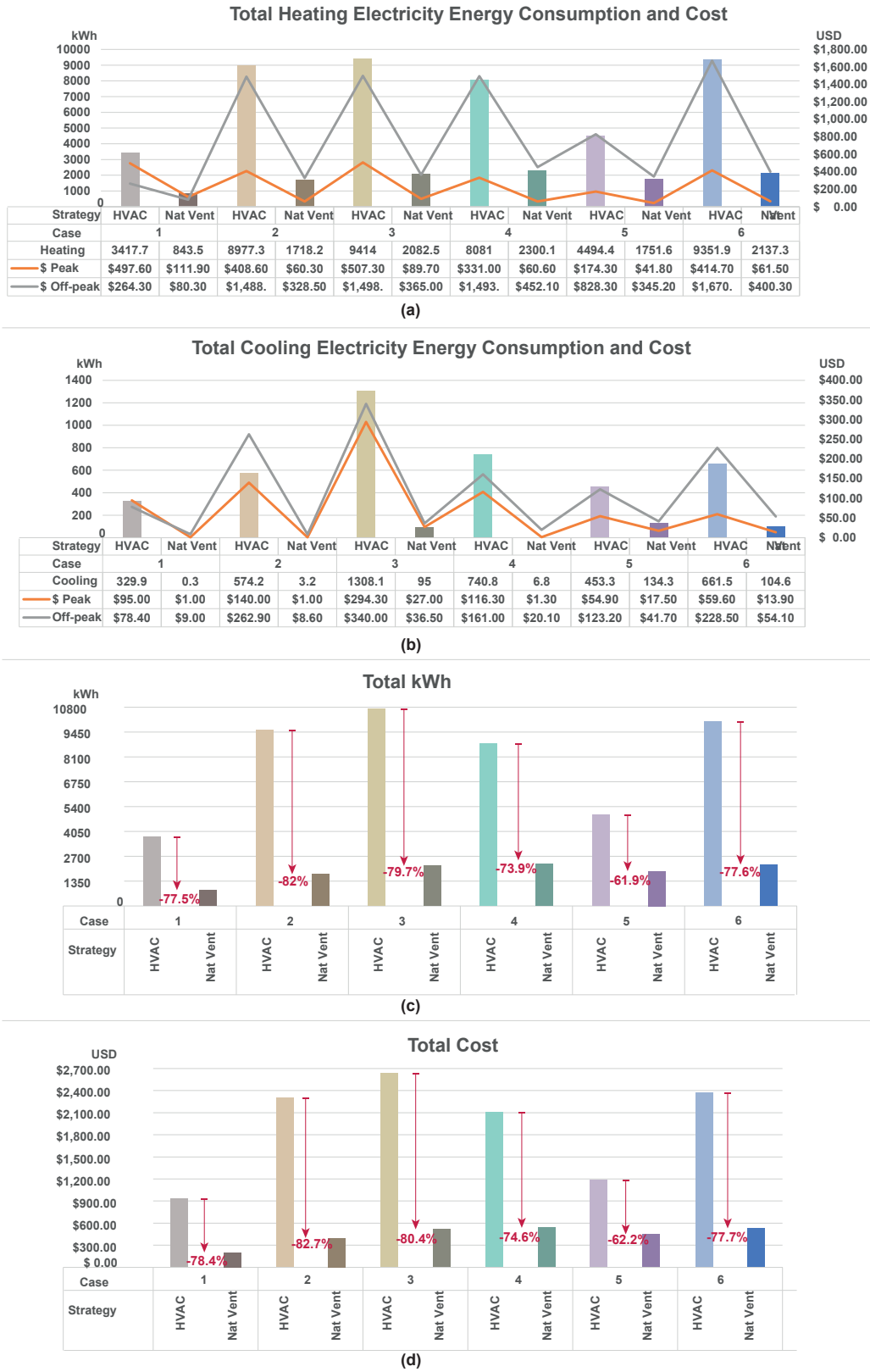


Fig. 14. (a) Total heating electricity energy consumption and cost. (b) Total cooling electricity energy consumption and cost. (c) Total HVAC electricity energy consumption and savings. (d) Total HVAC electricity cost and savings.

end-user. The kWh for cooling and heating was consistent with the HDD65 and CDD65 depicted in Fig. 9. For instance, Los Angeles' cases are the strategies that have less consumption compared with cases 2, 3, 5, and 6. Case 1, in this case, is out of this analysis as the owners are aware that their consumption are lower than the local metrics.

Furthermore, although the first case shows that theoretically, there is no thermal comfort at some hours, as Fergus Nicol and

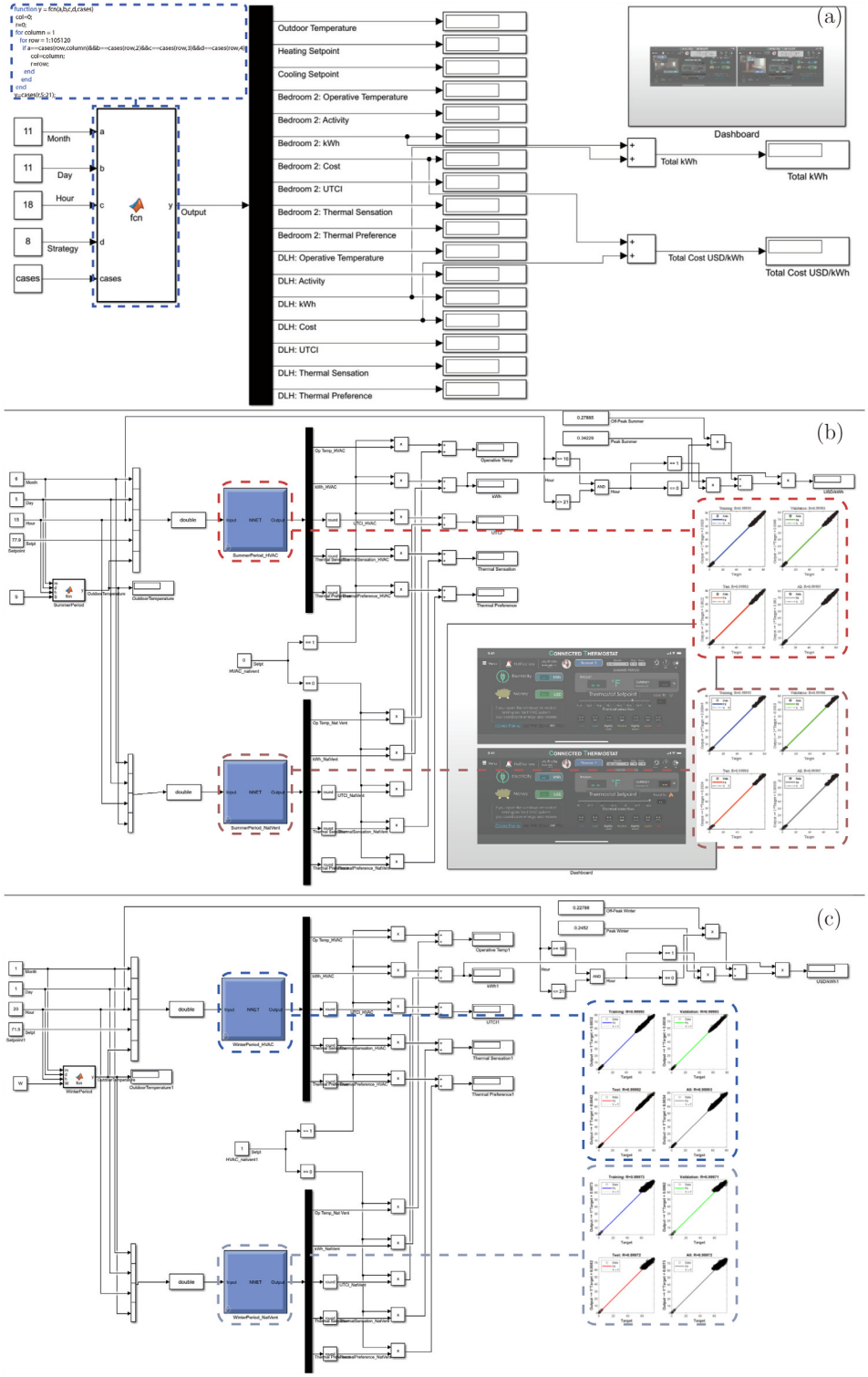


Fig. 15. Simulink diagram for the second type of the interactive interface. (a) shows the diagram for the summer period, and (b) for the winter period.

Humphreys [44] indicated, some of the measures of not losing thermal comfort during low temperatures are taking a nap or going to sleep, in this case, during the hours in which Bedroom 2 is uncomfortable, the individuals are sleeping. Thus, for the case of the DLH zone, there are unmet hours of thermal comfort. However, the individual feels comfortable as they are habituated to these temperatures; moreover, different strategies can be addressed to suggest that the end-user should use warmer clothes or possibly perform activities to improve their thermal comfort.

Besides, energy model simulators like the LB Tools [57] allow personalized schedules, activities, or clothes for a year simulation. However, this simulator lacks real-time feedback or usage; thus, the schedules remain constant, while real-time activities are dynamic. Nevertheless, as an approach to energy usage and thermal comfort, these models are ideal for framing out the general framework of energy consumption.

During the decision system process, two types of interfaces are depicted. The first interface adds the energy model results into an

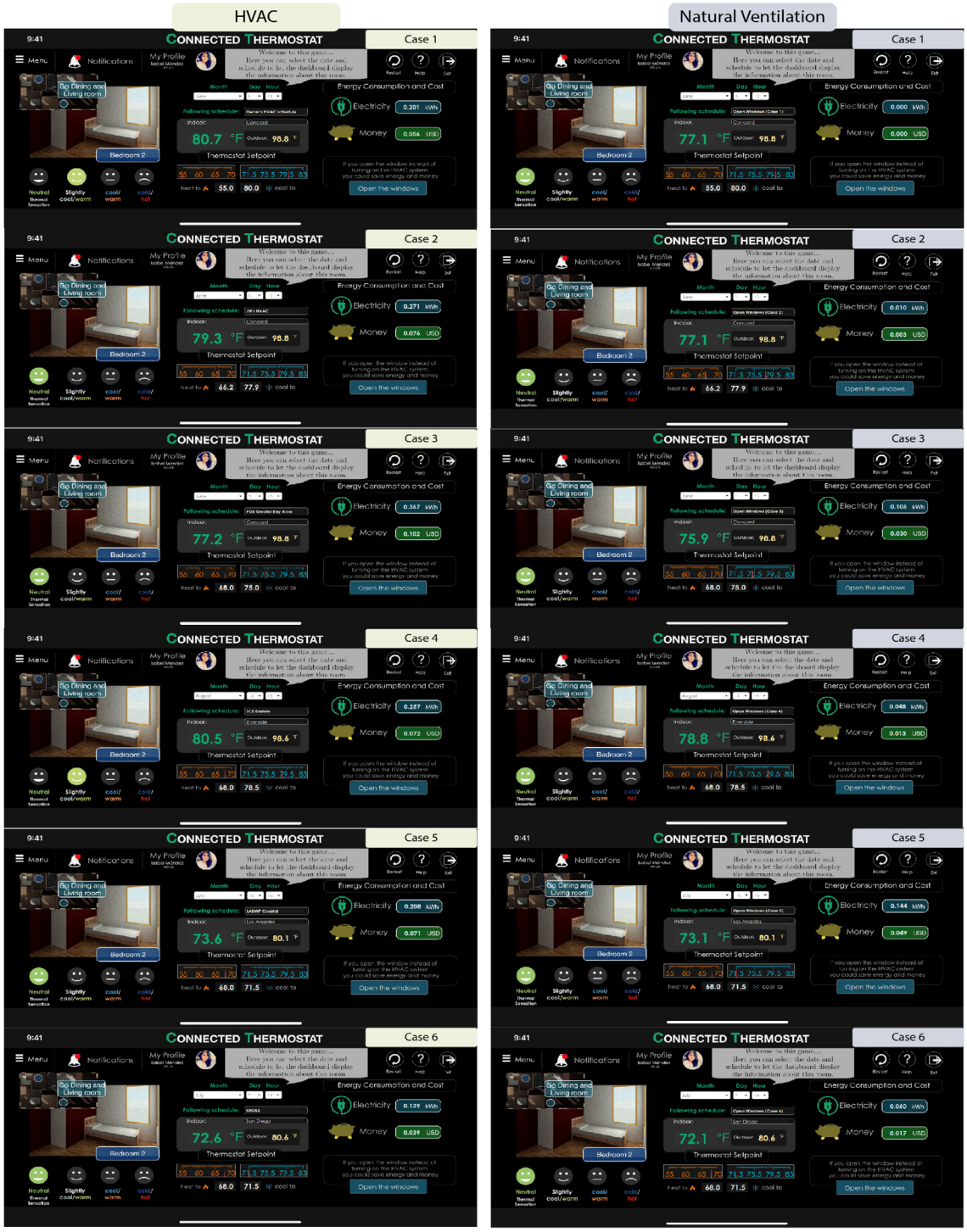


Fig. 16. Interactive Dashboard Results.

SG context, and the second interface includes a two-layer feed-forward ANN model. Regarding thermal comfort, using the NV strategy in bedroom 2, cases 5 and six show a reduction for the maximum values of the thermal sensation scale. Cases 3 to 6 show that the NV strategy changed from a slightly warm sensation to a neutral one for the dining and living room zone. Fig. 15(a) displays 17 variables; the activity and the other thermal scales are not displayed in the interfaces to avoid any overcharged dashboard. This research aims to display the thermal sensation while saving energy and money.

Finally, two types of interaction are promoted. First, the householder interacts with an SGs interface by selecting only the date and the schedule to watch the thermostat setpoint used for that specific scenario and the energy consumption. The idea is to open the individual's mind to the energy impacts of each setpoint case and how that setpoint and location affect the energy usage, money consumption, and thermal sensation. For instance, it is not the same consumption in Riverside as in Los Angeles. Second, the individuals interact with the ANN interface to teach their energy consumption and thermal sensation by selecting higher setpoints

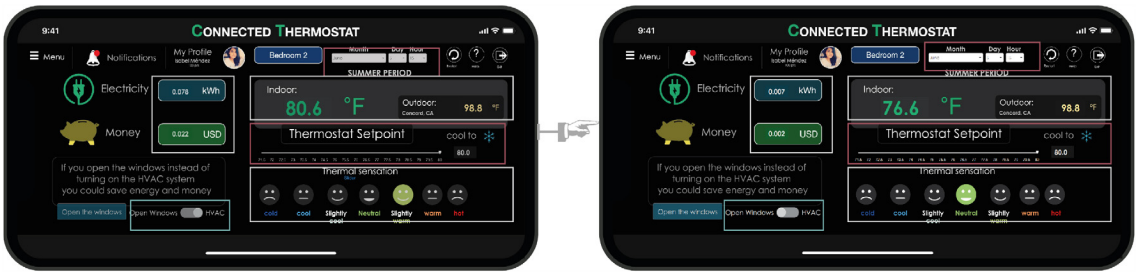


Fig. 17. ANN Dashboard results.

during summer periods or lower setpoints during winter. In addition, the end-user interacts directly with the thermostat setpoint to visualize the immediate effects of changing the setpoint or opening the windows.

On the other hand, low-income families suffer from energy poverty [13,35–37]. Thus, the interface can consider Ponce et al. [27] low-income thermostats. Nevertheless, some householders may not engage or not use an interface due to energy poverty conditions [13]. Therefore, further steps should address this topic by considering behavior under energy poverty conditions and finding strategies to help households achieve thermal comfort using 2/3 of their income for energy services [36].

6. Conclusion

The goals that are reached in this research are the following:

- Decreasing energy consumption in households by SGs in the connected thermostat interface;
- teaching the end-user the benefits of using an adaptive strategy to promote energy and money savings;
- Implementing ludic activities to keep acceptable thermal comfort ranges without increasing the energy consumption.

As a result, the interface needs to consider the community and not just the single home. This platform should consider the other homes, their electrical or energy consumption, and validate that opening the windows before turning on the air conditioning is suitable for this type of people because thermal comfort is mandatory to be considered beyond just looking for the reduction of energy or electricity billing.

Additionally, the interface must use different scenarios with contextual information to stimulate the user about the strategies adopted to reduce energy or cost savings, depending on their interest. In addition, the purpose of serious games is to motivate and teach the users without making them feel compromised to learn specific activities in a fun way. The interfaces proposed in this research were conceptualized under these concepts.

Hence, knowing the home consumption in detail and the day-to-day activities carried out in the home allows generating interfaces that provide feedback to the user. Therefore, managing a digital environment where the householders are in direct contact with their real electrical consumption allows them to interact with the interface and analyze the real implications of taking or not taking the decision regarding, for example, opening a window or decreasing or decreasing increasing the setpoint. All this, taking into account the primary interest of providing thermal comfort.

Two types of interfaces were proposed for a Serious Games context using a reference framework. The first interface took the energy model results into an interactive context. Thus, the end-user primarily interacted with the six scenarios to teach them the differences between strategies in an SG environment. The second interface predicted the energy consumption and thermal comfort based on the thermostat setpoint manipulation. Thus, the end-user visualized the differences between opening or using only HVAC during summer or winter.

During these scenarios and depending on the selected case, there was more consumption during off-peak than during peak periods during winter (Fig. 14(a)). During summer, cases like 1, 2, and 4 had lower consumption during peak periods (Fig. 14(b)). Furthermore, there were energy reductions up to 82% (Fig. 14)) and cost reductions from 62.2% to 82.7% (Fig. 14(d)).

Alternatively, interfaces, as proposed, gather information about end-users preferences. For instance, the thermal sensation component can collect end-user votes to better understand their thermal preferences and adjust techniques to engage them in activities to reduce consumption or money without affecting thermal comfort.

Hence, future work includes measuring how these SGs application affects or benefits the initial conditions selected in the energy model and the future implications of selecting other game techniques. For instance, LT provides a component to select a passive strategy and immediately visualize how these changes affect thermal comfort and energy reduction. Therefore, future research can include but are not limited to these topics:

- In terms of energy simulation impacts, optimization methods suggest a range of minimum or maximum setpoints needed to ventilate or heat the space without losing thermal comfort. Thus, future research should include optimization methods as Genetic Algorithms that can analyze those impacts.
- Use a FL decision system based on the thermal sensation to propose an adaptive strategy that reduces energy consumption and saves money.
- Use of ANFIS systems to connect multi-sensory systems to analyze the clothing insulation or activities to understand end-user behavior and therefore promote strategies that help in reducing energy without losing thermal comfort in real-time.
- Consider a decision system that includes the energy poverty topic and its impact on householder behavior, thermal comfort, and energy savings.

This framework helps build the energy model simulation and proposes the two types of interfaces to analyze the difference of using adaptive strategies; thus, the end-user behavior became energy aware. Besides, employing other adaptive strategies such as garments or metabolic rate to predict thermal comfort or even propose personal thermal comfort models can help better understand the end-user attitudes and behaviors toward saving energy.

Modeling and simulating energy cases require further knowledge of end-users' patterns and environments, such as their behavior during occupied spaces and their location. Besides, these simulations provide insights regarding thermal home and end-users characteristics. Thus, a novel approach analyzed in this research was using SG elements with educational purposes within

the thermostat interface and included the impact of thermal sensation on energy and money savings.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] EIA, U.s. energy information administration (eia) - data, 2020. url: https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T07.06#/?f=A..
[2] D. Bienvenido-Huertas, D. Sánchez-García, C. Rubio-Bellido, J. Pulido-Arcas, Influence of the improvement in thermal expectation levels with adaptive setpoint temperatures on energy consumption, Ann. Phys. 10 (2020) 5282, https://doi.org/10.3390/app10155282.
[3] R. de Dear, J. Xiong, J. Kim, B. Cao, A review of adaptive thermal comfort research since 1998, Energy Build. 214 (2020), https://doi.org/10.1016/j.enbuild.2020.109893 109893.
[4] V. Tomat, A.P. Ramallo-González, A.F. Skarmeta Gómez, A comprehensive survey about thermal comfort under the iot paradigm: Is crowdsensing the new horizon?, Sensors 20 (2020) 4647. doi:110.3390/s20164647..
[5] T. Chaudhuri, Y.C. Soh, H. Li, L. Xie, A feedforward neural network based indoor-climate control framework for thermal comfort and energy saving in buildings, Appl. Energy 248 (2019) 44–53, https://doi.org/10.1016/j.apenergy.2019.04.065.
[6] A. Meier, L. Rainer, A. Daken, T. Ueno, M. Pritoni, D. Baldewicz, What can connected thermostats tell us about american heating and cooling habits?, in: ECEEE SUMMER STUDY PROCEEDINGS, 2019, p. 10..
[7] R. de Dear, G. Brager, Developing an adaptive model of thermal comfort and preference, ASHRAE Trans. 104 (1998) 145–167.
[8] K.C. Parsons, Human thermal comfort, CRC Press/Taylor & Francis Group (2020), https://doi.org/10.1201/9780429294983.
[9] J. Nicol, M. Humphreys, Adaptive thermal comfort and sustainable thermal standards for buildings, Energy Build. 34 (2002) 563–572, https://doi.org/10.1016/S0378-7788(02)00006-3.
[10] J. Woods, Fiddling with thermostats: energy implications of heating and cooling set point behavior, in: Proceedings of the 2006 ACEEE summer study on energy efficiency in buildings, 2006.
[11] B. Huchuk, W. O'Brien, S. Sanner, A longitudinal study of thermostat behaviors based on climate, seasonal, and energy price considerations using connected thermostat data, Build. Environ. 139 (2018) 199–210, https://doi.org/10.1016/j.buildenv.2018.05.003.
[12] K.S. Cetin, Z. O'Neill, Smart meters and smart devices in buildings: A review of recent progress and influence on electricity use and peak demand, ACurrent Sustain./Renew. Energy Rep. 4 (2017) 1–7, https://doi.org/10.1007/s40518-017-0063-7.
[13] V. Fanghella, N. Della Valle, A behavioral model for in-home displays usage in social housing districts, in: International conference on Smart and Sustainable Planning for Cities and Regions, Springer, 2019, pp. 511–524.
[14] P. Ponce, A. Meier, J.I. Méndez, T. Peffer, A. Molina, O. Mata, Tailored gamification and serious game framework based on fuzzy logic for saving energy in smart thermostats, J. Clean. Prod. 262 (2020), https://doi.org/10.1016/j.jclepro.2020.121167 121167.
[15] J.I. Méndez, P. Ponce, O. Miranda, C. Pérez, A.P. Cruz, T. Peffer, A. Meier, T. McDaniel, A. Molina, Designing a consumer framework for social products within a gamified smart home context, in: International Conference on Human-Computer Interaction, Springer International Publishing, 2021, pp. 429–443, https://doi.org/10.1007/978-3-030-78092-0_29.
[16] J.I. Méndez, P. Ponce, A. Meier, T. Peffer, O. Mata, A. Molina, S<Superscript>4</Superscript> product design framework: A gamification strategy based on type 1 and 2 fuzzy logic, in: International Conference on Smart Multimedia, Springer, 2019, pp. 509–524.
[17] Pinkapp, Power tap: Idle clicker, 2017. url: https://appadvice.com/app/power-tap-idle-clicker/1236703625..
[18] EnerGAware, Energy game for awareness of energy efficiency in social housing communities, 2015. url: https://www.energaware.eu/..
[19] T.S. Expert, Energy manager the serious game, 2020. url: https://en.2makesense.com/productions/energy_manager.php..
[20] I. Chatzigeorgiou, G. Andreou, A systematic review on feedback research for residential energy behavior change through mobile and web interfaces, Renew. Sustain. Energy Rev. 135 (2021), https://doi.org/10.1016/j.rser.2020.110187 110187.
[21] A. Medina, J.I. Méndez, P. Ponce, T. Peffer, A. Meier, A. Molina, Using deep learning in real-time for clothing classification with connected thermostats, Energies 15 (2022) 1811, https://doi.org/10.3390/en15051811.
[22] T. Peffer, M. Pritoni, A. Meier, C. Aragon, D. Perry, How people use thermostats in homes: A review, Build. Environ. 46 (2011) 2529–2541, https://doi.org/10.1016/j.buildenv.2011.06.002.
[23] T. Peffer, D. Perry, M. Pritoni, C. Aragon, A. Meier, Facilitating energy savings with programmable thermostats: evaluation and guidelines for the thermostat user interface, Ergonomics 56 (2013) 463–479, https://doi.org/10.1080/00140139.2012.718370.
[24] J.I. Méndez, P. Ponce, O. Mata, A. Meier, T. Peffer, A. Molina, M. Aguilar, Empower saving energy into smart homes using a gamification structure by social products, in: 2020 IEEE International Conference on Consumer Electronics (ICCE), IEEE, 2020, pp. 1–7.
[25] J.I. Méndez, P. Ponce, A. Meier, T. Peffer, O. Mata, A. Molina, Framework for promoting social interaction and physical activity in elderly people using gamification and fuzzy logic strategy, in: 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), IEEE, 2019, pp. 1–5.
[26] O. Mata, P.P.J.I. Méndez, A. Molina, A. Meier, T. Peffer, A model using artificial neural networks and fuzzy logic for knowing the consumer on smart thermostats as a s 3 product, in: Mexican International Conference on Artificial Intelligence, Springer, 2019, pp. 430–439.
[27] P. Ponce, T. Peffer, A. Molina, S. Barcena, Social creation networks for designing low income interfaces in programmable thermostats, Technol. Soc. 62 (2020) 101299.
[28] J. Oliver, S. Srivastava, The big five trait taxonomy: History, measurement, and theoretical perspectives, Handbook of personality: Theory and research 2 (1999) 102–138.
[29] R. Bartle, Hearts, clubs, diamonds, spades: Players who suit muds, J. MUD Res. 1 (1996) 19.
[30] G.F. Tondello, R.R. Wehbe, L. Diamond, M. Busch, A. Marczewski, L.E. Nacke, The gamification user types hexad scale, in: Proceedings of the 2016 annual symposium on computer-human interaction in play, 2016, pp. 229–243..
[31] G.F. Tondello, A. Mora, A. Marczewski, L.E. Nacke, Empirical validation of the gamification user types hexad scale in english and spanish, Int. J. Hum Comput Stud. 127 (2019) 95–111.
[32] P. Ponce, T. Peffer, A. Molina, Framework for communicating with consumers using an expectation interface in smart thermostats, Energy Build. 145 (2017) 44–56.
[33] D. Frankel, S. Heck, H. Tai, Using a consumer segmentation approach to make energy efficiency gains in the residential market, McKinsey and Company: Chicago, IL, USA (2013) 1–9..
[34] J.I. Méndez, P. Ponce, A. Medina, A. Meier, T. Peffer, T. McDaniel, A. Molina, Human-machine interfaces for socially connected devices: From smart households to smart cities, in: Multimedia for Accessible Human Computer Interfaces, Springer, 2021, pp. 253–289, https://doi.org/10.1007/978-3-030-70716-3_9.
[35] J. Malik, R. Bardhan, P. Banerji, Rethinking indoor thermal comfort in the era of rebound and pre-bound effect for the developing world: A systematic review, Indoor air 30 (2020) 377–395.
[36] H. Thomson, S. Bouzarovski, C. Snell, Rethinking the measurement of energy poverty in europe: A critical analysis of indicators and data, Indoor Built Environ. 26 (2017) 879–901.
[37] S. Petrova, M. Gentile, I.H. Mäkinen, S. Bouzarovski, Perceptions of thermal comfort and housing quality: exploring the microgeographies of energy poverty in stakhanov, ukraine, Environ. Plann. A: Econ. Space 45 (2013) 1240–1257.
[38] K. Karyono, B.M. Abdullah, A.J. Cotgrave, A. Bras, The adaptive thermal comfort review from the 1920s, the present, and the future, Develop. Built Environ. 4 (2020), https://doi.org/10.1016/j.dibe.2020.100032 100032.
[39] P.O. Fanger, Thermal Comfort: Analysis and Applications in Environmental Engineering, Danish Technical Press, 1970.
[40] M. Jenkins, What is ashrae 55? basics of thermal comfort, 2020. url: https://bit.ly/2WZmRD2..
[41] S. Carlucci, L. Bai, R. de Dear, L. Yang, Review of adaptive thermal comfort models in built environmental regulatory documents, Ann. Phys. 137 (2018) 73–89, https://doi.org/10.1016/j.buildenv.2018.03.053.
[42] F. Nicol, M. Humphreys, S. Roaf, Adaptive thermal comfort: principles and practice, Routledge, 2012.
[43] M. Humphreys, F. Nicol, S. Roaf, Adaptive thermal comfort: foundations and analysis, Routledge, 2015.
[44] J. Fergus Nicol, M.A. Humphreys, Principles of adaptive behaviours, in: Sustainable Houses and Living in the Hot-Humid Climates of Asia, volume 24, Springer Singapore, 2018, pp. 209–217. doi:10.1007/978-981-10-8465-2_20..
[45] D. Bienvenido-Huertas, J.A. Pulido-Arcas, C. Rubio-Bellido, A. Pérez-Fargallo, Feasibility of adaptive thermal comfort for energy savings in cooling and heating: A study on europe and the mediterranean basin, Urban Clim. 36 (2021), https://doi.org/10.1016/j.uclim.2021.100807 100807.
[46] J.I. Méndez, A.V. Meza-Sánchez, P. Ponce, T. McDaniel, T. Peffer, A. Meier, A. Molina, Smart homes as enablers for depression pre-diagnosis using phq-9 on hmi through fuzzy logic decision system, Sensors 21 (2021) 7864.

[47] J.I. Méndez, P. Ponce, T. Peffer, A. Meier, A. Molina, A gamified hmi as a response for implementing a smart-sustainable university campus, Working Conference on Virtual Enterprises, Springer (2021) 683–691.
[48] M. Ávila, J.I. Méndez, P. Ponce, T. Peffer, A. Meier, A. Molina, Energy management system based on a gamified application for households, Energies 14 (2021) 3445, https://doi.org/10.3390/en14123445.
[49] J.I. Méndez, P. Ponce, M. Pecina, G. Schroeder, A.S. Castellanos, T. Peffer, A. Meier, A. Molina, A rapid hmi prototyping based on personality traits and ai for social connected thermostats, in: Mexican International Conference on Artificial Intelligence, Springer, 2021, pp. 216–227. doi:0.1007/978-3-030-89820-5_18..
[50] J.I. Méndez, P. Ponce, A. Medina, T. Peffer, A. Meier, A. Molina, A smooth and accepted transition to the future of cities based on the standard iso 37120, artificial intelligence, and gamification constructors, in: 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), IEEE, 2021, pp. 65–71..
[51] J.I. Méndez, O. Mata, P. Ponce, A. Meier, T. Peffer, A. Molina, Multi-sensor system, gamification, and artificial intelligence for benefit elderly people, in: Challenges and Trends in Multimodal Fall Detection for Healthcare, Springer International Publishing, 2020, pp. 207–235, https://doi.org/10.1007/978-3-030-38748-8_9.
[52] A.H. Al Ka'bi, Comparison of energy simulation applications used in green building, Ann. Telecommun. 75 (2020) 271–290, https://doi.org/10.1007/s12243-020-00771-6.
[53] EnergyPlus, Energyplus, 2021. url: https://energyplus.net/..
[54] D.B. Crawley, C.O. Pedersen, L.K. Lawrie, F.C. Winkelmann, Energyplus: Energy simulation program, ASHRAE J. 24 (2000) 49–56.
[55] L. Rincón, A. Carrobé, I. Martorell, M. Medrano, Improving thermal comfort of earthen dwellings in sub-saharan africa with passive design, J. Build. Eng. 24 (2019), https://doi.org/10.1016/j.jobe.2019.100732 100732.
[56] G.Y. Yun, Influences of perceived control on thermal comfort and energy use in buildings, Energy Build. 158 (2018) 822–830, https://doi.org/10.1016/j.enbuild.2017.10.044.
[57] L. Tools, Ladybug tools: Making environmental design knowledge and tools freely accessible to every person, project and design process, 2021. url: https://www.ladybug.tools/..
[58] E. Naboni, A. Milella, R. Vadalà, F. Fiorito, On the localised climate change mitigation potential of building facades, Energy Build. 224 (2020), https://doi.org/10.1016/j.enbuild.2020.110284 110284.
[59] G. Evola, V. Costanzo, C. Magrì, G. Margani, L. Marletta, E. Naboni, A novel comprehensive workflow for modelling outdoor thermal comfort and energy demand in urban canyons: Results and critical issues, Energy Build. 216 (2020), https://doi.org/10.1016/j.enbuild.2020.109946 109946.
[60] S. Motamedi, P. Liedl, Integrative algorithm to optimize skylights considering fully impacts of daylight on energy, Energy Build. 138 (2017) 655–665, https://doi.org/10.1016/j.enbuild.2016.12.045.
[61] P. Hoseinzadeh, M.K. Assadi, S. Heidari, M. Khalatbari, R. Saidur, K.H. nejad, H. Sangin, Energy performance of building integrated photovoltaic high-rise building: Case study, tehran, iran, Energy Build. 235 (2021) 110707. doi:10.1016/j.enbuild.2020.110707..
[62] E.D. Giouri, M. Tenpierik, M. Turrin, Zero energy potential of a high-rise office building in a mediterranean climate: Using multi-objective optimization to understand the impact of design decisions towards zero-energy high-rise buildings, Energy Build. 209 (2020), https://doi.org/10.1016/j.enbuild.2019.109666 109666.
[63] G. Lobaccaro, S. Croce, D. Vettorato, S. Carlucci, A holistic approach to assess the exploitation of renewable energy sources for design interventions in the early design phases, Energy Build. 175 (2018) 235–256, https://doi.org/10.1016/j.enbuild.2018.06.066.
[64] F. Jazizadeh, F.M. Marin, B. Becerik-Gerber, A thermal preference scale for personalized comfort profile identification via participatory sensing, Build. Environ. 68 (2013) 140–149, https://doi.org/10.1016/j.buildenv.2013.06.011.
[65] K. Błażejczyk, G. Jendritzky, P. Bröde, D. Fiala, G. Havenith, Y. Epstein, A. Psikuta, B. Kampmann, An introduction to the universal thermal climate index (utci), Geographia Pol. 86 (2013) 5–10, https://doi.org/10.7163/GPol.2013.1.
[66] S. Hong, J. Lee, J. Moon, K. Lee, Thermal comfort, energy and cost impacts of pmv control considering individual metabolic rate variations in residential building, Energies 11 (2018) 1767, https://doi.org/10.3390/en11071767.
[67] J. Ngarambe, G.Y. Yun, M. Santamouris, The use of artificial intelligence (ai) methods in the prediction of thermal comfort in buildings: energy implications of ai-based thermal comfort controls, Energy Build. 211 (2020), https://doi.org/10.1016/j.enbuild.2020.109807 109807.
[68] Y.I. Alamin, J.D. Álvarez, M. del Mar Castilla, A. Ruano, An artificial neural network (ann) model to predict the electric load profile for an hvac system, IFAC-PapersOnLine 51 (2018) 26–31, https://doi.org/10.1016/j.ifacol.2018.06.231.
[69] W. Zhang, Y. Wen, K. Tseng, G. Jin, Demystifying thermal comfort in smart buildings: An interpretable machine learning approach, IEEE Internet Things J. 8 (2021) 8021–8031, https://doi.org/10.1109/JIOT.2020.3042783.
[70] J.W. Moon, Y. Yoon, Y.-H. Jeon, S. Kim, Prediction models and control algorithms for predictive applications of setback temperature in cooling systems, Appl. Therm. Eng. 113 (2017) 1290–1302, https://doi.org/10.1016/j.applthermaleng.2016.11.087.
[71] M.H. Chung, Y.K. Yang, K.H. Lee, J.H. Lee, J.W. Moon, Application of artificial neural networks for determining energy-efficient operating set-points of the vrf cooling system, Build. Environ. 125 (2017) 77–87, https://doi.org/10.1016/j.buildenv.2017.08.044.
[72] P. Ponce, A. Meier, J. Miranda, A. Molina, T. Peffer, The next generation of social products based on sensing, smart and sustainable (s3) features: a smart thermostat as case study, IFAC-PapersOnLine 52 (2019) 2390–2395.
[73] M.H. Naraghi, Energy Dynamics of Green Buildings, Linus Learning (2020).
[74] U.D. of Energy, Energyplus version 9.5.0 documentation: Input output reference, 2021..
[75] Climate.OneBuilding.Org, Concord epw zip file, 2021. url: http://climate.onebuilding.org/WMO_Region_4_North_and_Central_ America/California_Climate_Zones/California_CTZ_2016/USA_CA_ Concord-Buchanan.Field. 724936_CTZ2016.zip..
[76] Climate.OneBuilding.Org, Riverside epw zip file, 2021. url: http://climate.onebuilding.org/WMO_Region_4_North_and_Central_ America/California_Climate_Zones/California_CTZ_2016/USA_CA_ Riverside-March.ARB.722860_CTZ2016.zip..
[77] Climate.OneBuilding.Org, Los angeles epw zip file, 2021. url: http://climate.onebuilding.org/WMO_Region_4_North_and_Central_ America/California_Climate_Zones/California_CTZ_2016/USA_CA_ Los.Angeles.Downtown.722874_CTZ2016.zip..
[78] Climate.OneBuilding.Org, San diego epw zip file, 2021. url: http://climate.onebuilding.org/WMO_Region_4_North_and_Central_ America/USA_United_States_of_America/CA_California/USA_CA_San. Diego-MCAS.Miramar. 722930_TMY3.zip..
[79] PG&E, Electric schedule e-tou-c, 2021. url: https://bit.ly/3jV6ZKX..
[80] R. Fassbender, What is energy model calibration? pt 1, 2021. url: https://energy-models.com/blog/what-energy-model-calibration-pt-1..
[81] M. Royapoor, T. Roskilly, Building model calibration using energy and environmental data, Energy Build. 94 (2015) 109–120.
[82] D. Coakley, PaulRaftery, MarcusKeane, A review of methods to match building energy simulation models to measured data, Renew. Sustain. Energy Rev. 37 (2014) 123–141..
[83] D.E. Insights, California statewide residential appliance saturation study, 2019. url: https://webtools.dnv.com/CA_RASS/..
[84] W. Terence, D. Lyrian, A new adaptive thermal comfort model for homes in temperate climates of australia, Energy Build. 210 (2020) 109728.
[85] MathWorks, Mathworks: Open network/data manager - matlab nntool, 2021. url: https://www.mathworks.com/help/deeplearning/ref/nntool.html..
[86] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 1), 2021. url: https://rpubs.com/IsabelMendezG/c1..
[87] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 2), 2021. url: https://rpubs.com/IsabelMendezG/c2..
[88] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 3), 2021. url: https://rpubs.com/IsabelMendezG/c3..
[89] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 4), 2021. url: https://rpubs.com/IsabelMendezG/c4..
[90] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 5), 2021. url: https://rpubs.com/IsabelMendezG/c5..
[91] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Adaptive thermal comfort: Operative temperatures for bedroom 2 and dining and living room (complementary data: Case 6), 2021. url: https://rpubs.com/IsabelMendezG/c6..
[92] J.I. Méndez, T. Peffer, P. Ponce, A. Meier, A. Molina, Github repository: Adaptivethermalcomfort_california, 2021. url: https://github.com/IsabelMendezG/AdaptiveThC_California..

Chapter 3

Smart Homes as Enablers for Depression Pre-diagnosis using PHQ-9 on HMI through Fuzzy Logic Decision System

3.1 Summary of the Chapter

This chapter focuses on the healthcare sector product platform. Currently, about 54 % of the houses have smart home devices [38]. Thus, this research proposes to take advantage of smart household appliances for working as a depression pre-diagnosis. It is relevant to mention that this proposal does not intend to substitute the medical expert option. On the contrary, this proposal aims to help the healthcare expert by providing information about the consumer and their behavior within a smart home environment.

Depression is a common mental illness characterized by sadness, lack of interest, or pleasure. According to the DSM-5, there are nine symptoms, from which an individual must present 4 or 5 in the last two weeks to fulfill the diagnosis criteria of depression. Nevertheless, the common methods that healthcare professionals use to assess and monitor depression symptoms are face-to-face questionnaires leading to time-consuming or expensive methods.

On the other hand, smart homes can monitor householders' health through smart devices such as smartphones, wearables, cameras, or voice assistants connected to the home. Although the depression disorders at smart homes are commonly oriented to the senior sector, depression affects everyone. Therefore, even though an expert must diagnose the depression disorder, questionnaires such as the PHQ-9 help spot any depressive symptomatology as a pre-diagnosis.

sensors

MDPI

Article

Smart Homes as Enablers for Depression Pre-Diagnosis Using PHQ-9 on HMI through Fuzzy Logic Decision System

Juana Isabel Méndez [1], Ana Victoria Meza-Sánchez [2], Pedro Ponce [1,*], Troy McDaniel [3], Therese Peffer [4], Alan Meier [5] and Arturo Molina [1]

1 School of Engineering and Sciences, Tecnologico de Monterrey, Mexico City 14380, Mexico; A01165549@itesm.mx (J.I.M.); armolina@tec.mx (A.M.)
2 Escuela Superior de Medicina, Instituto Politecnico Nacional, Mexico City 11340, Mexico; mezaana.med@gmail.com
3 The Polytechnic School, Arizona State University, Mesa, AZ 85212, USA; troy.mcdaniel@asu.edu
4 Institute for Energy and Environment, University of California, Berkeley, CA 94720, USA; tpeffer@berkeley.edu
5 Energy and Efficiency Institute, University of California, Davis, CA 95616, USA; akmeier@ucdavis.edu
* Correspondence: pedro.ponce@tec.mx

Abstract: Depression is a common mental illness characterized by sadness, lack of interest, or pleasure. According to the DSM-5, there are nine symptoms, from which an individual must present 4 or 5 in the last two weeks to fulfill the diagnosis criteria of depression. Nevertheless, the common methods that health care professionals use to assess and monitor depression symptoms are face-to-face questionnaires leading to time-consuming or expensive methods. On the other hand, smart homes can monitor householders' health through smart devices such as smartphones, wearables, cameras, or voice assistants connected to the home. Although the depression disorders at smart homes are commonly oriented to the senior sector, depression affects all of us. Therefore, even though an expert needs to diagnose the depression disorder, questionnaires as the PHQ-9 help spot any depressive symptomatology as a pre-diagnosis. Thus, this paper proposes a three-step framework; the first step assesses the nine questions to the end-user through ALEXA or a gamified HMI. Then, a fuzzy logic decision system considers three actions based on the nine responses. Finally, the last step considers these three actions: continue monitoring through Alexa and the HMI, suggest specialist referral, and mandatory specialist referral.

Keywords: smart home; PHQ-9; depression pre-diagnosis; HMI

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1. Introduction

According to the World Health Organization, depression is a common mental disease around the world. About 5% of depressed individuals are adults, and 5.7% are senior people [1]. Besides, depression increased by 60% during Coronavirus disease (COVID-19) [2]. Recurrent and moderate to severe intensity depression have serious health conditions and can lead to suicide [1]. Young adults and people older than 60 years may be the most vulnerable group [1,2].

The Patient Health Questionnaire 9 (PHQ-9) is a short, self-administered questionnaire and a mental health depression screener based on the Diagnostic and Statistical Manual of Mental Disorders, fifth edition (DSM-5) [3,4]. Nevertheless, the common methods that health care professionals use to assess and monitor depression symptoms are face-to-face questionnaires leading to time-consuming or expensive methods [5]. Thus, efforts require taking advantage of what is accessible to the end-user to provide information to the health care professional. Proposals include using a smartphone and smartwatch to classify depression, physical activity, mood, social activity, sleep, and food intake [5] or the use of a smartphone to assess the PHQ-9 [6].

Smartphones or wearables, like smartwatches, are often used by single individuals as an extension of their life; they are devices that can help detect and monitor depressive symptoms [5,7,8]. On the other hand, smart homes have been arising due to the Internet of Things; for instance, modern household appliances have increased the comfort level of householders [9–12]. Chatbots are used to track mood and help users deal with depression [13,14]; thus, voice assistants as Siri or Alexa have become appealing for individuals. It has been reported that end-users prefer to interact with technology rather than health professionals [15].

COVID-19 impacted daily life and increased anxiety, depression, and suicide because individuals were clustered at homes or as a secondary effect of economic disruption [16]. In addition, their restrictions included zero interaction with other users by closing schools, universities, recreational facilities, or workplaces [2,17,18]. As a response, technologies at smart homes accelerated due to their necessity for daily activities such as work, study, or socializing [19]. Moreover, smart homes can help the health care sector by monitoring householders' health through smartphones, wearables, cameras, or voice assistants connected to the home [10,20–23].

The structure of this paper is as follows: Section 2 presents the literature review regarding depression, the PHQ-9 questionnaire, and the smart homes as enablers for depression pre-diagnosis. Section 3 presents the three-step methodology used for this paper. Section 4 describes the proposed framework by step. Section 5 shows the proposed framework results and its linkage with gamified HMIs oriented for depression pre-diagnosis at home. Section 6 discusses the proposal with its advantages and limitations. Finally, Section 7 details the conclusions and future work.

2. Literature Review

Depression is a common mental illness characterized by sadness, lack of interest, or pleasure. It may also be accompanied by somatic characteristics such as disturbed sleep and appetite, tiredness, and poor concentration. Its effects on a patient's physical, mental, and social well-being can lead to disability and cause a huge burden for healthcare systems and society. According to the World Health Organization (WHO), this illness affects approximately 3.8% of the 280 million people [1].

Consequently, depression is not exclusive to the older population; it can happen at any age leading to poor quality of life (QoL) and affecting the economically active population, as reported by Müller et al. [24]. They found that the self-reported mental distress, including depression and anxiety, was highly related to the days of incapacity to work through questionnaires and scales. Furthermore, this research reported that depressive patients presented 27 times more specific days of incapacity to work than healthy workers, leading to an economic burden of the disease due to its management costs.

According to the DSM-5, the diagnosis considers symptoms, behavioral changes, and the effect of these factors in someone's life. Hence, there are nine symptoms: sleep disturbance, interest/pleasure reduction, guilt feelings or thoughts of worthlessness, energy changes, concentration impairment, appetite or weight changes, psychomotor disturbances, suicidal thoughts, and depressed mood. In addition, an individual must present 4 or 5 (one of them being depressed mood or loss of interest or pleasure) in the last two weeks to fulfill the diagnosis criteria [25].

A specialist must perform the diagnosis based on the criteria through a guided interview. However, many questionnaires and scales have been developed due to the importance of identifying early cases; these cannot diagnose the patient. However, they can spot depressive symptoms and be used as screening or pre-diagnosis methods. In addition, suicidal thoughts are an important factor to consider; they are assessed in interviews and questionnaires. Based on the WHO reports, 700,000 people die due to suicide each year, therefore, the importance of its prompt diagnosis and management [1].

2.1. Diagnostic and Statistical Manual of Mental Disorders, Fifth Edition (DSM-5)

This manual has been used as the base for mental diseases since 1952 when its first edition was released [26]. It helps to standardize diagnosis for research, treatment, and prognosis across different physicians, hospitals, and countries. For its development, more than 160 researchers and physicians were gathered to reach a consensus for the criteria of the different disorders based on the most updated information and studies [27]. However, this manual does not include information about treatment or management. It can only be used for diagnosis, prognosis, and assessment of treatment effectiveness [27].

2.2. Patient Health Questionnaire 9 (PHQ-9)

The PHQ-9 consists of 9 Likert-type questions (0 to 3). The total punctuation ranges from 0 to 27, and it allows to classify the symptomatology in no depression (0–4), mild depression (5–9), moderate depression (10–14), moderately severe depression (15–19), and severe depression (20–27). This tool was developed in 1999 by Robert Spitzer, Janet Williams, and Kurt Kroenke, and since then, it has been translated and validated in many languages and countries. The items in the questionnaire are listed below (Table 1). The shaded section means that if there are at least four or more selected answers thus, there is an existence of a depressive disorder.

Table 1. Patient Health Questionnaire (PHQ-9).

Over the Last 2 Weeks, How Often Have You Been Bothered by Any of These Following Problems?	Not at All	Several Days	More than Half the Days	Nearly Every Day
1-5 1. Little interest or pleasure in doing things	0	1	2	3
2. Feeling down, depressed, or hopeless	0	1	2	3
3. Trouble falling or staying asleep, or sleeping too much	0	1	2	3
4. Feeling tired or having little energy	0	1	2	3
5. Poor appetite or overeating	0	1	2	3
6. Feeling bad about yourself—or that you are a failure or have let yourself of your family down	0	1	2	3
7. Trouble concentrating on things, such as reading the newspaper or watching television	0	1	2	3
8. Moving or speaking so slowly that other people could have noticed? Or the opposite—being so fidgety or restless that you have been moving around a lot more than usual?	0	1	2	3
9. Thoughts that you would be better off dead, or of hurting yourself.	0	1	2	3

Furthermore, this screening tool includes an item to assess the effect of the symptoms in the individual's QoL and relationship with others and an item assessing suicidal tendencies. The suicidal item or item nine must be considered an important factor for management and possible hospitalization of the patient [25,28]. The approximated application time is 5 min, it is usually self-administered, but it could also be administered through an interview in person or by telephone [28].

The questionnaire has been translated and validated in different languages and countries. Most of them have found it with adequate internal consistency, reliability, and excellent correlation with other scales such as the Beck Depression Inventory. For example, in the meta-analysis by He et al., considering a cut-off point of 10, they reported a pooled sensitivity of 0.88 and specificity of 0.86, compared with the structured and semi-structured interviews for diagnosis of depression [29]. The 2019 study by McCord and Provost in a university in the US reported the internal consistency of this tool with Cronbach's Alpha of 0.76 [30].

In June 2021, National Health and Nutrition Examination Survey (NHANES) program released a dataset corresponding to the 2017–2018 cycle and from 2019 to March 2020 answers of the PHQ-9 [31,32].

2.3. Smart Homes

A Smart Home (SH) monitors and manages home electronics and appliances through an Internet connection [33]. These devices or social products include thermostats, cameras, voice assistants, lights, doorbells, household appliances [9,20,34,35], and provide homeowners information on how much energy they have used on certain equipment or systems [11]. Moreover, an SH collects and analyzes data about the home environment, communicates that data to users and service providers, and improves the ability to manage various domestic systems through social products [12].

In addition, Marikyan et al. [10] classified the SHs into four groups based on the technology services:

1. Surveillance home: Householders receive alerts about possible natural disasters or security interventions. Besides, the SH gathers data from the environment to detect burglary threats.
2. Assistive home: This home type promotes the householders' well-being through action recognition. Hence, three types of services are offered:
    a. Senior oriented
    b. Child oriented
    c. Overall health-oriented
3. Detection and multimedia home: This home type detects and collects information from videos and photos of householders' daily lives.
4. Ecological awareness home: Householders monitor and control their energy supply against demand through special sensors and automatic monitoring systems. Thus, this home type promotes environmental sustainability.
    a. Smart Home Energy Management Systems have advanced IoT devices to convert a traditional home into an energy-aware home to reduce energy consumption and promote money savings [36].

However, a fifth type of home should be added, the Gamified SH. This type of home uses socially connected products [20,21,35,37–43] that profile end-users based on their personality traits, type of gamified user, and energy user [9,34,44,45] to propose tailored interfaces that help them understand the benefits of becoming pro-environmental or energy-aware. Figure 1 depicts an example of this type of home.

Fuzzy Logic and Smart Homes for Detection of Depressive Disorders

The computer scientist, Lotfi Zadeh from the University of California Berkeley, proposed in 1965 the fuzzy set theory as a class of sets based on membership grades from 0 to 1 [46]. The fuzzy set has inference rules that do not require a mathematical model of the real system but rather rules generated by experts, polls, or consensus-building [47,48]. Hence, fuzzy logic (FL) was created to model uncertainty based on linguistic words and sentences, known as linguistic variables, to associate them with human logic rather than the use of numerical values. The process begins with the fuzzification step that classifies in fuzzy sets the variables with an uncertainty metalinguistic degree. Following, the experts propose the linguist inference rules with an antecedent IF and a consequent THEN. Finalizing with the defuzzification step is the final process that determines the output values through fuzzy inference methods such as the Mamdani and the Sugeno inference [48].

Multi-sensor data fusion is a framework that collects information from multiple sensors to make inferences and create functions that compensate, process information, communicate, and integrate to provide quantitative measurements consistently [20,42,47]. The multi-sensor data fusion bases its concept on human beings' and animals' fundamental tasks, using multiple sensors to survive and track possible threats. Furthermore, this

a. Smart Home Energy Management Systems have advanced IoT devices to convert a traditional home into an energy-aware home to reduce energy consumption and promote money savings [36].

However, a fifth type of home should be added, the Gamified SH. This type of home uses socially connected products [20,21,35,37–43] that profile end-users based on their personality traits, type of gamified user, and energy user [9,34,44,45] to propose tailored interfaces that help them understand the benefits of becoming pro-environmental or energy-aware. Figure 1 depicts an example of this type of home.

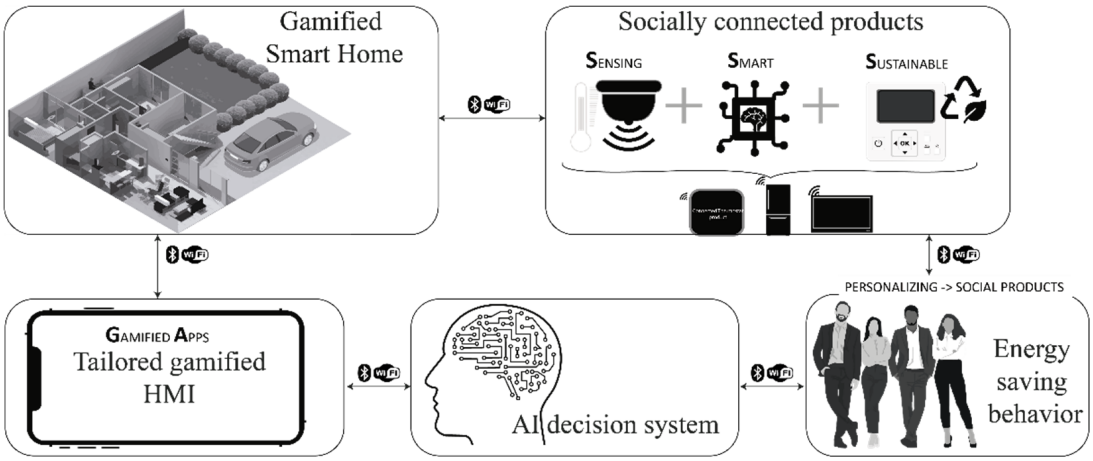

Figure 1. Gamified Smart Home structure.

Wlodarczyk et al. [49] proposed SWRL-F as an FL extension of the Semantic Web Rule Language because no precise information can be used. Hence, the knowledge representation in SWRL was simplified. Thus, their SWRL-F ontology constructed fuzzy rules in SWRL using Web Ontology Language. Thakur et al. [50] proposed a fuzzy inference system for diagnosing depression through the PHQ-9 to get the correct level of severity of depression among patients. They collected data from 50 patients from hospitals in Bangladesh. Leon et al. [51] proposed the SENTIENT project to identify early signs of depressive disorders in senior householders to ease affective support and care. A systematic review concluded that SHs influence senior users' QoL, but low technology readiness requires diversification [52]. VandeWeerd et al. [53] deployed the HomeSense project in the community of older adults in The Villages, Florida. This ambient health and wellness platform monitors the age of senior people to recognize any relevant event that may affect their QoL. In [20], they used a voice assistant and cameras to track the householders' daily mood to improve their QoL by promoting social inclusion and physical exercise. The multi-sensor system was used within the SH to identify the senior householders' emotions.

The depression disorders at SHs are currently oriented to the senior householders [20,39,50–53]; however, depression affects all of us [1,2]. Hence, experts need to diagnose the depression disorder; questionnaires as the PHQ-9 help spot any depressive symptomatology as a pre-diagnosis.

Therefore, using artificial intelligence (AI) decision systems like adaptive neuro-fuzzy inference systems (ANFIS), fuzzy logic, or neural networks can provide reliable information about end-users behavior because AI techniques emulate human making decisions [47,54]. In addition, AI platforms have been used to ease conversation and social support within communities to assess digital health interventions [55,56]. Thus, it is possible to think of an integrated and complex system that monitors householders' mental health to help as a pre-diagnostic depression symptom and send that information to the clinicians.

2.4. Gamification for Treatment Depression

Gamification uses game elements and game-design techniques in real context environments [57]. In [58], they performed a systematic review to identify how gamification and serious games were applied to support the treatment of depression. The gamification elements included scores, goals, and progress levels. For example, Lukas et al. [59], proposed a gamified smartphone-based intervention to reduce depressive symptoms. Thus, the gamification elements considered goals, progress levels, and a total number of views.

Hungerbuehler et al. [60], considered story and feedback gamification elements for their chatbot proposal.

The Octalysis framework [57] helps as a guideline to develop gamified applications through two types of motivations to fulfill specific activities, for instance, avoid householders' depression at home. Therefore, the communication between interfaces and the end-user is from a tailored human machine interface (HMI) within a gamification structure that includes feedback and adjustments based on the user's level of depression to teach, motivate, and engage them to perform specific goals that avoid isolation or depression. Hence, Table 2 lists the two types of gamification structures used in this research. In extrinsic motivation, people are motivated because they want something they cannot get, and acquiring it infers outer recognition. For intrinsic motivation, the activity is rewarding by itself.

Table 2. Extrinsic and intrinsic motivations used in gamification.

Extrinsic Motivation	Intrinsic Motivation
Challenges	Notifications
Levels	Messages
Dashboard	Tips
Statistics	Community
Profile picture or avatar	Collaboration
Points, badges, leaderboard	Competition

Consequently, to the best of the authors' knowledge, proposals consider the householders to monitor any depression symptomatology at SHs using the PHQ-9, either through voice assistants or tailored human–machine interfaces (HMIs), has not been proposed.

Therefore, the research question proposed in this research was:

- What characteristics should an HMI framework consider helping the healthcare workers pre-diagnose depression using SHs as enablers?

To answer the research question, this paper proposes a three-step framework that assesses the nine questions to the end-user through ALEXA or a gamified HMI. Then, a fuzzy logic decision system considers three actions based on the nine responses: continue monitoring through Alexa and the HMI, suggest specialist referral, and mandatory specialist referral. These actions can only be seen by the healthcare system and/or to the end user's emergency contact. Besides, a statistical analysis was performed on the NHANES dataset [30,31] to get the depression severity by age group as a guideline for the specialist to know how the householder behaves compared to the national dataset; in other words, if the householder has an expected behavior, is outside the expected behavior, or has an abnormal behavior compared with the NHANES dataset.

3. Material and Methods

The NHANES dataset that had the (PHQ-9) answers [31,32] were melted with the Demographic Variables and Sample Weights (P_DEMO) [61,62] to get the gender and age of each observation and perform further statistical analysis. Then, the SEQN or ID from the P_DEMO was compared to add the three additional variables to the PHQ-9 dataset. Thus, the melted dataset had 8965 observations and 13 variables; the last variable was the total score of the nine questions. Any observations with NA and the tenth question (DPQ100) were deleted as the DPQ100 required a healthcare professional to answer. The scope of this research is related to the depression symptomatology pre-diagnosis. Therefore, the cleaned dataset had 7882 observations. Table 3 depicts the code and description of each variable from the melted dataset.

Table 3. Code and description of the melted dataset.

Code	Description
SEQN	Respondent sequence number.
RIAGENDR	Gender of the participant.
RIDAGEYR	Age in years of the participant at the time of screening. Individuals 80 and over were coded at 80 years of age.
DPQ010 to DPQ090	Represent each question described in Table 1.
Total	Total score up to 27.

The software employed during this research were:

- The statistical analysis and data cleaning considered the SPSS v. 25 and R-studio v. 1.4.1106.
- The fuzzy logic decision systems used LabVIEW v. 20.0.1.

Thus, the statistical analysis considered the cleaned dataset and consisted in:

- Demographic characteristics of the sample (mean age, male and female proportion, and median PHQ9 scores), for normally distributed data, the mean and standard deviation were reported. The median and interquartile range were reported for non-normally distributed data.
- Setting the normal, expected, and abnormal depression thresholds for each age group, by obtaining the 3, 25, 50, 75, and 97 percentiles.
- The associations between age group and depression severity and sex and depression severity were determined. These associations were achieved with a frequency table and a chi-squared analysis; if the chi-squared analysis was found significant, a Crammer's V was performed to obtain the strength of the association. Furthermore, a Spearman's correlation test was performed between age and PHQ9 score.
- Items 1, 2, and 9 are crucial, because according to DSM, to make a depression diagnosis, 4 of the nine questions have to be positive, and at least one of the five must be items 1 or 2 [25,28]. Moreover, if item 9 is positive, the psychological referral is mandatory. In order to assess the distribution and association of these items in the different age groups and sex, frequency tables and chi-squared tests were performed with Crammer's V test whenever it applied.
- p-values below 0.05 were considered statistically significant.
- Cramer's V results were interpreted as follows: 0.0–0.1 negligible; 0.1–0.2 weak; 0.2–0.4 moderate; 0.4–0.6 relatively strong; 0.6–0.8 strong; 0.8–1.0 very strong [63].

3.1. Fuzzy Logic Decision System

Figure 2 shows the PHQ-9 algorithm used for the fuzzy logic decision system. This algorithm considers that if the nine answers had a score of less than ten and item nine had a "not at all" response, the action is to continue monitoring. On the contrary, if the score was greater than or equal to 10 and the ninth item was zero, the action is to consider depressive symptomatology. Nevertheless, if the ninth answer was greater or equal to 1, it is mandatory.

Two fuzzy logic decision systems were proposed. The first fuzzy logic decision system examined item 9 and the total score in the input system; the output system reflected the decisions explained in Figure 2: Continue monitoring, mental health specialist referral, and mental health specialist referral is mandatory. This decision system had 20 rules.

The second FL decision system considered the percentile score divided by age group starting with 20 to 29 years old, 30 to 39 years old, 40 to 49 years old, 50 to 59 years old, 60 to 69 years old, and ending with 70 to 80 years old age group for the input system. The output system was the same as the first FL decision system. This decision system had 18 rules. The fuzzy logic decision system was modeled in LabVIEW v. 20.0.1.

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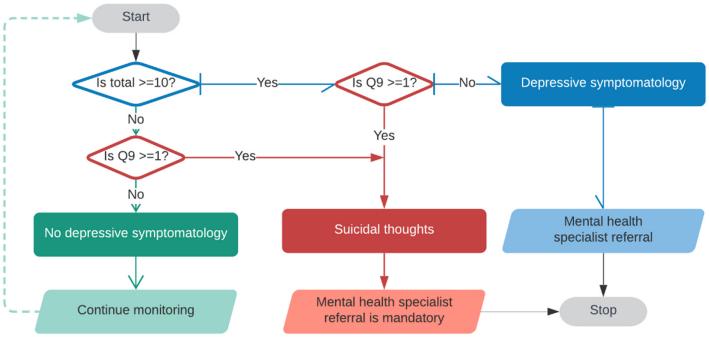

Figure 2. PHQ-9 algorithm for the fuzzy logic decision system.

Figure 2. PHQ-9 algorithm for the fuzzy logic decision system.

3.2. Human Machine Interface

In [21], some of the authors of this research proposed SH gamified HMIs for energy reductions. Hence, based on the premise of considering socially connected products at SHs such as connected thermostats, smart refrigerators, smart lightings, or smart TVs [9,38], a novel interface was proposed to take advantage of this type of HMIs to survey the householders the nine questions from the PHQ-9. Hence, the householders would not feel obligated to answer, and they could answer the survey if they want to, or even request Alexa to ask the questions instead of reading them.

Figure 3 depicts the interaction in the SH to monitor householders and run the pre-diagnosis PHQ-9. There are six types of interactions involved in this diagram: user-house, house-product, product-product, product-user, product-interface, and user-interface. This diagram reflects how the end-user is continuously in touch with the household appliances and elements. Thus, the interaction between the house and the product knows the profile usage at home, besides these appliances can be linked with the voice assistant as Alexa or the mobile phone to provide the interaction between products. Therefore, through the multi-sensor system, Alexa and the HMI can communicate with the end-user providing this interaction of product-user. The relevant part of this structure is the product–user interaction because the fuzzy logic decision system provides the actions required to pre-diagnose any depressive symptoms and, therefore, request a health care specialist.

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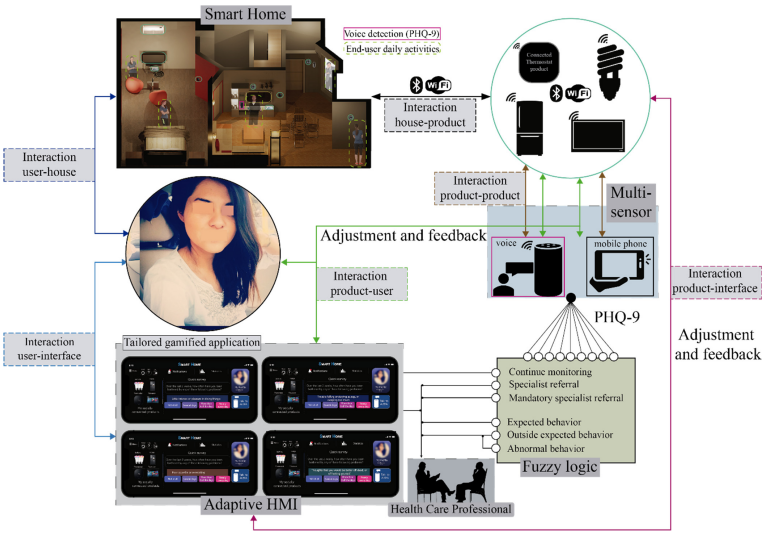

Figure 3. Smart Home Structure considering the PHQ-9 and the inclusion of Alexa.

Figure 3. Smart Home Structure considering the PHQ-9 and the inclusion of Alexa.

4. Proposed Framework

Figure 4 shows the proposed framework for the depressive pre-diagnosis in the SH environment. This framework has three steps:

Knowledge base step: During this step, the NHANES dataset and P_DEMO were collected. The statistical analysis was performed to understand the depressive symptomatology better and take three actions based on the total score and question 9. Besides, the expected behavior by age group was proposed, so the health care professional can quickly review if the householder's answers are with the national database or if the householder is behaving unexpectedly. In addition, the gamified elements for depression depicted in Table 2 were analyzed to propose them on the HMI.

Fuzzy logic step: This step has two parts. The first part considers question 9 and the total score to display which three actions were required to consider. The second part uses the age and the age group to display the type of behavior based on the three actions

PHQ-9 and P_DEMO datasets. Then, the fuzzy logic decision system step provided the two types of decision systems and proposed rules for the depression pre-diagnosis. During this step, a LabVIEW program was suggested to interact with the ALEXA or HMI PHQ-9 questionnaire and the actions required based on the input values. Then, the evaluation step showed the results of the LabVIEW front panel and its connection to the HMI into an SH environment.

4. Proposed Framework

Figure 4 shows the proposed framework for the depressive pre-diagnosis in the SH environment. This framework has three steps:

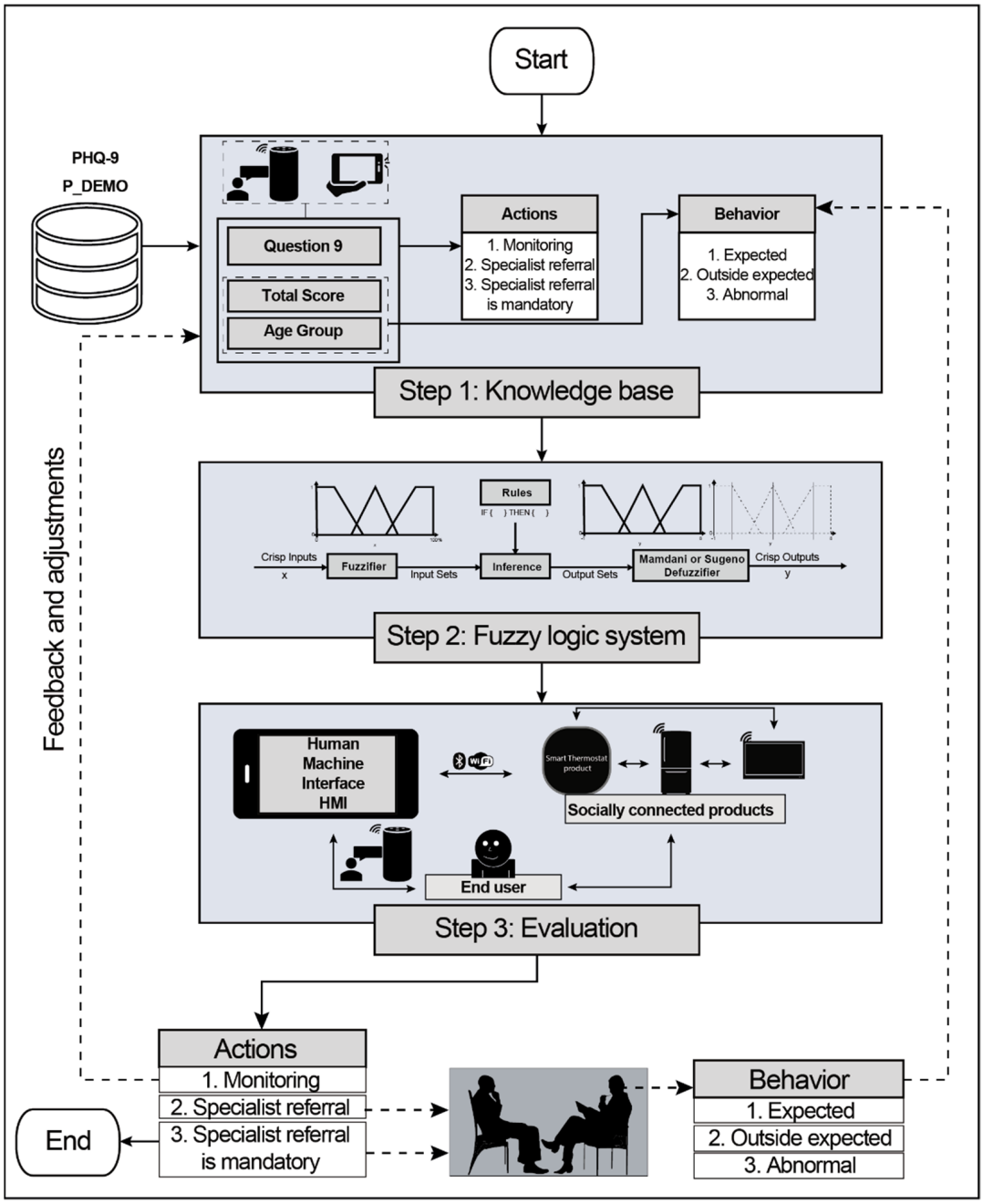

Figure 4. Proposed Framework.

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5.1. Knowledge Base Step: Statistical Analysis

During this step, the NHANES dataset and P_DEMO were collected. The statistical analysis was performed to understand the depressive symptomatology better and take three actions based on the total score and question 9. Besides, the expected behavior by age group was proposed, so the health care professional can quickly review if the householder's answers are with the national database or if the householder

The melted and cleaned database from NHANES PHQ-9 [51,52] and P_DEMO [61,62] containing 7882 observations were explored to obtain the main characteristics of the sample. The sample included 3865 (49%) males and 4017 (51%) females, with a mean age of 50.73 (s.d.: 17.42) and a median PHQ-9 score of 2 (IQR: 0–5). The division of PHQ-9 scores by age group reported a similar distribution with a median of 2, IQR of 0–5 or 0–6, third percentile of 0, and 97th percentile of 14, 15, or 16 (See Table 4).

is behaving unexpectedly. In addition, the gamified elements for depression depicted in Table 2 were analyzed to propose them on the HMI.

Fuzzy logic step: This step has two parts. The first part considers question 9 and the total score to display which three actions were required to consider. The second part uses the age and the age group to display the type of behavior based on the three actions explained in the previous section.

Evaluation step: This step evaluates the interaction between the user and the household appliances to provide the interaction between product–product, product–user, and product–interface to help the health care professional better understand how the householder is behaving regarding the depressive symptomatology. This step provides continuous feedback to the user and the knowledge base to continue monitoring the end-user and pre-diagnose any householder's depression.

5. Results

This section provides the results of each step and the HMI proposal in an SH Context. First, the knowledge base step provides the statistical analysis performed in the PHQ-9 and P_DEMO datasets. Then, the fuzzy logic decision system step provided the two types of decision systems and proposed rules for the depression pre-diagnosis. During this step, a LabVIEW program was suggested to interact with the ALEXA or HMI PHQ-9 questionnaire and the actions required based on the input values. Then, the evaluation step showed the results of the LabVIEW front panel and its connection to the HMI into an SH environment.

5.1. Knowledge Base Step: Statistical Analysis

The melted and cleaned database from NHANES PHQ-9 [31,32] and P_DEMO [61,62] containing 7882 observations were explored to obtain the main characteristics of the sample. The sample included 3865 (49%) males and 4017 (51%) females, with a mean age of 50.73 (s.d.: 17.42) and a median PHQ-9 score of 2 (IQR: 0–5). The division of PHQ-9 scores by age group reported a similar distribution with a median of 2, IQR of 0–5 or 0–6, third percentile of 0, and 97th percentile of 14, 15, or 16 (See Table 4).

Table 4. PHQ-9 percentile score divided by age group.

Score Percentile	Age Group					
	20–29	**30–39**	**40–49**	**50–59**	**60–69**	**70–80**
P3 (Expected low limit)	0	0	0	0	0	0
P25 (Expected)	0	0	0	0	0	0
P50 (Median)	2	2	2	2	2	2
P75 (Expected)	5	4	5	5	5	4
P97 (Expected high limit)	14	15	15	16	16	14.67

Table 5 shows the depression severity by gender. The analysis reported a higher prevalence of depressive symptoms in women. A chi-squared test was performed to assess the association between gender and depression severity, and a weak association was found (p-value = 1.46×10^{-17}; Crammer's V = 0.104).

Table 5. Depression severity by gender.

Depression Severity	Male	Female
No	3033	2790
Mild	553	780
Moderate	180	296
Moderately severe	69	108
Severe	30	43

In depression severity by age group, a spearman correlation was performed using the age and PHQ-9 scores. No correlation was found between both variables (p-value = 0.000038; Rho = −0.046). A chi-squared test was performed to assess the association between age group and presence of depression, and a weak association was found (p-value = 1.23×10^{-68}; Crammer's V = 0.197) (See Table 6).

Table 6. Depression by age group.

Score Percentile	Age Group					
	20–29	**30–39**	**40–49**	**50–59**	**60–69**	**70–80**
No Depression	861	920	941	964	1143	994
Total Depression	336	289	869	397	402	316

Due to the importance of item 9 in the questionnaire, since it assesses suicidal or self-harm thoughts, the distribution on its presence was explored by sex, age group, and depression severity. No association was found between sex or age group and suicidal thoughts in this sample (p-value = 0.545; p-value = 0.226, respectively); however, a relatively strong association was found between depression severity and presence of suicidal or self-harm thoughts (p-value = 0; Crammer's V = 0.476).

Items 1 and 2 are crucial, because according to DSM, to make a depression diagnosis, 4 of the 9 questions must be positive, and at least one of the 5 must be items 1 or 2. These two items include depressive mood and reduced pleasure. Talking about question 1, a negligible association was found between its presence and sex or age group (p-value = 0.012, Crammer's V = 0.028; p-value = 0.000085, Crammer's V = 0.058, respectively). In question 2, a negligible association was found between it being positive and sex (p-value = 0.000028, Crammer's V = 0.047), and no association was found between it being positive and age group (p-value = 0.086).

5.2. Fuzzy Logic Decision System Step

Figure 5 shows the two types of FL decision systems created. Figure 5a shows the first FL decision system, the input and output rules used for Question 9. The input variables considered the four-scale answer depicted in Table 1 as the membership functions. The output variables were the three actions to perform depending on Question 9 and the total score. Figure 5b shows that the input variables considered the total score and the membership functions were the depression severity. Figure 5c shows the second FL decision system; the input variables considered for the age and the membership functions; Figure 5d shows the input variables considered by each age group and the type of behavior for the membership functions. In both Figure 5c,d, the output variables were the same as the first FL decision system. Besides, Table 7 shows the FL rules employed for the first decision system, and Table 8 depicts the FL rules for the second decision system.

Figure 6a depicts the block diagram used for the LabVIEW project. This diagram linked both FL decision systems to provide a single front panel. Figure 6b displays the front panel.

This proposal adds the nine questions and based on the last question and the total score, the actions are displayed on the lower part of the panel. Besides, considering the age and the total score, the expectation of depression by age group is displayed.

The output variables were the three actions to perform depending on Question 9 and the total score. Figure 5b shows that the input variables considered the total score and the membership functions were the depression severity. Figure 5c shows the second FL decision system; the input variables considered for the age and the membership functions; Figure 5d shows the input variables considered by each age group and the type of behavior for the membership functions. In both Figure 5c,d, the output variables were the same as the first FL decision system. Besides, Table 7 shows the FL rules employed for the first decision system, and Table 8 depicts the FL rules for the second decision system.

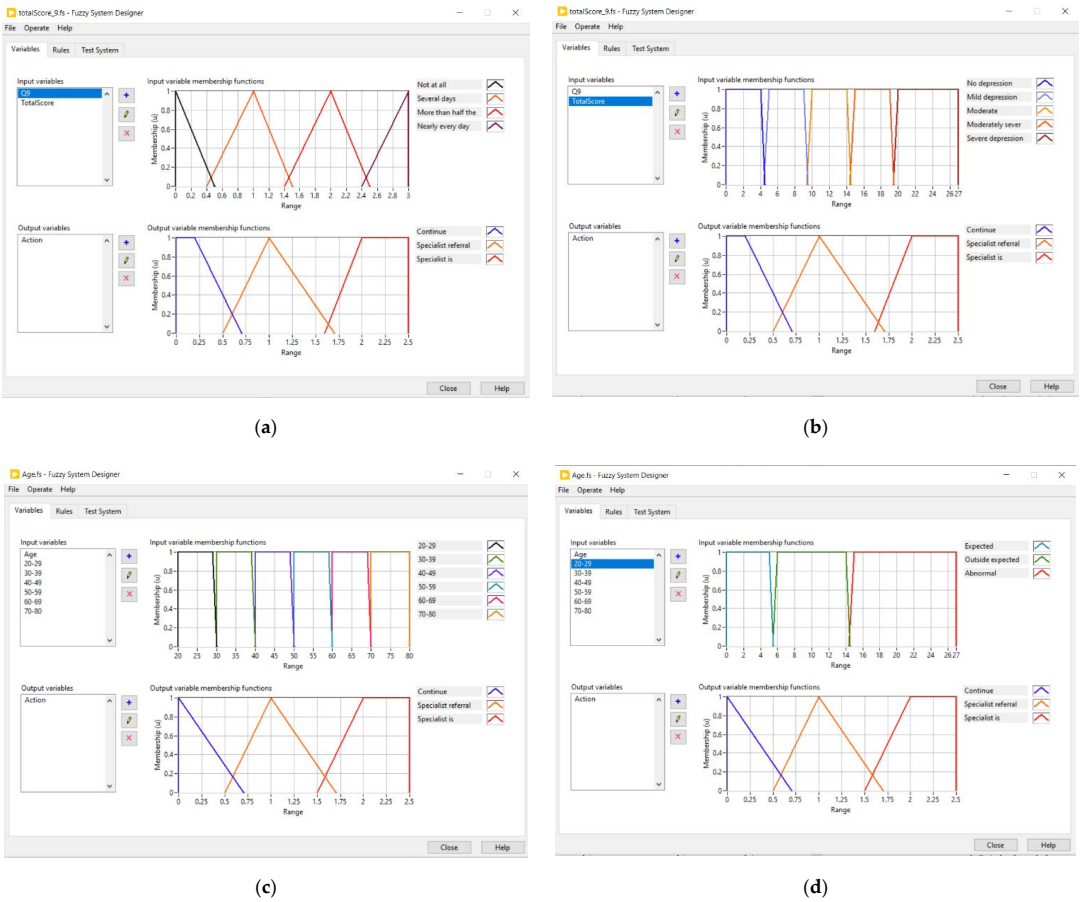


Figure 5. Fuzzy logic decision system: (**a**) first FL input and output variables: Q9; (**b**) first FL input and output variables: TotalScore.; (**c**) second FL input and output variables: age; (**d**) second FL input and output variables: age group.

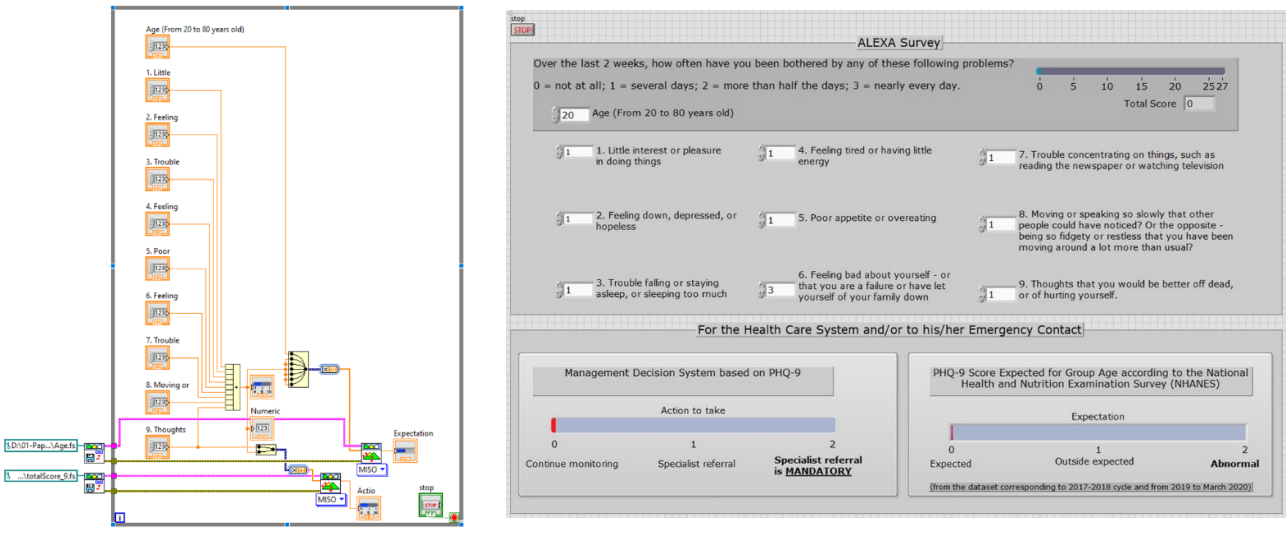
Figure 6a depicts the block diagram used for the LabVIEW project. This diagram linked both FL decision systems to provide a single front panel. Figure 6b displays the front panel.

Table 7. First FL decision system rules.

Rule	IF	AND	THEN
1	Q9 is "Not at all"	TotalScore is "No depression"	Action is "Continue monitoring"
2	Q9 is "Not at all"	TotalScore is "Mild depression"	Action is "Continue monitoring"
3	Q9 is "Not at all"	TotalScore is "Moderate depression"	Action is "Specialist referral"
4	Q9 is "Not at all"	TotalScore is "Moderately severe depression"	Action is "Specialist referral"
5	Q9 is "Not at all"	TotalScore is "Severe depression"	Action is "Specialist referral"
6	Q9 is "Several days"	TotalScore is "No depression"	Action is "Specialist referral is mandatory"
7	Q9 is "Several days"	TotalScore is "Mild depression"	Action is Specialist referral is mandatory
8	Q9 is "Several days"	TotalScore is "Moderate depression"	Action is Specialist referral is mandatory
9	Q9 is "Several days"	TotalScore is "Moderately severe depression"	Action is Specialist referral is mandatory
10	Q9 is "Several days"	TotalScore is "Severe depression"	Action is Specialist referral is mandatory
11	Q9 is "More than half the days"	TotalScore is "No depression"	Action is "Specialist referral is mandatory"
12	Q9 is "More than half the days"	TotalScore is "Mild depression"	Action is Specialist referral is mandatory
13	Q9 is "More than half the days"	TotalScore is "Moderate depression"	Action is Specialist referral is mandatory
14	Q9 is "More than half the days"	TotalScore is "Moderately severe depression"	Action is Specialist referral is mandatory
15	Q9 is "More than half the days"	TotalScore is "Severe depression"	Action is Specialist referral is mandatory
16	Q9 is "Nearly every day"	TotalScore is "No depression"	Action is "Specialist referral is mandatory"
17	Q9 is "Nearly every day"	TotalScore is "Mild depression"	Action is Specialist referral is mandatory
18	Q9 is "Nearly every day"	TotalScore is "Moderate depression"	Action is Specialist referral is mandatory
19	Q9 is "Nearly every day"	TotalScore is "Moderately severe depression"	Action is Specialist referral is mandatory
20	Q9 is "Nearly every day"	TotalScore is "Severe depression"	Action is "Specialist referral is mandatory

Table 8. Second FL decision system rules.

Rule	IF	AND	THEN
1	Age is "20–29"	20–29 is "Expected"	Action is "Continue monitoring"
2	Age is "20–29"	20–29 is "Outside expected"	Action is "Specialist referral"
3	Age is "20–29"	20–29 is "Abnormal"	Action is "Specialist referral is mandatory"
4	Age is "30–39"	30–39 is "Expected"	Action is "Continue monitoring"
5	Age is "30–39"	30–39 is "Outside expected"	Action is "Specialist referral"
6	Age is "30–39"	30–39 is "Abnormal"	Action is "Specialist referral is mandatory"
7	Age is "40–49"	40–49 is "Expected"	Action is "Continue monitoring"
8	Age is "40–49"	40–49 is "Outside expected"	Action is "Specialist referral"
9	Age is "40–49"	40–49 is "Abnormal"	Action is "Specialist referral is mandatory"
10	Age is "50–59"	50–59 is "Expected"	Action is "Continue monitoring"
11	Age is "50–59"	50–59 is "Outside expected"	Action is "Specialist referral"
12	Age is "50–59"	50–59 is "Abnormal"	Action is "Specialist referral is mandatory"
13	Age is "60–69"	60–69 is "Expected"	Action is "Continue monitoring"
14	Age is "60–69"	60–69 is "Outside expected"	Action is "Specialist referral"
15	Age is "60–69"	60–69 is "Abnormal"	Action is "Specialist referral is mandatory"
16	Age is "70–80"	70–80 is "Expected"	Action is "Continue monitoring"
17	Age is "70–80"	70–80 is "Outside expected"	Action is "Specialist referral"
18	Age is "70–80"	70–80 is "Abnormal"	Action is "Specialist referral is mandatory"



(**a**) (**b**)

Figure 6. LabView project: (**a**) block diagram; (**b**) front panel.

5.3. Evaluation Step

Figure 7 shows some results on the LabVIEW front panel. The answers were based on the NHANES datasets. For instance, Figure 7a shows the answers received from SEQN 109441. This individual is 20 years old and had a score of 5, which is the same as mild depression; thus, the action required for this individual is to continue monitoring, and this individual is under the expected behavior. On the contrary, Figure 7b displays the SEQN 109342 for a 23-year-old individual with moderately severe depression. This individual answered "several days" for the 9th question, and the system immediately moved toward the "health specialist referral." This is mandatory. This individual behavior is not normal, and it is totally outside the expected behavior. Figure 7c shows an example for a 26-year-old individual with suicidal tendencies due to question 9; however, based on the total score and the age, this individual is outside the expected behavior. Finally, Figure 7d depicts the information for a 54-year-old user with a total score of 16 but with no suicidal thoughts; therefore, the action is to suggest a specialist referral but not in a mandatory manner; besides, this user is outside expected behavior but not abnormal behavior.

thoughts; therefore, the action is to suggest a specialist referral but not in a mandatory manner; besides, this user is outside expected behavior but not abnormal behavior.

Figure 7. Dashboard results: (**a**) 20 years old individual with a total score of 5; (**b**) 43 years old individual with a total score of 16 and suicidal thoughts; (**c**) 26 years old individual with a total score of 8 and suicidal thoughts; (**d**) 54 years old user with a total score of 16.

Furthermore, Table 9 exemplifies five of the 7882 observations, including the LabVIEW dashboard results. The full observations are available at [64].

Table 9. Exemplification of the results, including the LabVIEW decision system. The complete table is reported in [64].

SEQN	RIDAGEYR	DPQ010	DPQ020	DPQ030	DPQ040	DPQ050	DPQ060	DPQ070	DPQ080	DPQ090	Total	Action to Take	Expectation
109266	29	0	0	0	0	0	0	0	0	0	0	Continue monitoring	Expected
119042	75	0	0	0	0	0	0	0	0	1	1	Specialist referral is MANDATORY	Expected
109994	73	3	3	3	3	3	2	2	0	0	17	Specialist referral	Abnormal
121279	28	1	1	2	1	1	2	2	1	1	9	Continue monitoring	Outside expected
124698	51	2	2	3	1	1	2	2	1	1	13	Specialist referral	Outside expected

5.4. Human Machine Interface in a Smart Home Context

Figure 8 depicts the proposal of a gamified HMI in an SH context. This interface shows how to use interfaces that include connected products such as the thermostat, television, refrigeration, or lighting. This interface focuses mainly on the quick survey so the householder can answer either by clicking one of the four options of each question of the PHQ-9 or by selecting the option of "Talk to ALEXA". Figure 8a shows the homepage, the extrinsic gamified elements that consider the challenges, the statistics, the pic-

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the extrinsic gamified elements that consider the challenges, the statistics, the picture profile, the points, and the leaderboard. On the contrary, the intrinsic gamified elements are related to the notifications, the tips, the ALEXA or contacting the doctor, and by answering the survey. Figure 8b displays an example of this survey; thus, question 9 is asked. Therefore, once the householder answered the first question, the second question was displayed, and so on, until the tenth question. Hence, in both ways, the end-user can answer the questionnaire. However, this interface did not provide information to the householder regarding his/her mental health score. Therefore, the psychologist or psychiatrist needs to analyze the result to provide further actions to avoid any suicidal thoughts. Besides, this type of interface aims to engage the end-user in activities to achieve specific goals. For instance, this interface was connected to a thermostat where the householder interacted with the device and became energy aware [38].

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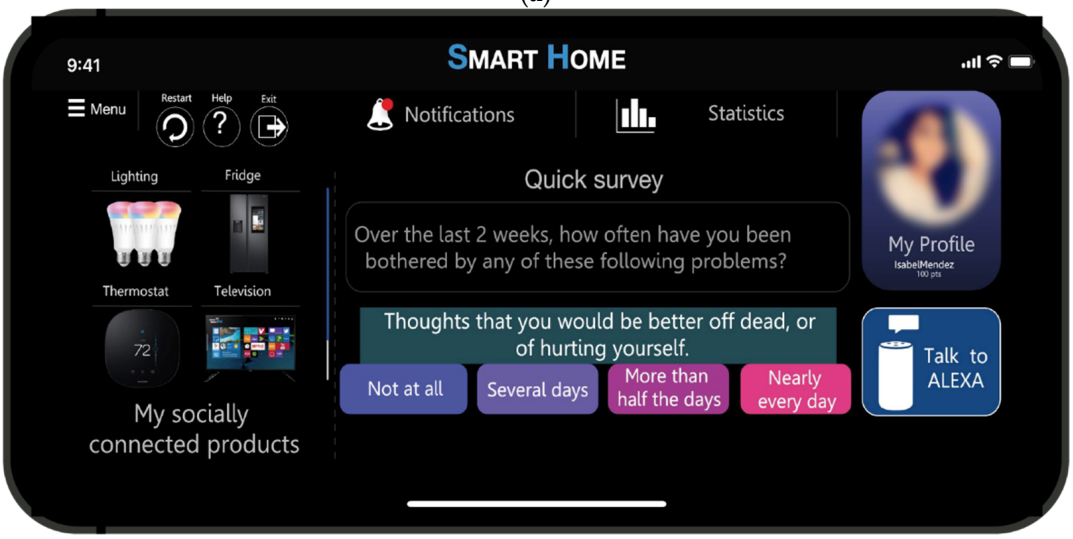
(**a**)



(**b**)

Figure 8. HMI oriented to pre-diagnosis using the PHQ-9: (**a**) Homepage of the gamified HMI; (**b**) Question 9 is depicted in the gamified HMI.

Figure 8. HMI oriented to pre-diagnosis using the PHQ-9: (**a**) Homepage of the gamified HMI; (**b**) Question 9 is depicted in the gamified HMI.

6. Discussion

The characteristics that an HMI framework needs to consider to help the healthcare sector in the pre-diagnosis of depression using SHs as enablers are as follows:

1. A knowledge base gathers the population with depression symptomatology through available PHQ-9 answers to relate them with the proposal and identify if the householder is within the range of expected depression or requires more atten-

6. Discussion

The characteristics that an HMI framework needs to consider to help the healthcare sector in the pre-diagnosis of depression using SHs as enablers are as follows:

1. A knowledge base gathers the population with depression symptomatology through available PHQ-9 answers to relate them with the proposal and identify if the householder is within the range of expected depression or requires more attention. During this step, the most common gamification elements for depression are collected.
2. A fuzzy logic step that helps as a decision system triggers three actions: continue monitoring, specialist referral, and specialist referral is mandatory. Furthermore, three expected behaviors are analyzed: expected, outside expected, or abnormal behavior.
3. The evaluation step assesses the interaction between the householder and depression by taking advantage of household appliances through gamified interfaces. The interface uses gamification elements to help as an enabler for helping in the pre-diagnosis of depression. The elements are divided into extrinsic and intrinsic. Moreover, this pre-diagnosis runs into a feedback and adjustment environment; hence, the householder receives points by answering the survey, contacting the doctor, and interacting with ALEXA or through video call. In [20], it is proposed to use video callings as social connectors to avoid social isolation or depression.

This proposal considered the NHANES PHQ-9 [31,32] and P_DEMO [61,62] datasets to build the three-step framework. For the first phase of the knowledge base, a statistical analysis was explored to obtain the main characteristics of the dataset and determine based on the age group the acceptable limits for expected behavior, outside behavior, and abnormal behavior of depression symptomatology. Then, the FL decision systems were built during the second step based on the statistical analysis and the algorithm depicted in Figure 2. Finally, the evaluation phase consisted in analyzing the database and comparing the results with the dashboard depicted in Figure 6. Besides, an HMI that considers the household appliances and takes advantage of the home page of this HMI is proposed. Hence, the HMI uses this home page of the SH interface to provide the PHQ-9 survey in two modalities: through the HMI or ALEXA.

This paper proposes a novel approach by considering the SH environment and household devices to monitor the householder. This depressive symptomatology monitoring is directly proposed considering either the HMI questionnaire or through ALEXA. Due to the increase and acceptance of voice assistants, this option is preferred for individuals who feel more comfortable talking rather than interacting with mobile phones or tablets. This proposal is novel in terms of considering all the householders above 20 years old instead of just focusing on the senior users that the literature review had widely indicated [20,40,51–54]. Besides, depression is not exclusive to the older population [1]; depression can happen at any age, leading to poor QoL and affecting the economically active population [1,2]. The age range was considered for this proposal due to the sample analyzed in the PHQ-9 and P_DEMO datasets [31,32,61,62].

In addition, COVID-19 had accelerated anxiety, depression, and suicide due to economic and face-to-face restrictions. Therefore, this proposal aims to use smart homes as enablers for depression pre-diagnosis through the PHQ-9 assessment on HMI and help the health care system and professionals detect any symptoms of depression at home to improve the QoL of the householders.

However, this proposal has its limitation regarding which type of user could interact, for instance, with the HMI [5,7,8]. Consequently, research suggests that certain personality traits are open to using new gadgets or new technology as the openness or extraversion personality trait. However, for the neuroticism personality trait is complicated to accept new technology [34,44]. Moreover, to propose gamified interaction for depressed householders, further research is required to propose tailored activities that improve their mental health.

7. Conclusions

Employing fuzzy logic decision system allows the healthcare systems to monitor the householder's health and avoid suicidal thoughts or depressive disorders. Furthermore, depending on the total score and the ninth item, this system compared the total score with the NHANES dataset to provide insights into the health care sector. Thus, it makes it easy to review if the householder is behaving according to the national metrics or requires further actions. Hence, this proposal is designed to be implemented in SHs by considering all end-users (non-typical and typical users). However, further research is needed to develop and fully test the interface, for instance, by enrolling a representative sample of subjects to evaluate using this HMI continuously.

This research aims to propose the integration of ALEXA and gamified HMI to assess the PHQ-9 and provide a pre-diagnosis of depression symptomatology to help the health care system and professionals detect any symptoms of depression at home. Besides, this proposal considers three actions based on the total score and the suicidal item: to continue monitoring through the HMI and ALEXA, health care specialist referral, and mandatory specialist referral. In addition to this integration, a statistical analysis was performed to provide the dashboard information that helps as a comparison for the specialist. For instance, the householder can have a score of 16 but can have an outside expected behavior or abnormal behavior. This conduct is related to the age group provided by the NHANES dataset. Another aspect to include in further research is to include, if possible, the use of household appliances and cameras to track householders' activities and compare their activities with their responses. For instance, the householder could feel with poor appetite; however, the refrigerator could register and compare how many times the householder opened the refrigerator and check with the camera if the householder ate more or less than two weeks ago. Another example is checking if the individual is having trouble falling or staying asleep, or feeling tired. Besides, ALEXA or another voice assistant can track the householder's voice to identify possible changes in their modulation if the householder is speaking slower or faster than a couple of weeks ago.

Although this proposal includes all types of users above 20 years old (non-typical and typical users), to validate this proposal meticulously in the real end-user market, these future actions are required:

- Evaluate and improve the proposed application with different scenarios and target populations. For instance, there are sectors with chronic diseases such as rheumatoid arthritis that commonly have depression. With this proposal, evaluate their performance through their treatment to analyze if this proposal helps in improving their depression symptomatology. Besides, the proposal should be evaluated outside controlled environments and in several countries in which any cultural factor needs to consider the framework.
- Update the framework and HMI by including SWRL technologies as they have more robust rules than FL. However, this research did not propose SWRL or SWRL-F because the objective was to generate a conventional knowledge base. Afterward, future work will explore the use of these rules, and their optimization will be evaluated.
- Submit this proposal into medical protocols to assess the system in a pilot study with real users.
- Include, if possible, the camera tracking to develop facial recognition and compare the answers with the camera feedback.
- Employ ALEXA in combination with cameras or other household appliances to analyze householders' patterns and compare their behavioral patterns with their survey answers. For example, the perception of depression is important. Thus, if the end-user is feeling depressed, but the actions reflect the opposite, a message could be displayed through the gamified interfaces. Moreover, ALEXA could talk to the householders and explain how they have been acting to cheer them up.

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References

1. World Health Organization. Depression. Available online: https://www.who.int/news-room/fact-sheets/detail/depression (accessed on 14 October 2021).
2. Daly, M.; Sutin, A.R.; Robinson, E. Depression Reported by US Adults in 2017–2018 and March and April 2020. *J. Affect. Disord.* **2021**, *278*, 131–135. [CrossRef] [PubMed]
3. NHANES 2017-March 2020 Pre-Pandemic Questionnaire Data. Available online: https://wwwn.cdc.gov/nchs/nhanes/search/datapage.aspx?Component=Questionnaire&Cycle=2017-2020 (accessed on 13 October 2021).
4. Spitzer, R.L.; Williams, J.B.W.; Kroenke, K. Test Review: Patient Health Questionnaire–9 (PHQ-9). *Rehabil. Couns. Bull.* **2014**, *57*, 246–248. [CrossRef]
5. Narziev, N.; Goh, H.; Toshnazarov, K.; Lee, S.A.; Chung, K.-M.; Noh, Y. STDD: Short-Term Depression Detection with Passive Sensing. *Sensors* **2020**, *20*, 1396. [CrossRef] [PubMed]
6. Torous, J.; Staples, P.; Shanahan, M.; Lin, C.; Peck, P.; Keshavan, M.; Onnela, J.-P. Utilizing a Personal Smartphone Custom App to Assess the Patient Health Questionnaire-9 (PHQ-9) Depressive Symptoms in Patients with Major Depressive Disorder. *JMIR Ment. Health* **2015**, *2*, e8. [CrossRef] [PubMed]
7. Hickey, B.A.; Chalmers, T.; Newton, P.; Lin, C.-T.; Sibbritt, D.; McLachlan, C.S.; Clifton-Bligh, R.; Morley, J.; Lal, S. Smart Devices and Wearable Technologies to Detect and Monitor Mental Health Conditions and Stress: A Systematic Review. *Sensors* **2021**, *21*, 3461. [CrossRef] [PubMed]
8. Malwade, S.; Abdul, S.S.; Uddin, M.; Nursetyo, A.A.; Fernandez-Luque, L.; Zhu, X.; Cilliers, L.; Wong, C.-P.; Bamidis, P.; Li, Y.-C. (Jack) Mobile and Wearable Technologies in Healthcare for the Ageing Population. *Comput. Methods Programs Biomed.* **2018**, *161*, 233–237. [CrossRef] [PubMed]
9. Avila, M.; Méndez, J.I.; Ponce, P.; Peffer, T.; Meier, A.; Molina, A. Energy Management System Based on a Gamified Application for Households. *Energies* **2021**, *14*, 3445. [CrossRef]
10. Marikyan, D.; Papagiannidis, S.; Alamanos, E. A Systematic Review of the Smart Home Literature: A User Perspective. *Technol. Forecast. Soc. Chang.* **2019**, *138*, 139–154. [CrossRef]
11. Harper, R. (Ed.) *Inside the Smart Home*; Springer: London, UK, 2003; ISBN 978-1-85233-688-2.
12. Aldrich, F.K. Smart Homes: Past, Present and Future. In *Inside the Smart Home*; Harper, R., Ed.; Springer: London, UK, 2003; pp. 17–39. ISBN 978-1-85233-688-2.
13. Fulmer, R.; Joerin, A.; Gentile, B.; Lakerink, L.; Rauws, M. Using Psychological Artificial Intelligence (Tess) to Relieve Symptoms of Depression and Anxiety: Randomized Controlled Trial. *JMIR Ment. Health* **2018**, *5*, e64. [CrossRef] [PubMed]

14. Robinson, A. Can a Chatbot Help My Mental Health? Available online: https://onemindpsyberguide.org/blog/can-a-chatbot-help-my-mental-health/ (accessed on 14 October 2021).
15. Quiroz, J.C.; Bongolan, T.; Ijaz, K. Alexa Depression and Anxiety Self-Tests: A Preliminary Analysis of User Experience and Trust. In Proceedings of the Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers, ACM: Virtual Event Mexico, 10 September 2020; pp. 494–496. Available online: https://dl.acm.org/doi/abs/10.1145/3410530.3414374 (accessed on 12 November 2021).
16. Brenner, M.H.; Bhugra, D. Acceleration of Anxiety, Depression, and Suicide: Secondary Effects of Economic Disruption Related to COVID-19. *Front. Psychiatry* **2020**, *11*, 592467. [CrossRef] [PubMed]
17. Lii Inn, T. Smart City Technologies Take on COVID-19–Penang Institute. Available online: https://penanginstitute.org/publications/issues/smart-city-technologies-take-on-covid-19/ (accessed on 7 July 2020).
18. Bueno-Notivol, J.; Gracia-García, P.; Olaya, B.; Lasheras, I.; López-Antón, R.; Santabárbara, J. Prevalence of Depression during the COVID-19 Outbreak: A Meta-Analysis of Community-Based Studies. *Int. J. Clin. Health Psychol.* **2021**, *21*, 100196. [CrossRef]
19. Maalsen, S.; Dowling, R. Covid-19 and the Accelerating Smart Home. *Big Data Soc.* **2020**, *7*, 205395172093807. [CrossRef]
20. Méndez, J.I.; Mata, O.; Ponce, P.; Meier, A.; Peffer, T.; Molina, A. Multi-Sensor System, Gamification, and Artificial Intelligence for Benefit Elderly People. In *Challenges and Trends in Multimodal Fall Detection for Healthcare*; Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E., Eds.; Springer International Publishing: Cham, Switzerland, 2020; Volume 273, pp. 207–235. ISBN 978-3-030-38747-1.
21. Méndez, J.I.; Ponce, P.; Medina, A.; Meier, A.; Peffer, T.; McDaniel, T.; Molina, A. Human-Machine Interfaces for Socially Connected Devices: From Smart Households to Smart Cities. In *Multimedia for Accessible Human Computer Interfaces*; McDaniel, T., Liu, X., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 253–289. ISBN 978-3-030-70715-6.
22. Maharjan, R.; Bækgaard, P.; Bardram, J.E. "Hear Me out": Smart Speaker Based Conversational Agent to Monitor Symptoms in Mental Health. In Proceedings of the Adjunct Proceedings of the 2019 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2019 ACM International Symposium on Wearable Computers, London, UK, 9–13 September 2019; Association for Computing Machinery: New York, NY, USA, 2019; pp. 929–933.
23. Holmlund, T.B.; Chandler, C.; Foltz, P.W.; Cohen, A.S.; Cheng, J.; Bernstein, J.C.; Rosenfeld, E.P.; Elvevåg, B. Applying Speech Technologies to Assess Verbal Memory in Patients with Serious Mental Illness. *NPJ Digit. Med.* **2020**, *3*, 33. [CrossRef] [PubMed]
24. Müller, G.; Bombana, M.; Heinzel-Gutenbrenner, M.; Kleindienst, N.; Bohus, M.; Lyssenko, L.; Vonderlin, R. Socio-Economic Consequences of Mental Distress: Quantifying the Impact of Self-Reported Mental Distress on the Days of Incapacity to Work and Medical Costs in a Two-Year Period: A Longitudinal Study in Germany. *BMC Public Health* **2021**, *21*, 625. [CrossRef] [PubMed]
25. Chand, S.P.; Arif, H. Depression. In *StatPearls*; StatPearls Publishing: Treasure Island, FL, USA, 2021.
26. Del Barrio, V. Raíces y Evolución Del DSM. *Rev. Hist. Psicol.* **2009**, *30*, 81–90.
27. Psychiatry DSM-5 FAQ. Available online: https://www.psychiatry.org/psychiatrists/practice/dsm/feedback-and-questions/frequently-asked-questions (accessed on 21 October 2021).
28. Marvin, K. Patient Health Questionnaire (PHQ-9)—Strokengine. Available online: https://strokengine.ca/en/assessments/patient-health-questionnaire-phq-9/ (accessed on 21 October 2021).
29. He, C.; Levis, B.; Riehm, K.E.; Saadat, N.; Levis, A.W.; Azar, M.; Rice, D.B.; Krishnan, A.; Wu, Y.; Sun, Y.; et al. The Accuracy of the Patient Health Questionnaire-9 (PHQ-9) Algorithm for Screening to Detect Major Depression: An Individual Participant Data Meta-Analysis. *Psychother. Psychosom.* **2020**, *89*, 25–37. [CrossRef]
30. McCord, D.M.; Provost, R.P. Construct Validity of the PHQ-9 Depression Screen: Correlations with Substantive Scales of the MMPI-2-RF. *J. Clin. Psychol. Med. Settings* **2020**, *27*, 150–157. [CrossRef] [PubMed]
31. National Health and Nutrition Examination Survey 2017—March 2020 Data Documentation, Codebook, and Frequencies–Mental Health–Depression Screener (P_DPQ). Available online: https://wwwn.cdc.gov/Nchs/Nhanes/2017-2018/P_DPQ.htm (accessed on 13 October 2021).
32. National Health and Nutrition Examination Survey P_DPQ_Dataset. Available online: https://wwwn.cdc.gov/Nchs/Nhanes/2017-2018/P_DPQ.XPT (accessed on 13 October 2021).
33. Holst, A. Smart Home in the United States—Statistics & Facts. Available online: https://www.statista.com/topics/6201/smart-home-in-the-united-states/ (accessed on 13 October 2021).
34. Ponce, P.; Meier, A.; Mendez, J.; Peffer, T.; Molina, A.; Mata, O. Tailored Gamification and Serious Game Framework Based on Fuzzy Logic for Saving Energy in Smart Thermostats. *J. Clean. Prod.* **2020**, *262*, 121167. [CrossRef]
35. Mendez, J.I.; Ponce, P.; Mata, O.; Meier, A.; Peffer, T.; Molina, A.; Aguilar, M. Empower Saving Energy into Smart Homes Using a Gamification Structure by Social Products. In Proceedings of the 2020 IEEE International Conference on Consumer Electronics (ICCE), IEEE, Las Vegas, NV, USA, 4–6 January 2020; pp. 1–7.
36. Aliero, M.S.; Qureshi, K.N.; Pasha, M.F.; Jeon, G. Smart Home Energy Management Systems in Internet of Things Networks for Green Cities Demands and Services. *Environ. Technol. Innov.* **2021**, *22*, 101443. [CrossRef]
37. Méndez, J.I.; Ponce, P.; Meier, A.; Peffer, T.; Mata, O.; Molina, A. S4 Product Design Framework: A Gamification Strategy Based on Type 1 and 2 Fuzzy Logic. In *Smart Multimedia*; Lecture Notes in Computer Science; McDaniel, T., Berretti, S., Curcio, I.D.D., Basu, A., Eds.; Springer International Publishing: Cham, Switzerland, 2020; Volume 12015, pp. 509–524. ISBN 978-3-030-54406-5.

38. Méndez, J.I.; Ponce, P.; Miranda, O.; Pérez, C.; Cruz, A.P.; Peffer, T.; Meier, A.; McDaniel, T.; Molina, A. Designing a Consumer Framework for Social Products Within a Gamified Smart Home Context. In *Universal Access in Human-Computer Interaction. Design Methods and User Experience*; Lecture Notes in Computer Science; Antona, M., Stephanidis, C., Eds.; Springer International Publishing: Cham, Switzerland, 2021; Volume 12768, pp. 429–443. ISBN 978-3-030-78091-3.
39. Mendez, J.I.; Ponce, P.; Meier, A.; Peffer, T.; Mata, O.; Molina, A. Framework for Promoting Social Interaction and Physical Activity in Elderly People Using Gamification and Fuzzy Logic Strategy. In Proceedings of the 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), Ottawa, ON, Canada, 11–14 November 2019; pp. 1–5.
40. Mata, O.; Ponce, P.; McDaniel, T.; Méndez, J.I.; Peffer, T.; Molina, A. Smart City Concept Based on Cyber-Physical Social Systems with Hierarchical Ethical Agents Approach. In Proceedings of the Universal Access in Human-Computer Interaction. Access to Media, Learning and Assistive Environments, Washington, DC, USA, 24–29 July 2021; Antona, M., Stephanidis, C., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 424–437.
41. Ponce, P.; Mendez, J.I.; Medina, A.; Mata, O.; Meier, A.; Peffer, T.; Molina, A. Smart Cities Using Social Cyber-Physical Systems Driven by Education. In Proceedings of the 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), Dortmund, Germany, 18 March 2021; pp. 155–160.
42. Mendez, J.I.; Ponce, P.; Medina, A.; Peffer, T.; Meier, A.; Molina, A. A Smooth and Accepted Transition to the Future of Cities Based on the Standard ISO 37120, Artificial Intelligence, and Gamification Constructors. In Proceedings of the 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), Dortmund, Germany, 18 March 2021; pp. 65–71.
43. Méndez, J.I.; Ponce, P.; Peffer, T.; Meier, A.; Molina, A. A Gamified HMI as a Response for Implementing a Smart-Sustainable University Campus. In Proceedings of the Smart and Sustainable Collaborative Networks 4.0, Saint-Étienne, France, 22–24 November 2021; Camarinha-Matos, L.M., Boucher, X., Afsarmanesh, H., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 683–691.
44. Méndez, J.I.; Ponce, P.; Pecina, M.; Schroeder, G.; Castellanos, S.; Peffer, T.; Meier, A.; Molina, A. A Rapid HMI Prototyping Based on Personality Traits and AI for Social Connected Thermostats. In *Advances in Soft Computing*; Batyrshin, I., Gelbukh, A., Sidorov, G., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 216–227.
45. Mata, O.; Ponce, P.; Méndez, I.; Molina, A.; Meier, A.; Peffer, T. A Model Using Artificial Neural Networks and Fuzzy Logic for Knowing the Consumer on Smart Thermostats as a S3 Product. In *Advances in Soft Computing*; Martínez-Villaseñor, L., Batyrshin, I., Marín-Hernández, A., Eds.; Springer International Publishing: Cham, Switzerland, 2019; Volume 11835, pp. 430–439. ISBN 978-3-030-33748-3.
46. Zadeh, L.A. Fuzzy Sets. *Inf. Control.* **1965**, *8*, 338–353. [CrossRef]
47. Ponce, P. *Inteligencia Artificial Con Aplicaciones a La Ingeniería, 1st ed.; Alfaomega: Mexico City, Mexico, 2011;* ISBN 978-607-7854-83-8.
48. Ponce-Cruz, P.; Molina, A.; MacCleery, B. *Fuzzy Logic Type 1 and Type 2 Based on LabVIEW(TM) FPGA*, 1st ed.; Studies in Fuzziness and Soft Computing; Springer: Cham, Switzerland, 2016; Volume 334, ISBN 3-319-26655-1.
49. Wlodarczyk, T.W.; Rong, C.; O'Connor, M.; Musen, M. SWRL-F: A Fuzzy Logic Extension of the Semantic Web Rule Language. In Proceedings of the International Conference on Web Intelligence, Mining and Semantics—WIMS '11, Sogndal, Norway, 25–27 May 2011; ACM Press: New York, NY, USA, 2011; pp. 1–9.
50. Thakur, A.; Alam, M.S.; Abir, R.M.H.; Kushal, M.A.A.; Rahman, R.M. A Fuzzy Approach for the Diagnosis of Depression. In *Modern Approaches for Intelligent Information and Database Systems, Studies in Computational Intelligence*; Sieminski, A., Kozierkiewicz, A., Nunez, M., Ha, Q.T., Eds.; Springer International Publishing: Cham, Switzerland, 2018; Volume 769, pp. 199–211. ISBN 978-3-319-76080-3.
51. Leon, E.; Montejo, M.; Dorronsoro, I. Prospect of Smart Home-Based Detection of Subclinical Depressive Disorders. In Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare, Dublin, Ireland, 23–26 May 2011.
52. Pal, D.; Triyason, T.; Funikul, S. Smart Homes and Quality of Life for the Elderly: A Systematic Review. In Proceedings of the 2017 IEEE International Symposium on Multimedia (ISM), Taichung, Taiwan, 11–13 December 2017; pp. 413–419.
53. VandeWeerd, C.; Yalcin, A.; Aden-Buie, G.; Wang, Y.; Roberts, M.; Mahser, N.; Fnu, C.; Fabiano, D. HomeSense: Design of an Ambient Home Health and Wellness Monitoring Platform for Older Adults. *Health Technol.* **2020**, *10*, 1291–1309. [CrossRef]
54. Silva, D.C.B.; Cruz, P.P.; Gutiérrez, A.M.; Avendaño, L.A.S. *Applications of Human-Computer Interaction and Robotics Based on Artificial Intelligence*; Editorial Digital del Tecnológico de Monterrey: Monterrey, Mexico, 2020.
55. Summers, C.; Wu, P.; Taylor, A.J.G. Supporting Mental Health During the COVID-19 Pandemic Using a Digital Behavior Change Intervention: An Open-Label, Single-Arm, Pre-Post Intervention Study. *JMIR Form Res.* **2021**, *5*, e31273. [CrossRef]
56. Mangrulkar, R.S.; Michalas, A.; Shekokar, N.M.; Narvekar, M.; Chavan, P.V. *Design of Intelligent Applications Using Machine Learning and Deep Learning Techniques*, 1st ed.; Chapman and Hall/CRC: Boca Raton, FL, USA, 2021; ISBN 978-1-00-313368-1.
57. Chou, Y. *Actionable Gamification Beyond Points, Badges, and Leaderboards*; Octalysis Media: Fremont, CA, USA, 2015; ISBN 978-1-5117-4404-1.
58. Dias, L.P.S.; Barbosa, J.L.V.; Vianna, H.D. Gamification and Serious Games in Depression Care: A Systematic Mapping Study. *Telemat. Inform.* **2018**, *35*, 213–224. [CrossRef]
59. Lukas, C.A.; Eskofier, B.; Berking, M. A Gamified Smartphone-Based Intervention for Depression: Randomized Controlled Pilot Trial. *JMIR Ment. Health* **2021**, *8*, e16643. [CrossRef] [PubMed]
60. Hungerbuehler, I.; Daley, K.; Cavanagh, K.; Garcia Claro, H.; Kapps, M. Chatbot-Based Assessment of Employees' Mental Health: Design Process and Pilot Implementation. *JMIR Form Res.* **2021**, *5*, e21678. [CrossRef]

61. National Health and Nutrition Examination Survey 2017–March 2020 Data Documentation, Codebook, and Frequencies–Demographic Variables and Sample Weights (P_DEMO). Available online: https://wwwn.cdc.gov/Nchs/Nhanes/2017-2018/P_DEMO.htm#RIAGENDR (accessed on 14 October 2021).
62. National Health and Nutrition Examination Survey P_DEMO_Dataset. Available online: https://wwwn.cdc.gov/Nchs/Nhanes/2017-2018/P_DEMO.XPT (accessed on 13 October 2021).
63. Lee, D.K. Alternatives to P Value: Confidence Interval and Effect Size. *Korean J. Anesthesiol.* **2016**, *69*, 555. [CrossRef]
64. Méndez, J.I.; Meza-Sánchez, A.V.; Ponce, P.; McDaniel, T.; Meier, A.; Molina, A. PHQ9-LabVIEW Results. Available online: https://github.com/IsabelMendezG/PHQ9_FuzzyLogicResults (accessed on 14 November 2021).

Chapter 4

Evolving Gamified Smart Communities in Mexico to Save Energy in Communities through Intelligent Interfaces

4.1 Summary of the Chapter

This chapter presents the implementation of a tailored gamified platform for smart communities by providing a platform that teaches residential consumers how the electricity bill affects depending on the location. Furthermore, this platform proposes specific gamified buttons depending on the level of electricity consumption and the personality traits associated with the gamified user type.

In 2021, the residential sector had an electricity consumption of around 39% in México. Householders influence the quantity of energy they manage in a home due to their preferences, culture, and economy. Hence, profiling the householders' behavior in communities allows designers or engineers to build strategies that promote energy reductions. The household socially connected products ease routine tasks and help profile the householder. Furthermore, gamification strategies model householders' habits by enhancing services through ludic experiences.

Therefore, a gamified smart community concept emerged during this research as an understanding that this type of community does not need a physical location but has similar characteristics. Thus, this paper proposes a three-step framework to tailor interfaces. During the first step, the householder type and consumption level were analyzed using available online databases for Mexico. Then, two artificial neural networks were built, trained, and deployed during the second step to tailor an interactive interface. Thus, the third step deploys an interactive and tailored dashboard.

Moreover, the research analysis reflected the predominant personality traits. Besides, some locations have more electricity consumption than others associated with relative humidity, outdoor temperature, or poverty level. The interactive dashboard provides insights about the game elements based on personality traits, location, and electricity bills. Therefore, this proposal considers all consumers (typical and non-typical) to deploy tailored interfaces designed for smart communities. Currently, the game elements proposed during this research are reported by the literature, so their adoption is assured.

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Evolving Gamified Smart Communities in Mexico to Save Energy in Communities through Intelligent Interfaces

Juana Isabel Méndez [1], Adán Medina [1], Pedro Ponce [1,*], Therese Peffer [2], Alan Meier [3] and Arturo Molina [1]

[1] Institute of Advanced Materials for Sustainable Manufacturing, Tecnologico de Monterrey, Monterrey 64849, Mexico; isabelmendez@tec.mx (J.I.M.); a01331840@tec.mx (A.M.); armolina@tec.mx (A.M.)
[2] Institute for Energy and Environment, University of California, Berkeley, CA 94720, USA; tpeffer@berkeley.edu
[3] Energy and Efficiency Institute, University of California, Davis, CA 95616, USA; akmeier@ucdavis.edu
* Correspondence: pedro.ponce@tec.mx

Abstract: In 2021, the residential sector had an electricity consumption of around 39% in México. Householders influence the quantity of energy they manage in a home due to their preferences, culture, and economy. Hence, profiling the householders' behavior in communities allows designers or engineers to build strategies that promote energy reductions. The household socially connected products ease routine tasks and help profile the householder. Furthermore, gamification strategies model householders' habits by enhancing services through ludic experiences. Therefore, a gamified smart community concept emerged during this research as an understanding that this type of community does not need a physical location but has similar characteristics. Thus, this paper proposes a three-step framework to tailor interfaces. During the first step, the householder type and consumption level were analyzed using available online databases for Mexico. Then, two artificial neural networks were built, trained, and deployed during the second step to tailor an interactive interface. Thus, the third step deploys an interactive and tailored dashboard. Moreover, the research analysis reflected the predominant personality traits. Besides, some locations have more electricity consumption than others associated with the relative humidity, the outdoor temperature, or the poverty level. The interactive dashboard provides insights about the game elements needed depending on the personality traits, location, and electricity bill. Therefore, this proposal considers all householders (typical and non-typical users) to deploy tailored interfaces designed for smart communities. Currently, the game elements proposed during this research are reported by the literature, so their adoption is assured.

Keywords: gamification; personality traits; HMI; ANN; socially connected products; gamified communities; tailored interfaces; interactive interface

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1. Introduction

In 2021, the residential and commercial sectors had an electricity consumption of 39% and 35%, respectively [1]. About 60% of the energy consumption in a home belongs to the Heating, Ventilation, and Air-Conditioning (HVAC) systems [2–4]. Thermostats control these HVAC systems in about 86% of households [5]. Connected thermostat usage reported a reduction from 10 to 35% of the peak load [6,7]. In Ref. [8], they indicated that behavioral factors explain up to 50% of the variance in HVAC consumption. Moreover, research suggests that gamification strategies can reduce energy by 22% [9]. Messages or feedback approaches, including energy consumption and comparison with the last period, can reduce energy by between 5% and 12% [10].

End-users influence the quantity of energy they manage in a home due to their thermal preferences, habits, culture, and economy [2,11–16]. Thus, they represent a crucial element in reducing electricity consumption; hence, their attitudes need to be oriented into a pro-environmental one [17–19]. Regrettably, trying to shape users' habits is challenging, as it is in human nature to return to old habits [13,20–22]. Thus, Ponce et al. [19] proposed using gamification or game elements within products to motivate and engage householders in adopting new attitudes toward saving energy [2,19]. Besides, as the Internet of Things has increased, the appliances have become more available at home, and the householders are therefore interacting with the household appliances by monitoring their products through their phones. Hence, these household products facilitate routine tasks, provide security and safety, or even adjust visual and thermal comfort [2,19,23].

Nevertheless, the householders did not adopt these devices correctly due to usability and behavioral problems [2,19,24] and due to the lack of personalization and interaction with the product and the Human–Machine Interface (HMI) [19,25]. Usability provides effortless interaction with customers through user-friendly products, services, or software [26–29]. For instance, Nielsen [24,30,31] evaluates software interfaces using usability heuristics, successfully identifying usability problems in a fast, low-cost, and successful way [27,32]. In that sense, Ponce et al. [19] emerged with the social product concept to explain that the communication between the householder and the product and between products needs to provide a tailored service, for instance, in an intelligent home.

Smart homes were initially known as *wired* homes due to their technological features and usage [33]. On the other hand, the building sector defined the smart home as a dwelling equipped with information and computing technology that foresees and answers the requirements of the dwellers. Marikyan et al. [34] classified smart homes into four categories: surveillance home, assistive home, detection and multimedia home, and ecological awareness home. Furthermore, Méndez et al. [35] defined a gamified smart home as a home that uses socially connected products to profile dwellers depending on their personality traits, type of gamified user, and energy consumer sector. This home provides tailored interfaces that help the dwellers to understand the benefits of becoming energy aware.

Thus, a smart home is a dwelling supplied with software and hardware technology throughout household appliances or social products that serve and fulfill the occupants' comfort, demands [33], recreation, safety, and well-being [35,36]. Therefore, the social products (or household appliances) track and profile the individual [2,12,37]. In Ref. [19], they proposed customized interfaces with gamification elements within the product to engage, motivate, and teach users how to lower electrical energy consumption. Hence, social interaction allows for a better understanding of the householders' patterns to profile them [2,19]. Moreover, gamification strategies can influence dwellers' habits [2,19,35,37]. Gamification enhances a service through ludic experiences to support the customers' general value creation [38].

Ponce et al. [19] defined the *social product* as a product that observes, registers, analyzes, and changes the householder's behavior or adapts its features online/offline to improve its performance and acceptability in the market.

The S^4 product development framework produces social products by implementing sensing, smart, sustainable, social features within the social features [39]:

- Sensing features detect events, get information, and measure changes through sensors that observe physical or environmental conditions;
- Smart features consolidate the physical parts, smart components, and connectivity to enable the intelligence of the product by providing accessible interfaces;
- Sustainable features produce balanced and optimized performance by incorporating social, environmental, and economic aspects;
- The social features use communication between consumers and products and between products.

Identifying the behavior and usability problems in using connected devices and involving residential energy users in the planning, implementation, and monitoring process can help lower energy consumption. This set of homes can build a community and the set of communities can build a city.

Adopting socially connected products requires that users know that they are acquiring connected products so they can exploit their advantages. Besides, these products interpret individuals' lifestyles and requirements. These devices are cheap and quick to obtain. Furthermore, they reduce physical demands for their operation that do not require high user knowledge levels. Moreover, these household appliances have privacy and security features and consider end-user skills not to fail or act unpredictably [40].

Moreover, understanding the householders' behavior in communities allows designers or engineers to build strategies that promote energy reductions [41]. Consequently, a smart community has a set of smart dwellings, commodities, and green areas where its neighborhoods socially interact and relate with their peers [41]. These homes virtually interact in a specific location, surrounded by phone line communication, wireless communication technology, power line communication technology, and technology that involves dedicated wiring, such as Ethernet [42]. The smart community's concept is relatively new [42–48]; it is in the infancy stage and is a smart city component [48]. Besides, a smart community can be, for instance, a university campus [49–53], a residential complex, or an industrial park. For this research, the smart community is conceptualized by using two available datasets that have in common the location to build this community and show the householder if their consumption is the habitual consumption for their site or if it is above or below the regular consumption.

Besides, the concept of a smart and sustainable city is based on promoting citizens' quality of life using technology and data. Hence, this type of city must have the following characteristics [54]:

- Citizen Centered Design;
- Optimal technology deployment;
- Transparency and efficiency;
- Residents involved, informed and connected.

Furthermore, KPMG indicates that a smart and sustainable city must consider at least eight essential cores focused on the citizen [54].

- Telecommunications: Connectivity is a fundamental foundation.
  - Key elements: Broadband access, open standards (interoperability), and privacy and security)
- Healthcare services: New technologies have the potential to change healthcare services.
  - Key elements: Electronic medical records, telemedicine, and data and analysis applied to health services
- Transportation: Transport and mobility are key challenges.
  - Key elements: Smart traffic routing, smart parking, and infrastructure planning
- Security: Changes and trends require informed decisions.
  - Key elements: Access and integration of multiple data, scalability and compatibility, and information shared between various entities
- Buildings: They generate one of the most important energy consumption.
  - Key elements: Sensors and devices, smart design systems, and smart energy management systems.
- Education: Technology will allow the adoption of new tools and techniques.
  - Key elements: Accessibility, collaboration and motivation, and efficiency
- Tourism: Better understanding of interests.
  - Key elements: Incorporation of advanced technologies, optimized access to destinations and activities, and smart destinations.

- Other services: Resource consumption optimization.
  - Key elements: Water management consumption, use of Smart Grid for energy, and waste management system.

Currently, in Mexico, there are three recognized smart cities [54]:

- 2015: The Inter-American Development Bank (BID) recognized Guadalajara as the first smart city in Mexico [55]. Guadalajara was the first metropolis recognized for its digital and intelligent transformation initiatives after the implementation of the Digital Creative City (CCD) project;
- 2016: BID recognized Chihuahua as the second smart city for its wireless internet coverage;
- 2019: Mexico City received the *Gobernante* award for its innovative use of data in the public policy cycle.

In 2021, the Smart Cities Commission of the Confederation of Industrial Chambers Mexico (CONCAMIN) presented the first version of the Strategic Agenda for the Development of Mexican Smart Cities, starting with the first group of 13 cities [56]. Their objective is to help Mexico's cities and municipalities develop good planning that includes the city's infrastructure and services. The evaluation of the performance of the city's management is through the quality of life indicators having sustainability as a general principle. The 13 cities are: Aguascalientes, Chetumal (Quintana Roo), Coatzacoalcos (Veracruz), Cuernavaca (Morelos), Leon (Guanajuato), Merida (Yucatan), Mexicali (Baja California), Morelia (Michoacan), Oaxaca de Juarez, Pachuca (Hidalgo), Salina Cruz (Oaxaca), Tuxtla Gutierrez (Chiapas), and Xalapa (Veracruz).

Moreover, the smart city (smart community, smart home, and social products) involves human decisions and reasonings that positively or negatively affect electrical consumption [41]. In that sense, Artificial Intelligence (AI) mimics the solution process of the brain. Artificial Neural Networks (ANN) extract information from experimental data or databases determined by human experts. One of the most used topologies is the feed-forward propagation network and the recurrent network. In the first type, the information flows from inputs to outputs, is entirely forward with no feedback connection, and uses supervised learning methods.

Hence, this paper proposes categorizing the householder type and consumption level by analyzing databases available about the electricity consumption in Mexican households and the user type based on Mexico's personality traits. Thus, once the type of householder around Mexico is understood, interactive and tailored interfaces for communities are deployed. The interface is based on an interactive dashboard built using LabVIEW™ V.20.0.1. This interactive dashboard collects information about the user's personality traits and the level of home consumption for a specific location to retrieve these interfaces.

This paper is organized as follows. Section 2 describes the materials and methods used for the proposal. Section 3 shows the results of the proposal. Section 4 discusses and presents the gamified structure's scope, advantages, and disadvantages. Finally, Section 5 presents the conclusion and future work.

2. Material and Methods

Figure 1 depicts how a connected thermostat behaves to be considered a socially connected thermostat. The user is the primary linkage between the device and the interface. The socially connected thermostat has four modes: (a) heating or cooling mode, (b) fan mode, (c) automatic mode, and (d) tailored mode. The last mode is proposed based on the householder profile and household consumption.

The energy consumption control considers four features: (a) energy saving, (b) thermal comfort, (c) forecast of energy consumption, and (d) gamified interface. The gamified interface aims to teach, engage, and motivate the householder to reduce energy consumption without affecting their thermal comfort and shows predictions of consumption based

on the thermostat set point. This thermostat interface considers game elements that teach the householder the differences in energy consumption depending on the set point, location, and date so that they can visualize the possible energy consumption impact based on their actions. An example of this consumption prediction is proposed in Ref. [2]. In Ref. [57], they used image classification to predict thermal comfort and energy consumption based on clothing insulation.

The communication with other products provides information about the performance of the other household appliances and the energy consumption to create a consumption profile. Besides, it provides a social connector within the thermostat interface to promote energy savings and social interaction. In Ref. [36], they proposed a voice assistant to track seniors' moods to promote social interaction, avoid social isolation, and link seniors with their peers. Moreover, in Refs. [35,58], they proposed a voice assistant to interact with the householders and survey them to work as a depression pre-diagnosis. All of these proposals are managed at a residential level. Furthermore, in Ref. [41], they proposed a gamified community based on the ranks of household energy consumption to provide game elements. Nevertheless, this proposal only focused on the type of home, not on the individual.

Thus, connected thermostats can be considered a social product representing an opportunity to optimize and save energy. Besides, an additional element requires the profiling of the householder to promote this interaction through gamification elements [2,19] to provide the possible reductions that research suggests [9].

- Knowledge base step: this step gathers the data from two datasets: the 2018 National Survey on Energy Consumption in Private Homes (ENCEVI) [59] and Big Five Personality Test [60]. Then, two new datasets were created. The first dataset considered the location and personality traits from Mexico and related them with the game elements associated with each personality trait and gamified user. This association was based on what Marczewski proposed for the game elements in Ref. [61]. The second dataset included the ENCEVI dataset that deployed information about household electrical consumption in Mexico and was filtered to consider a single household member with an air conditioning system and whose home had no retailing services;
- AI decision system step: Two two-layer feed-forward ANN were modeled in MATLAB R2021a. One was for the personality trait, and the second was for household consumption. Thus, one of the ANNs classified the gamified element based on personality traits and location. The other ANN classified the three types of consumption based on the home cost consumption; in this case, it did not use information about the kWh because the ENCEVI dataset only included information about the previous billing. Once created MATLAB's ANNs, they were built into the LabVIEW™ environment to create the interactive dashboard;
- Evaluation step: This step evaluates the AI algorithm through an interactive dashboard created at LabVIEW™ to propose tailored interfaces for each household type and home electricity bill. Regarding the smart community, during this step, the householder can select the location to learn how the consumption is different among other locations and in their same location how it changes depending on whether it is a habitual consumption or whether it is below or above this consumption. This phase provides continuous feedback to the user and the knowledge base to determine whether the user is engaged or if some adjustments are required.

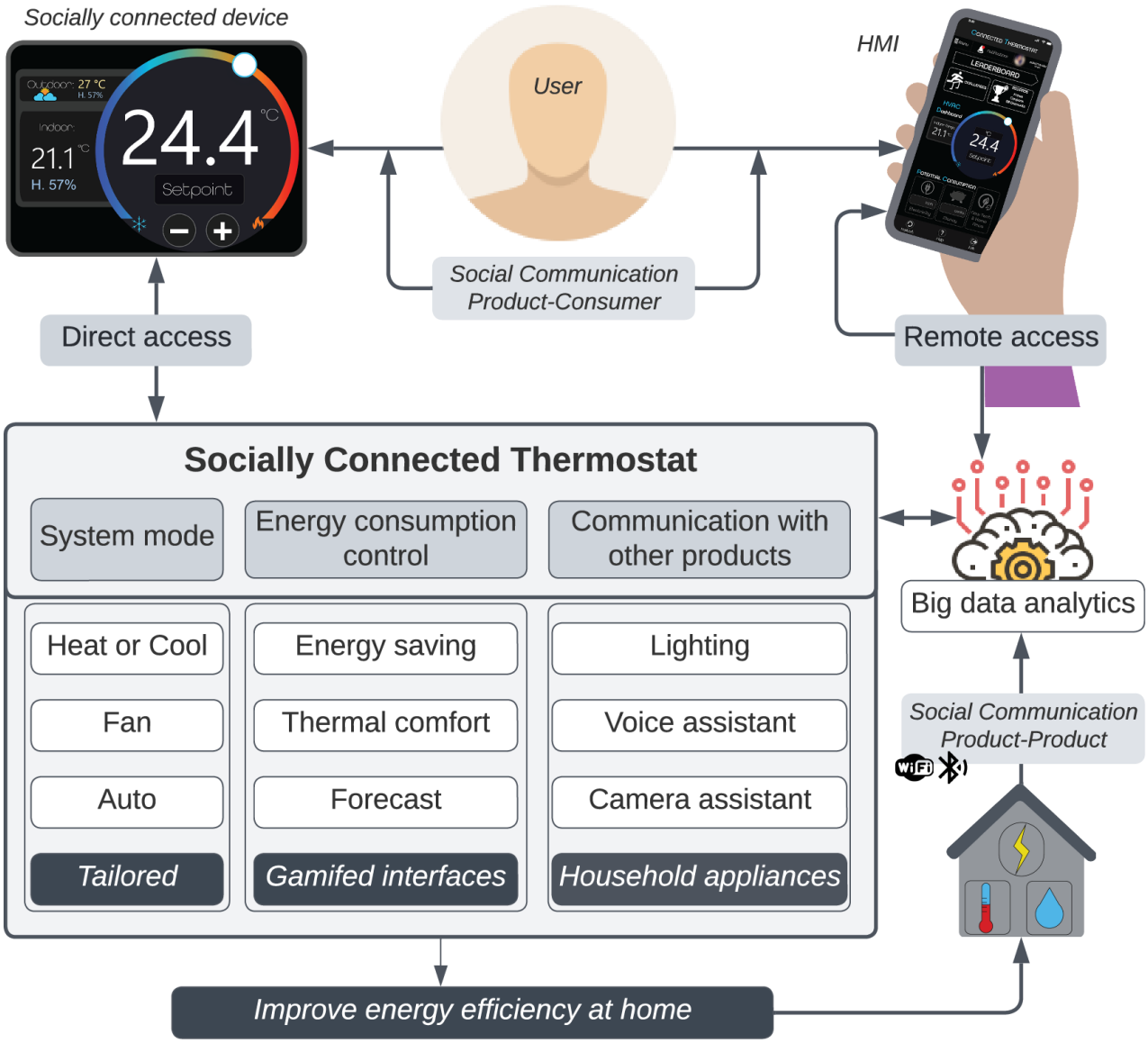


Figure 1. Socially connected products: Connected thermostats are used as an example of this communication.

This proposal comprises three steps to deploy a tailored interface based on the type of home and the type of householder. Figure 2 depicts the proposed diagram flow to this interactive interface based on the interactive dashboard results. Therefore, the methodology used is the framework proposed by the authors [19]:

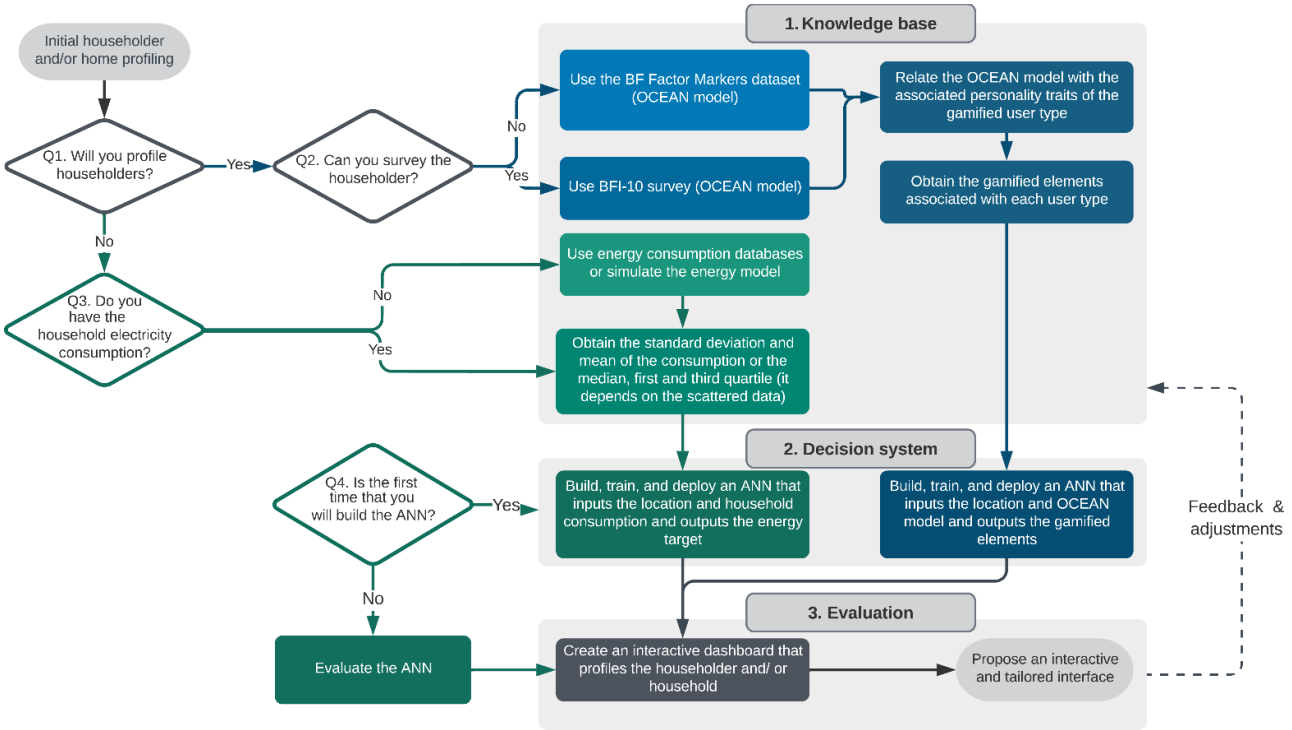


Figure 2. Diagram flow for the socially connected interface proposal.

2.1. Knowledge Base

In Refs. [62,63], the OCEAN model, or the "*Big Five*" personality traits, describe five personality traits depending on the perception and attitudes of the individual. The openness (O) personality trait has a positive attitude toward learning new things and an appreciation of divergent thinking where new ideas are explored. The conscientiousness (C) trait is responsible for a rational and clear purpose in life. The extraversion (E) personality is optimistic, assertive, and loves social interactions that allow diverse activities. The agreeableness (A) individual cooperates with sympathy and empathy for others. Higher levels of E and A are inclined to save energy. The neuroticism (N) trait is bad-tempered, impulsive, and experiences negative emotions. The O, C, and higher levels of E, A, and N have a positive attitude toward energy conservation and are strongly associated with their attitudes and actions in different domains [2,11,64–67]. Moreover, each personality learns things and adopts technology differently [64,68–72].

Goldberg deployed the Big-Five Factor Markers, which is a 50-question survey. Furthermore, in Ref. [60], they deployed a dataset with 1,015,341 responses from 223 countries worldwide and collected from 2016 to 2018 in an interactive online Goldberg's 50-question survey. Rammstedt and John [73] deployed the short version of the Big Five Inventory (BFI-44) from 44 questions into 10. Thus, the BFI-10 is a 10-question survey that measures personality traits in a minute using a Likert response scale: (1) Very inaccurate; (2) Moderately inaccurate; (3) Neither accurate nor accurate; (4) Moderately accurate; (5) Very accurate. Goldberg's 50-question survey is available in Ref. [74] and Big Five Inventory-10 (BFI-10) test is available in Ref. [73].

Frankel et al. [75] surveyed 2500 Americans to measure their behavioral tendencies in the United States. They aimed to detect practical tools to focus on buyers and their needs and recognize what it would need to scale up enhanced energy-efficiency-performance implementation. Besides, they identified five types of energy consumers. The green-advocate (G-A) sector has energy-saving behavior attitudes with interest in new technologies. This sector is driven by perceived environmental benefits from more efficient energy usage. The segment's profile is not just green; it also includes an interest in

using new technologies. The traditionalist cost-focused energy saver (TC-F) segment has broad energy-saving behavior motivated by cost savings. The TC-F has limited interest in new technologies. The home-focused selective energy saver (H-F) group pursues home improvement through technological and cost-saving dimensions. The H-F has an interest in saving energy.

The nongreen selective energy saver (N-G) users save energy as long as they do not have to think about it ("set and forget" interventions). Hence this type does not concern with environmental considerations. Opposite to G-A, the disengaged energy waster (D.E.W.) sector worries neither about saving energy nor money. The D.E.W. does not interest in new technologies or the environment. Ponce et al. [76] suggested classifying the O trait with the G-A, the C with the TC-F, the E with the H-F, the A with the N-G, and the N with the D.E.W.

Peham et al. [77] proposed three energy target groups regarding household appliances, user availability, characteristics, and energy awareness. Early adopters buy household appliances with cutting-edge technology, available anywhere through their modern technology gadgets. The early adopter is not energy-aware and is part of the social media communities. Besides, the early adopter relates to the N-G and D.E.W. [19]. The cost-oriented users orient their life through cost savings and select their household appliances based on the cost-savings of the devices. They are social media users and are mostly connected through their mobiles. The cost-oriented individuals look for a sustainable lifestyle depending on their capabilities because energy savings are essential. Hence, this group relates to TC-F and H-F [19]. The energy-conscious group has a sustainable lifestyle. This group is energy-aware and acquires household electrical devices with low energy consumption and a long lifetime. This group is not active on social media. Furthermore, in Ref. [19], they related the energy-conscious sector with the G-A.

Marczewski [61] proposed six types of gamified users and the game design elements associated with each user type. Purpose motivates the philanthropist (Ph) user, who is altruistic and willing to give without expecting anything in return. The suggested design elements for the Phs are collection and trading, gifting, knowledge sharing, and administrative roles. Relatedness motivates the socializer (S) type. This user type interacts with others to create social connections; thus, the suggested design elements include teams, social networks, comparison, competition, and discovery.

Autonomy motivates the free spirits (F) users, who want the freedom to express themselves and act without external control. The suggested design elements include exploratory tasks, easter eggs, unlockable content, creativity tools, and customization [62]. Competence motivates the achiever (Ach) because these individuals seek to progress within the system by completing tasks. Hence, the suggested design elements consider challenges, certificates, learning new skills, quests, levels, and epic challenges. Extrinsic rewards motivate the players (Pl) type [61]. They do whatever activity is required to gain a bonus. Thus, the suggested design elements are points, rewards, leaderboards, badges, and a virtual economy. Opposite to the Ph, change motivates the disruptor (D) type. The D users disrupt the system directly or through others to force positive or negative changes. Often the Ds are seen as cheaters or griefers; there are Ds that work to improve the system. Therefore, the suggested design elements are voting mechanisms, development tools, anonymity, innovation platforms, or anarchic gameplay [61].

Tondello et al. [78] conducted a survey and associated the six gamification user types with personality traits. The philanthropist positively correlates with O, C, E, and A personality traits. The socializer positively correlates with E and A traits. The free spirit positively correlates with O and E personality traits and negatively correlates with N. The achiever positively correlates with the C trait. The disruptor negatively correlates with the N trait, and the player type positively correlates with the C personality trait.

Thus, Figure 3 presents the personality traits as the central axis and their relationship with the gamified user to the left and the game elements associated with each one [61,78],

and to the right with the energy segment [75]. Besides, each energy segment shows its belonging to one of the three energy targets [77].

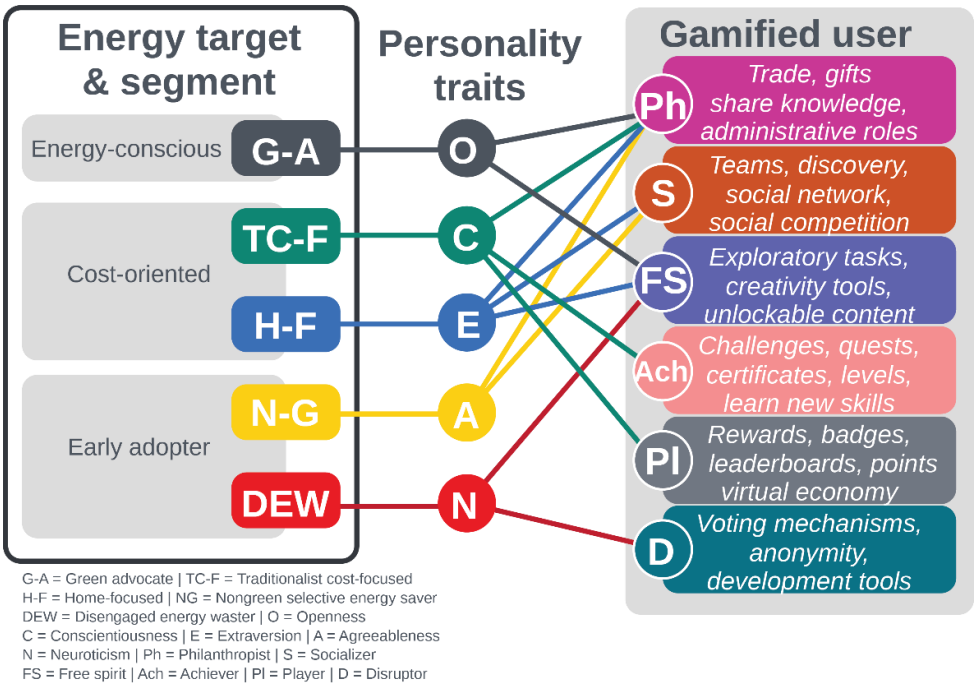


Figure 3. Personality traits as the central axis and their relationship with gamification and energy consumer type.

Shen et al. [79] suggest considering eco-feedback interventions to influence personality traits in energy-saving attitudes. Eco-feedback aims to inform householders about their energy consumption and help them become aware through informed decisions. Besides, in Ref. [80], they performed a study of 394 households in 8 communities in Singapore, and the communities had a similar type of construction. They found that C traits are strongly associated with personal energy-conservation attitudes and efforts to influence peers toward pro-environmental behavior because this trait is associated with responsibility and thoroughness [62,63]. Furthermore, higher-income individuals are inclined to influence others in acquiring energy-saving behaviors as their basic needs are fulfilled, and they have the money to buy and understand the benefits of energy-saving attitudes.

In Ref. [10], they studied 179 households and found that E traits driven by curiosity have positive attitudes toward saving energy if they receive feedback. They found that if N traits receive feedback and ranking information, they will not save energy. Thus, N traits prefer tips over feedback. Besides, N traits prefer to have detailed electricity billings to engage in energy attitudes. On the other hand, they found that high levels of O traits prefer face-to-face feedback rather than mobile feedback. Moreover, they found that A traits need an energy-efficient role model to have positive energy attitudes [11].

Income and education impact the electricity of householders' energy expenditure. Highly educated householders have stronger energy attitudes than lower educated individuals because their knowledge about energy-saving benefits is poor. Thus, personality traits are often considered control variables [80].

House type, orientation, location, temperature, and building materials impact residential energy consumption [2]. Surveys available at local governments provide information regarding household energy consumption. However, Shen et al. [71] found that the number of household members, cooking frequency, floor area, average area, gender,

and the number of rooms had no significant correlation with efforts to influence peers to participate in pro-environmental comportment.

For instance, the Residential Energy Consumption Survey from the U.S. Energy Information Administration collects energy characteristics of the household, usage patterns, and demographics from 18,500 statistically selected homes that represent the total housing units [1]. In Mexico, the National Institute of Statistics and Geography (INEGI) deployed the 2018 National Survey on Energy Consumption in Private Homes (ENCEVI) [59]. Thus, the database collected 28,953 individuals surveyed regarding the patterns of energy consumption of homes in Mexico, the billing cost, the hours of use per domestic appliance, the type of fuel used, and the air conditioning use, among others.

When dealing with energy consumption, it is relevant to perform descriptive statistics to obtain three types of consumption: habitual consumption, above this consumption, and below this consumption. Thus, if the data is very scattered, the median, first, and third quartile frame out this habitual consumption; on the contrary, if the information is not so scattered, the mean and standard deviation should be considered.

A gamified community does not need to stay in the same physical location but has similar characteristics to build one. The set of gamified homes belongs to specific attributes of square meters of construction, the number of household members, region, or climate zone (dry, temperate, humid). Thus, a community between homes can be established, as they have similar household characteristics. However, the concept of a smart city changes because this type of city needs to be attached to a specific location. Therefore, the gamified communities, for this case, need to be in the same place to consider that set part of a smart city.

Figure 4 displays an example of this gamified community. This picture shows two interfaces for the same community of a single householder in Mexico City with an electricity bill of 110 MXN. Besides, an example of the first home is given to show a comparison with Chiapas, depicted as another community. The differences between locations relied on the "potential waste" and "potential consumption" because although there is the same electricity bill, the difference is that the consumption in Chiapas is below the habitual consumption rather than in Mexico City, where this consumption is habitual. Besides, different buttons are related to the type of personality trait. Hence, the difference between a gamified community and the standard community definition is that the gamified community does not require to be bounded in the same residential complex.

2.2. Decision System

In 1943, McCulloch and Pitts [81] introduced the first simple artificial neuron. A Neural Network is characterized by a set of processing units or neurons, an activation state for each unit equivalent to the unit's output, and connections between units. These neurons are usually defined by a weight that determines the effect of an input signal on the unit; a propagation rule that determines the effective input of a unit from external inputs; a trigger function that updates the new trigger level based on input effect, and previous action; an external input that is the bias for each unit; a method of gathering information corresponding to the learning rule; and an environment where the system will operate, with input signals and error signals.

The most used topologies are the feed-forward or forward propagation network and the recurrent network [82]. The feed-forward network's information flows from inputs to outputs and is exclusively forward. Therefore, it continues through multiple layers of units with no feedback connection. Opposite, the recurrent network has feedback connections derived from a process of evolution towards a stable state with no changes in the activation state of neurons.

Figure 4. Conceptualization of a gamified community.

Remaida et al. [83] performed an exploratory data analysis from a literature review of 125 research papers that published information related to ANN with personality traits analysis. The three most common topics were the cultural and socio-cognitive effect on personality traits, the correlation between brain structure and traits, and the human decisions and judgments interactions depending on the personality trait.

Méndez et al. [2] used ANN to predict energy consumption and thermal comfort depending on the location and, thus, deployed a generic gamified prototype based on a *persona* that was not initially profiled. Therefore, the generic *persona* includes all the personality traits, the gamified user type, and the give energy end-user segment type. In other words, those interfaces were generic, and they lacked personalization.

In Ref. [84], they launched a survey to request the respondents to select one of three possible connected thermostat interfaces. Therefore, they proposed a rapid prototype that predicted the gamified interface based on personality traits.

In Ref. [49], they used the Automoto database [85], filtered the data by country to select Mexico, and proposed a dashboard prototype that predicted the gamified user type depending on the personality traits.

Medina et al. [57] proposed a dynamic interface based on an energy model simulation to predict energy savings and thermal comfort depending on clothing insulation.

Thus, the proposed interactive interface must consider the personality traits, the location, and the consumption in that location. Figure 5 displays the neural networks considered during this research.

This ANN topology had been used in Refs. [2,49,84]. In Ref. [2], this type of ANN was used to predict the electricity consumption, thermal sensation, and indoor temperature depending on the month, day, hour, setpoint, outdoor temperature, and if the householder uses HVAC or opens the window when required. In Ref. [84], an ANN was used to deploy three types of interfaces due to a Mexican survey launched at Tecnologico de Monterrey, Mexico City Campus, depending on the personality traits. In Ref. [49], an

ANN was used to deploy the game elements depending on the personality traits using the Automoto dataset.

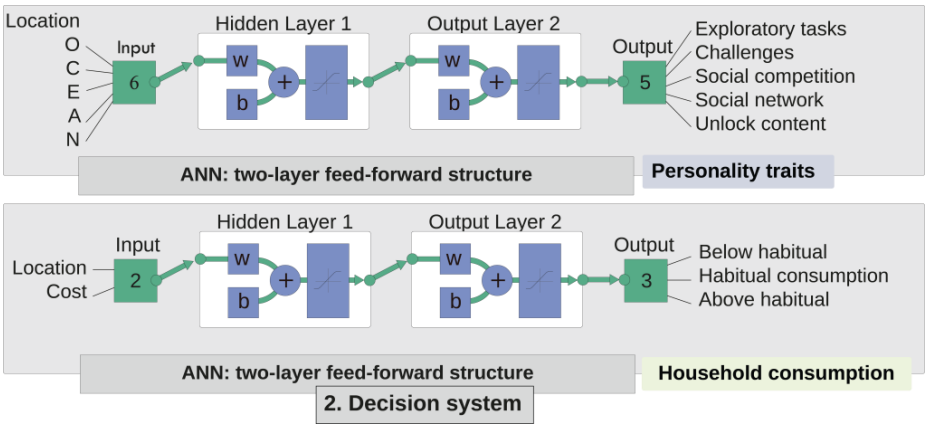


Figure 5. Decision system proposed in this research.

2.3. Evaluation

Table 1 depicts the elements considered for the interactive dashboard, and the input values require location, personality traits, and consumption. The location is the main element that links the user and home types. Figure 6 depicts the gamified elements selected for the dashboard. The dashboard displays game elements for the energy target related to the potential of saving or spending either money or electricity. In the case of the energy conscious, the button is oriented to the potential electricity consumption; for the cost-oriented, the potential money waste, and for the early adopter, the potential money savings. In both the cost-oriented and the early adopter, money is the key element due to their motives of saving electricity, and for the energy-conscious is the electricity, as this user type is aware of the consequences of wasting energy.

Table 1. Elements considered for the gamified HMI.

Energy Target	Energy Segment	Personality	Gamified User	Priority
Early adopter	N-G and DEW	A and N	Ph, S, F.S., D: *Social competition, social network, exploratory tasks, unlock content*	None, but propose potential savings
Cost-oriented	TC-F and H-F	C and E	Ph, Ach, Pl, S, F.S.: *Challenges, levels, points, rewards, leaderboard, social competition, social network, exploratory tasks, unlock the content.*	Cost consumption
Energy-conscious	G-A	O	Ph, F.S.: *Exploratory tasks and unlock content*	Electricity consumption

Figure 6. These gamified elements change depending on the decision system.

3. Results

This section presents the results of each step of the diagram flow depicted in Figure 2. First, the knowledge bases' results are described and how the two datasets were created

to build the ANNs' decision system. During the evaluation step, four interfaces are depicted, and each interface's characteristics are explained.

3.1. Knowledge Base

The Goldberg 50-question survey was analyzed [60]. A total of 1,015,342 respondents in 223 answered this online test, which was filtered by selecting the Mexico variable (MX); thus, the total data had 11,152 observations with 111 variables, including the 50 questions described in Table 1. The data was cleaned, and the NULL values and the unanswered questions were removed, resulting in 8835 observations from the country. Then the personality trait by observation was obtained and normalized. Figure 7a shows the boxplot by location and personality trait. This map brings insights into how there are different personality traits by location, as an example is Chiapas versus Puebla. Chiapas had higher levels of O trait and lower levels of N trait than Puebla. Puebla had more individuals with N trait than O trait and had higher levels of A trait. Thus, these boxplots exemplified the importance of deploying tailored gamified interfaces.

The ENCEVI database [59] was converted into one dataset by combining the following: encevi, home, person, building, and A.C. This dataset had 28,953 variables. The cleaned dataset had 20,347 observations. Figure 7b depicts each State's boxplots based on the rate type and the total electricity bill. The figure reflects that the unknown rate type was available in all the states, followed by the rate type 1. Therefore, Figure 7c shows the boxplots for the filtered data considering a single household member living in the home and using an air conditioning system. These boxplots show that in Aguascalientes and Estado de Mexico, the rate type 1 considered more observations than another rate. The total observations were 2041. Thus, the cleaned dataset had 984 variables.

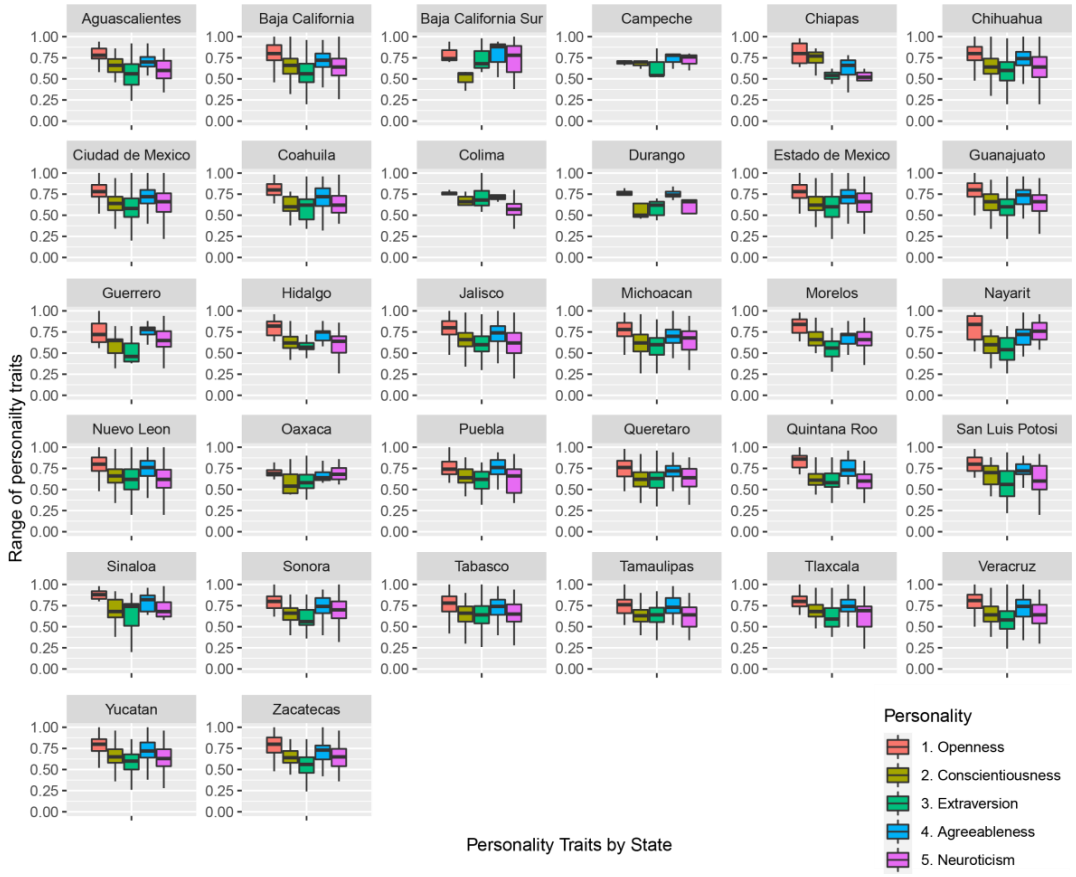
Therefore, two datasets were created, one considering the personality traits and the other dataset considering the bill cost. Figure 8 depicts an online map created with these two datasets [86]. For example, the ID 3797 shows that in this location, the higher levels of traits O and C must consider the exploratory tasks and challenges gamified elements. Besides, it shows that it is common to have an electricity bill ranging from MXN 67.5 to MXN 223.5.

The files used to build Figures 5, 7 and 8 were uploaded into a GitHub repository [87]. The files titled "ElectricityBill_and_gamification-Mexico.csv" and "PersonalityTraits_and_gamification-Mexico.csv" (Personality csv file) were used to build the ANN models. The files named "OCEAN_ggplot.csv" and "ENCEVI-ggplot.csv" were used to build the boxplots for Figure 7. Besides, the Personality csv file was used to build the map for Figure 8.

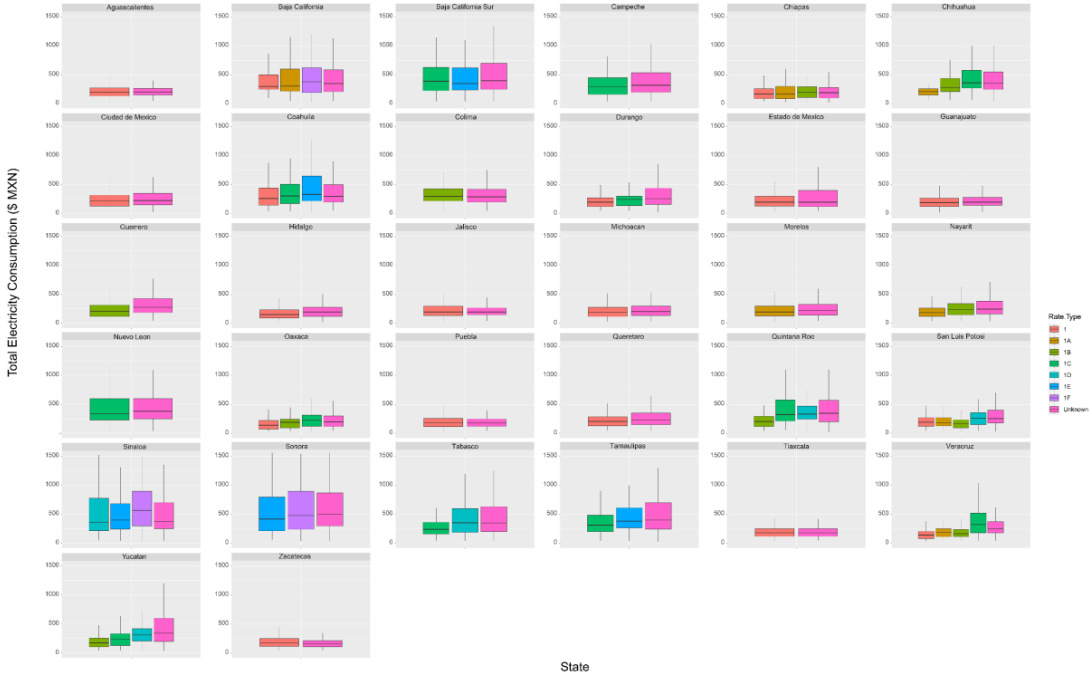
3.2. Decision System

The electricity bill dataset considered the median and the first to third quartile to assume that this was the habitual electricity bill at home or the cost-oriented house type. Above the third quartile, it was considered that the consumption was above the regular electricity bill; thus, it was an early-adopter house type. On the contrary, the energy-conscious house type was below the first quartile and was considered below the regular electricity bill. See Appendix A for more information about the statistics used to build the dataset. Moreover, the associated game elements for each type of house are as follows:

- Energy conscious-potential consumption game element;
- Cost-oriented-potential waste game element;
- Early adopter-potential savings game element.


Aguascalientes
Baja California
Baja California Sur
Campeche
Chiapas
Chihuahua
Ciudad de Mexico
Coahuila
Colima
Durango
Estado de Mexico
Guanajuato
Guerrero
Hidalgo
Jalisco
Michoacan
Morelos
Nayarit
Nuevo Leon
Oaxaca
Puebla
Queretaro
Quintana Roo
San Luis Potosi
Sinaloa
Sonora
Tabasco
Tamaulipas
Tlaxcala
Veracruz
Yucatan
Zacatecas
1.00
0.75
0.50
0.25
0.00
Range of personality traits
Personality Traits by State
Personality
1. Openness
2. Conscientiousness
3. Extraversion
4. Agreeableness
5. Neuroticism

(**a**)


Total Electricity Consumption ($ MXN)
State
Rate Type

(**b**)

(**c**)

Figure 7. Boxplots by location: (**a**) personality traits, (**b**) electricity bill by rate type, and (**c**) electricity bill by rate type considering a single householder using air conditioning systems.

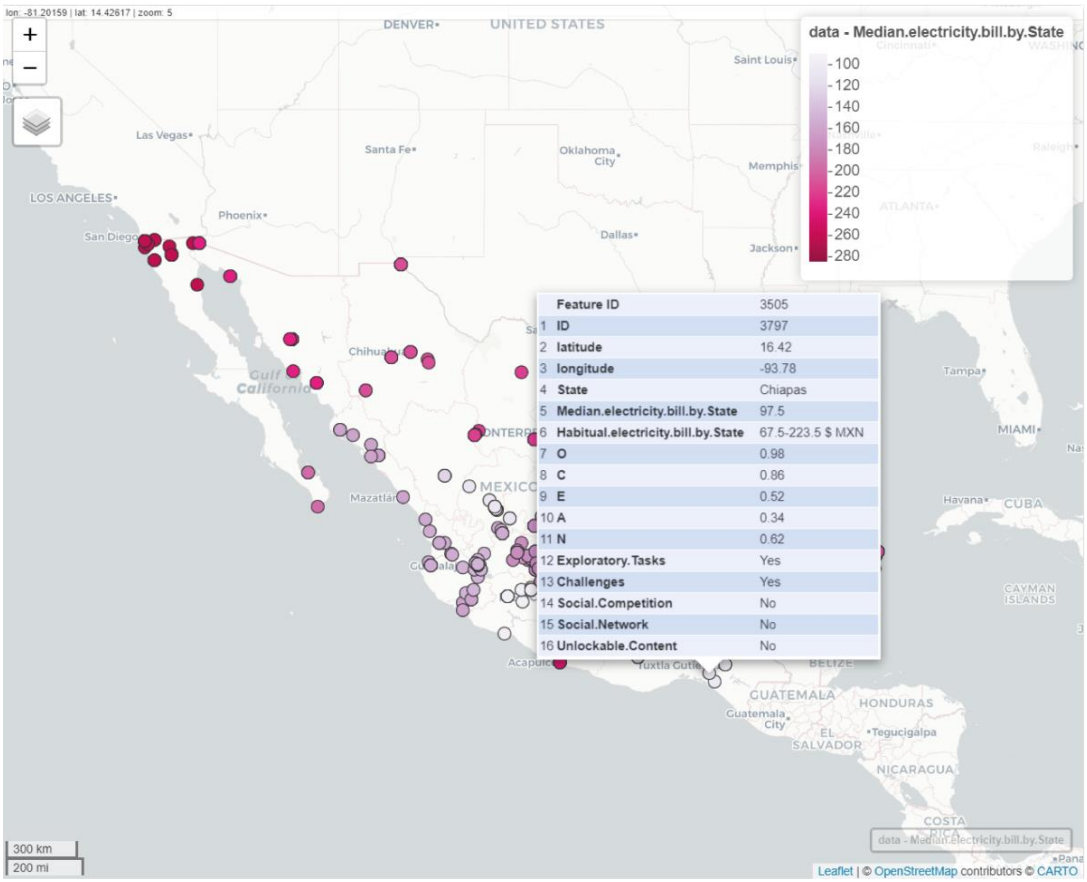


Figure 8. Map of Mexican personality traits and the electricity bill by state [87].

Besides, an additional analysis was performed by location, and six variables were analyzed: region, percentage of poverty, median, relative humidity (RH), minimum outdoor temperature, and maximum outdoor temperature. However, the RH varies depending on the location and the individual. It is considered that 30% to 50% or 30% to 60% range is the comfort range [88,89]. Due to the datasets of ENCEVI and personality traits ending in 2018, the percentage of poverty was obtained from that year [90].

See Appendix B for more information about the statistics obtained for each state and the percentage of poverty, median electricity bill, relative humidity, minimum outdoor temperature, and maximum outdoor temperature. For the median electricity bill column, the states considered habitual consumption range from 143.4 to 220, with a median of 176.5. The minimum median belongs to Michoacan and the Maximum to Nuevo Leon.

Michoacan had a 46.2% of poverty and was in the average maximum temperature; it had a 58% of RH. The predominant interface was the O trait with a range of 0.7 to 0.86 (first to the third quartile). Nuevo Leon had a 19.4% of poverty and 65% of RH, and the temperature ranged from 5 °C to 32 °C. The predominant personality was the A trait with a range of 0.68 to 0.8. Queretaro had a median bill consumption of 180, 26.4% of poverty, 54% of RH, and a temperature from 6 °C to 28 °C.; the predominant personality trait was the O. These ranges of RH fell between the comfort zone of RH, except for Nuevo Leon that was 5% above the comfort zone.

In the case of poverty, Baja California Sur was the less poor state, and Chiapas was the most impoverished state with more than ¾ of a poor population. Guanajuato was near the average poverty percentage, below the mean median, and had a higher % of RH. It was expected that above 60% of RH would be uncomfortable, so the use of HVAC was required; however, the costs did not reflect that. Veracruz had the highest percentage of RH, with 85%; the electricity bill was in the limit of the third quartile, and the predominant personality was O, with a range from 0.72 to 0.88. This electricity bill reflected higher consumption due to the RH, which was outside the comfort zone by 25 to 35%. The opposite was Sonora, which had a lower RH of 38% and poverty of 26.7%. It reflected higher electricity bills due to the temperature, which ranged from 5.5 to 38; the predominant personality was the O trait. However, Chihuahua had the most extreme temperatures, ranging from −5 °C to 40 °C, and it was within the limit of the third quartile consumption; it had 26.6% of poverty.

The personality traits dataset considered that personality traits above 0.7 had a strong personality, and the associated gamified elements were as follows:

- Openness—exploring tasks, game element;
- Conscientiousness—challenges game element;
- Extraversion—social competition;
- Agreeableness—social network game element.;
- Neuroticism—unlockable content game element.

In addition, as a generic interface, the rewards and PBL (points, badges, and leaderboard) elements were considered.

Thus, two datasets were created to feed two neural networks. Table 2 exemplifies the data used to build the first ANN, the location and personality traits were the input values, and the output values were the gamified elements. In contrast, Table 3 exemplifies the data used to build the second ANN, the input values were the location and electricity bill, and the output values were the gamified elements considered.

Table 2. Variables considered to build the personality traits' ANN.

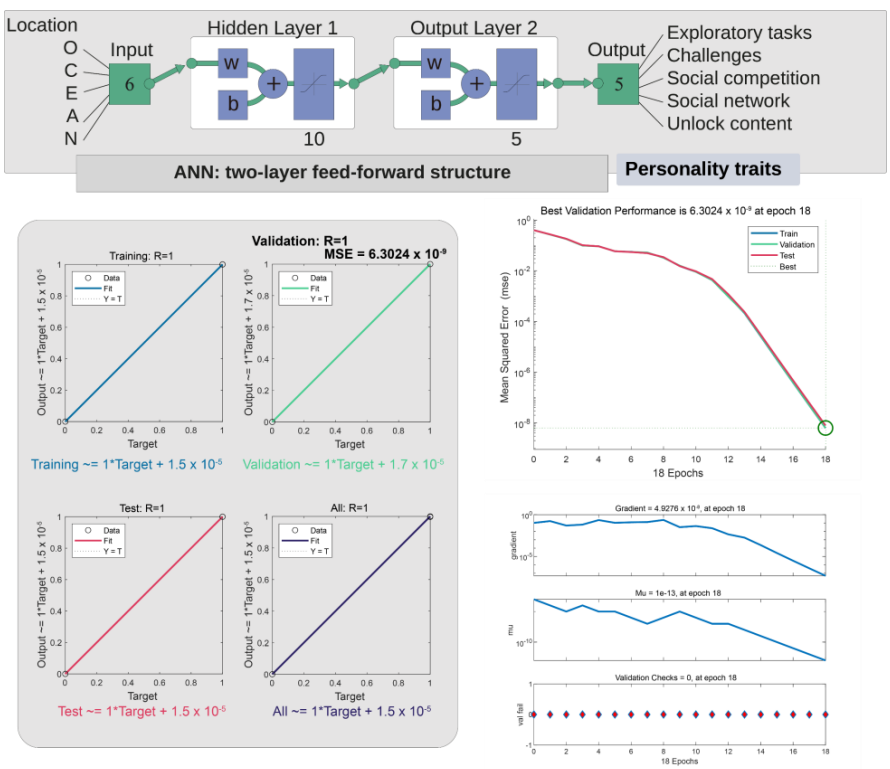
I.D.	Location	O	C	E	A	N	Exploratory Tasks	Challenges	Social Competition	Social Network	Unlock Content
Input Data							**Output Data**				
4173	Campeche	0.72	0.62	0.54	0.62	0.76	Yes	No	No	No	Yes
6956	Queretaro	0.68	0.46	0.72	0.6	0.58	No	No	Yes	No	No

629	Estado de Mexico	0.66	0.8	0.44	0.9	0.66	No	Yes	No	Yes	No
2201	Coahuila	0.66	0.74	0.8	0.34	0.4	No	Yes	Yes	No	No

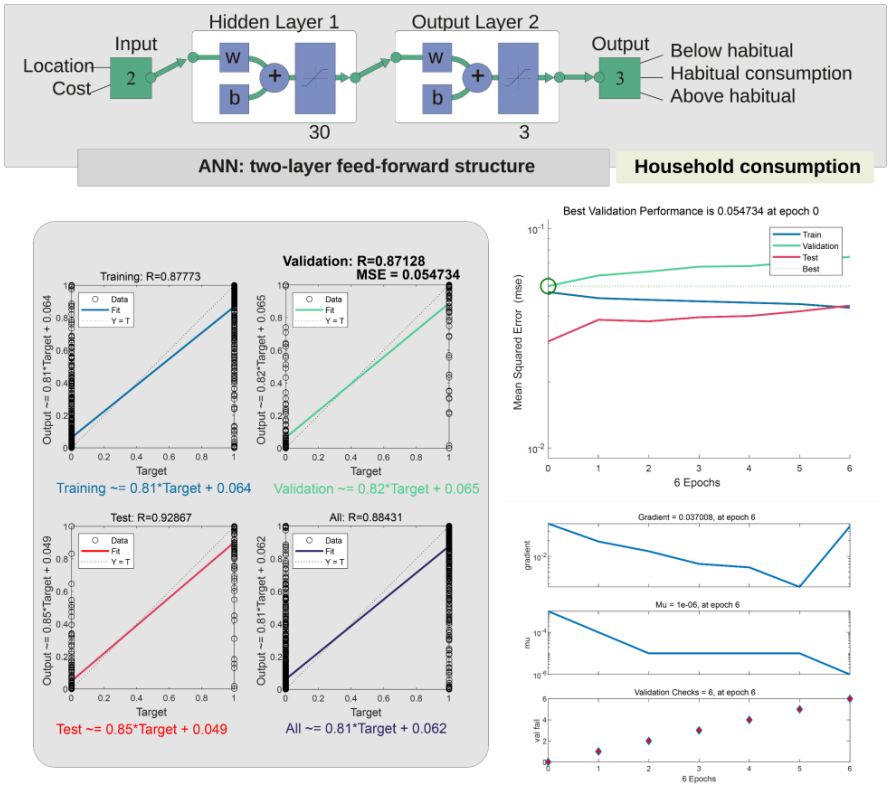
Table 3. Variables considered to build the electricity bill's ANN.

Location	Electricity Bill	Potential Consumption	Potential Waste	Potential Savings
Input Data		**Output Data**		
Campeche	120	1	0	0
Queretaro	120	0	1	0
Estado de Mexico	270	0	0	1
Coahuila	270	0	1	0

Thus, two neural networks were created using the nntool from MATLAB R2021a. Figure 9a displays the first neural network with 10 neurons in its hidden layer, and it is a two-later feed-forward ANN with an R equal to one. Figure 9b shows the second ANN with an R of 0.88 and 30 neurons in its hidden layer. Once the ANNs were obtained, the weights and biases were exported into LabVIEW V.20.0.1 to create the interactive dashboard and tailored interface. Figure 10a depicts the block panel, and Figure 10b shows the two ANN systems. In Figure 10c, the individual can select the location and the levels of personality traits on the front panel's left side. Hence, on the right side, the tailored gamified interface is displayed.

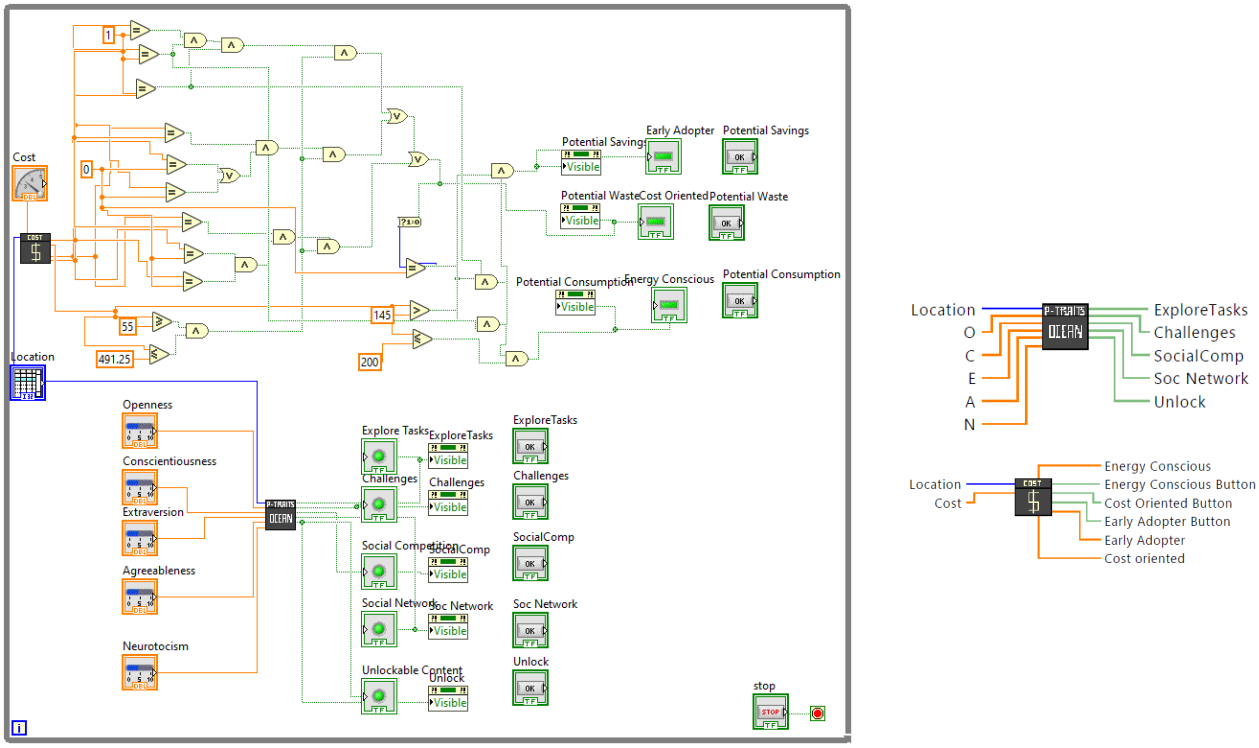


(**a**)

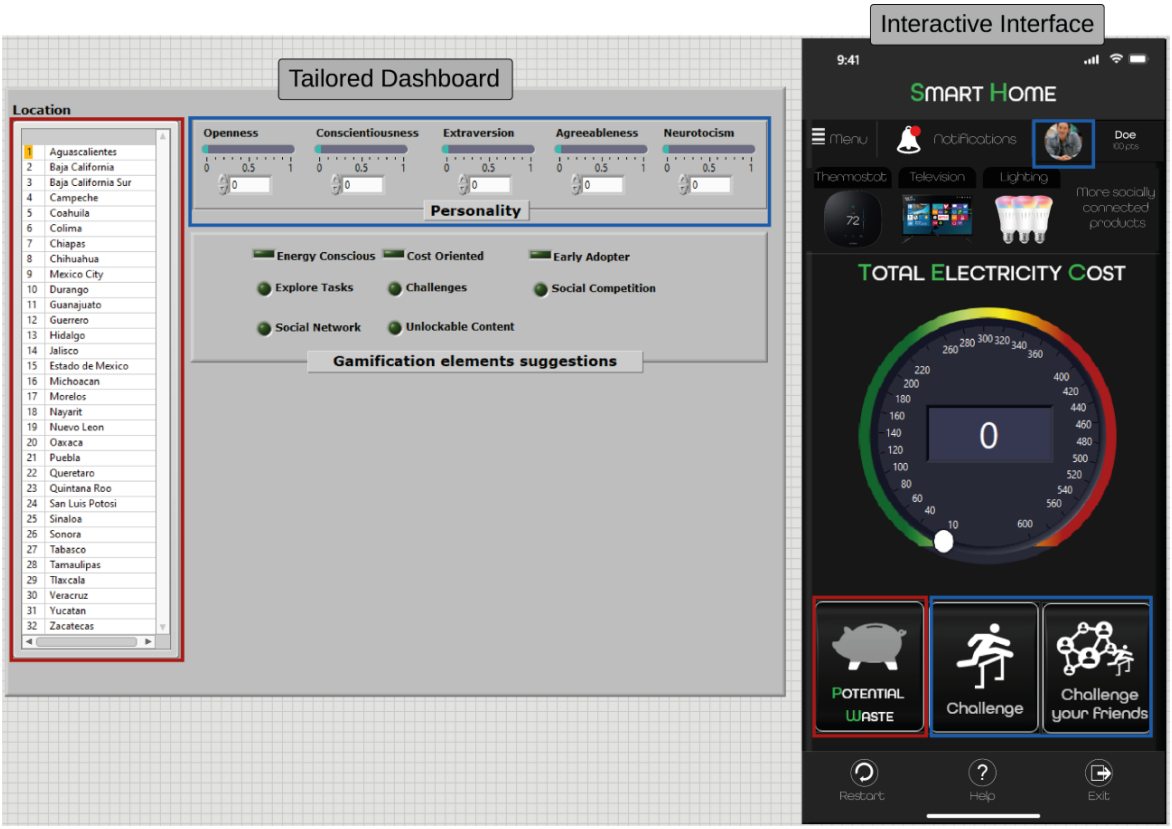


(**b**)

Figure 9. ANNs: (**a**) First ANN for the personality traits and (**b**) second ANN for the electricity bill.



(**a**) (**b**)

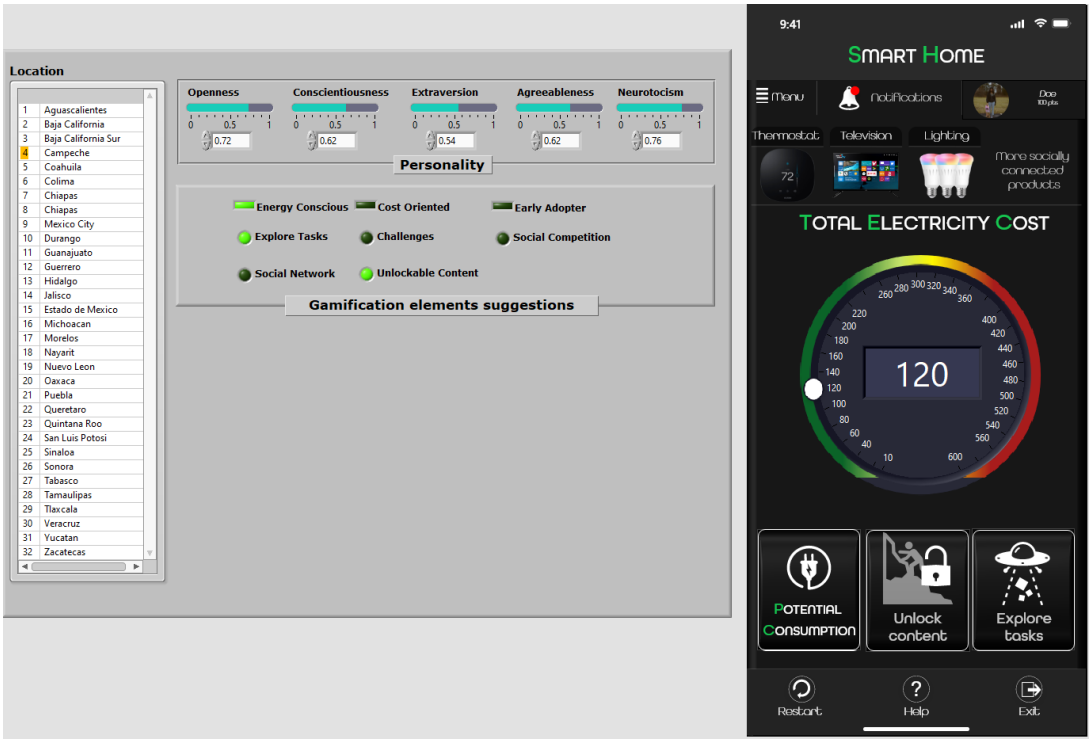


(**c**)

Figure 10. Proposed interactive dashboard: (**a**) block diagram, (**b**) subsystems that contain the two ANNs, and (**c**) left side: input values; right side: interactive interface.

3.3. Evaluation

Figure 11 displays different scenarios running the interactive dashboard considering the data from Tables 2 and 3 to exemplify how the interactive dashboard works. Hence, four locations were selected: Campeche, Queretaro, Estado de Mexico, and Coahuila. Campeche, Queretaro, and Estado de Mexico had a predominant personality trait of O. In the dataset, only three individuals answered the survey from Campeche; thus, there was not enough information to determine the principal personality. Figure 11a shows the dashboard and interface for an individual with high levels of O and N traits, an electricity bill of USD 120 located at Campeche, and the interface showed the "potential consumption", "unlockable content", and "explore tasks" gamified elements. On the other hand, Figure 11b displays the same electricity bill for the Queretaro location and an individual with a high E trait; hence, the interface showed the "potential waste" and "challenge your friends"; the PBL element was the same as the generic interface. Figure 11c shows the dashboard for an electricity bill of USD 270 at Estado de Mexico for a householder with high levels of C and A traits; thus, the interface depicted the "potential savings", "challenges", and "social network" game elements. Opposite to this interface, it was the case for Coahuila with a householder with higher levels of C and E traits; thus, the interface showed the "potential waste", "challenge", and "challenge your friends" buttons.


Location
1 Aguascalientes
2 Baja California
3 Baja California Sur
4 Campeche
5 Coahuila
6 Colima
7 Chiapas
8 Chiapas
9 Mexico City
10 Durango
11 Guanajuato
12 Guerrero
13 Hidalgo
14 Jalisco
15 Estado de Mexico
16 Michoacan
17 Morelos
18 Nayarit
19 Nuevo Leon
20 Oaxaca
21 Puebla
22 Queretaro
23 Quintana Roo
24 San Luis Potosi
25 Sinaloa
26 Sonora
27 Tabasco
28 Tamaulipas
29 Tlaxcala
30 Veracruz
31 Yucatan
32 Zacatecas
Openness 0.72
Conscientiousness 0.62
Extraversion 0.54
Agreeableness 0.62
Neurotocism 0.76
Personality
Energy Conscious
Cost Oriented
Early Adopter
Explore Tasks
Challenges
Social Competition
Social Network
Unlockable Content
Gamification elements suggestions
9:41
SMART HOME
Menu
notifications
Thermostat
Television
Lighting
More socially connected products
TOTAL ELECTRICITY COST
120
POTENTIAL CONSUMPTION
Unlock content
Explore tasks
Restart
Help
Exit

(**a**)


Location
1 Aguascalientes
2 Baja California
3 Baja California Sur
4 Campeche
5 Coahuila
6 Colima
7 Chiapas
8 Chihuahua
9 Mexico City
10 Durango
11 Guanajuato
12 Guerrero
13 Hidalgo
14 Jalisco
15 Estado de Mexico
16 Michoacan
17 Morelos
18 Nayarit
19 Nuevo Leon
20 Oaxaca
21 Puebla
22 Queretaro
23 Quintana Roo
24 San Luis Potosi
25 Sinaloa
26 Sonora
27 Tabasco
28 Tamaulipas
29 Tlaxcala
30 Veracruz
31 Yucatan
32 Zacatecas
Openness 0.68
Conscientiousness 0.46
Extraversion 0.72
Agreeableness 0.6
Neurotocism 0.58
Personality
Energy Conscious
Cost Oriented
Early Adopter
Explore Tasks
Challenges
Social Competition
Social Network
Unlockable Content
Gamification elements suggestions
9:41
SMART HOME
Menu
notifications
Thermostat
Television
Lighting
More socially connected products
TOTAL ELECTRICITY COST
120
POTENTIAL WASTE
Points Badges Leaderboard
Challenge your friends
Restart
Help
Exit

(**b**)

(**c**)

(**d**)

Figure 11. Tailored gamified interfaces for different locations and personalities: (**a**) Campeche interface, (**b**) Queretaro interface, (**c**) Estado de Mexico interface, and (**d**) Coahuila interface.

4. Discussion

This paper addresses how a tailored dynamic interface can be designed and deployed into thermostats. On the other hand, the main issue of providing a tailored interface by learning about the context of the householder and the household is shown. Thus, this research studies the databases' behavioral consumption and personality traits to get specific information to design the interface. The main advantage of this proposal is that it is a guide, step-by-step, that shows the researcher how to develop tailored interfaces that could be implemented not only in thermostats but also, they can be implemented in any household device for saving energy. This paper showed how to do it in the case of only having information about the total bill consumption. However, the interface can be modified by considering another household appliance, for instance, the lighting or the washing machine. This paper proposes a platform that could be extended to electrical devices in households or buildings. As the metaverse rises, future work could define the concept of a gamified smart city in terms of energy that does not need to be in a specific location, but the dynamic interface could be implemented in digital environments. Further research is required to determine if this is achievable.

The main drawback Is the limited information in the database. That means a huge database that covers all the possible locations in the world is required to implement this strategy in each location. Hence, the suggestion is to build a local database before using the proposed structure by surveying the individuals in that region and asking for their electricity bills. By analyzing Goldberg's database, we compare the results for the personality traits of individuals with similar behavior [60]. Therefore, this proposal aims to help the researcher with the minimum characteristics required to deploy a tailored interface that promotes energy reductions.

This proposal was built with databases; hence, in the future, these databases need to be updated with newer information. Thus, this proposal can be strengthened by adding a feature that links real-time information and running again—for instance—the electricity consumption ANN model to obtain new metrics about the behavioral consumption of the households. Furthermore, this proposal lacks a faster response for obtaining the personality traits of the household. Currently, it requires surveying the householder to detect their personality traits. Thus, an opportunity area for this proposal is to deploy a system that detects the traits faster and links them with behavioral consumption.

Therefore, this article analyzes two datasets to understand the type of householder and household in Mexico. Descriptive statistics were performed to determine the range of conventional electricity bills above and below this electricity bill and the predominant personality traits for each location. This paper considers two of eight cores of the smart and sustainable city cores that KPMG indicated [54]. The other core is the Other Services using a smart grid for energy. This proposal aims to help this key element to reduce energy consumption in households that impact the grids. This paper considers that the energy management systems can provide information, for instance, about the electrical or energy consumption; thus, profiling with this methodology can be performed.

Furthermore, two datasets were created from the original datasets to narrow it to Mexico; thus, the level of bill consumption and the personality traits were considered to deploy the interactive interfaces. Besides, these datasets can be updated depending on what variable is analyzed. For example, the dataset can consider the setpoint or the electricity consumption; thus, additional variables can be added.

Consequently, this paper proposes a novel approach for tailored gamified HMI in gamified smart communities. To deploy an accurate interface is essential to break down the intelligent community structure in two steps: get the personality traits using datasets or by surveying the householder and obtain the consumption; for this research, it was the bill consumption available at the ENCEVI database; however, the personality traits can be obtained by surveying the householder and the consumption by simulation different scenarios as done in Ref. [2]. If there is enough information about a single socially connected product, as in the case of the connected thermostat, the interface can provide tailored

interfaces about the thermostat. The starting point of these personalized interfaces depends on the available information. For instance, in this case, the information available was only the bill cost; thus, the starting point in this research was the home. Then, building gamified communities requires having information about the location so similar scenarios and analyses can be performed. For instance, Figure 11 displays interfaces depending on the bill cost; however, other interfaces can be displayed for the same location as suggested in Figure 4.

Regarding the interactive design, this proposal enhances tailored interfaces by bringing solutions that best suit the users' characteristics, having as an axis the personality traits; the gamified elements were reduced into five gamified elements so as not to overwhelm the dashboard and based on Figure 3. This proposal suggests that the game elements must change to engage the householder continuously [2,19]. A tailored gamified interface engages the householder by providing them user control and real-time interaction through the dashboard, responsiveness, and personalization through the AI decision system. Thus, the dashboard deploys tailored interfaces based on the type of user and household consumption.

This framework suggests continuous feedback from the householder and tailored interaction. Nevertheless, although theory suggests changes by providing customized interfaces, these interfaces require testing in physical environments to determine if reductions can be achieved by proposing tailored interfaces. Another limitation is that this proposal uses datasets, in the case of electricity bills requiring a constant update because the cost changes depending on the season. Therefore, the dataset requires regular updates for the bill cost ANN.

This paper presents a guideline for the designer or engineer who wants to propose a tailored interface; it describes the AI decision systems used and what data must be considered to build the ANNs and deploy interactive and tailored gamified applications. Hence, this typology allows its broadening into implementation in smart cities by combining several gamified communities. Besides, the complexity increases as communities consume more energy than others and the community's cultural characteristics. For instance, the Sonora community does not have the same bill cost range as Mexico City because it is unusual to have air conditioning systems in Mexico City. In contrast, in Sonora, it is common to have these systems due to the climate.

5. Conclusions and Directions for Future Work

Connected smart cities in developed countries are fundamental for improving citizens' quality of life. Moreover, there are specific governmental and private programs that promote societies to be more connected. Thus, this research aims to use the information available on the internet through databases or datasets to learn about the type of household and suggest tailored interfaces that citizens can adopt. Thus, this paper completely describes how to achieve these tailored interfaces systematically. This structure considers a knowledge base, AI decision system, and evaluation stage. The knowledge base step provides information about the personality traits and consumption in specific locations to have understanding of the game elements. Hence, a tailored interface can be deployed to promote saving energy attitudes and provide AI decision systems to tailor interfaces and engage householders to become energy aware.

On the other hand, this research provided insights into energy consumption and personality traits in Mexico by understanding the available personality traits. The database presented allows us to understand the behavioral community in that region. Since the personality that dominates a region usually does not dominate the others, a specific study must be conducted for getting the data from the individuals. For instance, there are locations whose predominance is the openness personality traits, and the gamified interaction must focus on activities that bring them new ideas that they will be willing to learn as well as information about recent trends. On the contrary, if the community has predominant neuroticism personality traits, the activities must be oriented to provide a faster response

but with the benefit of energy saving because this personality is impulsive. In the case of a community that predominates in extraversion, the activities must promote social interaction and foment social groups oriented to helping each other to save energy. An agreeableness community has an altruistic attitude with empathy for others. The conscientiousness community has a rational and clear purpose in targeting goals.

An additional feature is that aside from considering the community, the individual characteristics are considered. Although some communities predominate a particular personality trait, some individuals may have a different trait. For instance, the community is extraverted, but the individual has a neuroticism personality. Thus, specific activities are suggested to this individual.

For example, Nuevo Leon is 5% above the comfort zone; however, their electricity bill is higher than Veracruz. This difference may be affected by the lower temperatures registered in Nuevo Leon or by the differences between RH. Still, their electricity bill is not as high as Nuevo Leon's. Besides, Nuevo Leon predominates as an agreeableness location, whereas Veracruz has an openness personality trait. In other words, the population in Veracruz has a positive attitude toward learning new things, and Nuevo Leon has a cooperative attitude with sympathy and empathy for others.

On the contrary, Chiapas is the poorest location with 78% and a high level of RH (78%), but their electricity costs are not as high as expected due to the RH. This can happen because the temperature ranges from 17.5 °C to 30 °C. Michoacan is the State with the lowest median electricity bill, with an RH of 58% and temperatures that range from 8 to 31%, with 46.2% of poor people. Although the temperature ranges are lower than in Chiapas, due to the RH, the individuals feel comfortable, and it can be inferred that the usage of air conditioning systems is lower than in Chiapas. Chiapas and Michoacan—the same as Veracruz—have a predominance of the openness trait. Thus, two southeastern locations have openness personality traits (Chiapas and Veracruz).

Therefore, this paper proposes a gamified smart community based on location and personality traits in Mexico. This proposal considers the householder vital in promoting energy reductions in communities by showing how consumption changes depending on the location. This concept is supported by what KPMG indicates. A smart city must be a citizen-centered design. Hence, this framework is ideal for the designer of gamified communities, gamified smart homes, or even a gamified socially connected product to implement decision systems that tailor interfaces. However, further research must determine which characteristics define gamified smart cities.

This proposal is designed to be implemented in smart communities by considering all types of end-users (non-typical and typical users). Currently, the game elements proposed in this research are reported by the literature, so their adoption is guaranteed.

Author Contributions: Conceptualization, J.I.M., A.M. (Adan Medina) and P.P.; methodology, J.I.M.; software, J.I.M.; validation, P.P., T.P., A.M. (Alan Meier), and A.M. (Arturo Molina); formal analysis, J.I.M.; investigation, J.I.M.; resources, P.P., and A.M. (Arturo Molina); data curation, J.I.M.; writing—original draft preparation, J.I.M., A.M. (Adan Medina) and P.P.; writing—review and editing, J.I.M., A.M. (Adan Medina) and P.P.; visualization, J.I.M.; supervision, P.P., T.P., A.M. (Alan Meier), and A.M. (Arturo Molina); project administration, P.P., and A.M. (Arturo Molina); funding acquisition, P.P. and A.M. (Arturo Molina). All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data available in a publicly accessible repository. The datasets to build the ANNs models, boxplots, and the interactive map presented in this study are openly

available on GitHub at https://github.com/IsabelMendezG/MexicanGamifiedTailoredInterfaces (accessed on 13 April 2022).

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Electricity Bill Dataset Statistics

Table A1. Statistics used to build the electricity bill dataset.

	State	Q1 (25%)	Median	Q3 (75%)
1	Aguascalientes	108	151.5	224.5
2	Baja California	197.5	267	400
3	Baja California Sur	150	200	380
4	Campeche	200	265	327.5
5	Coahuila	127.5	220	325
6	Colima	125.75	161	250
7	Chiapas	67.5	97.5	223.5
8	Chihuahua	159	215	331.5
9	Mexico City (CDMX)	92.5	150	215
10	Durango	70	120	221.5
11	Guanajuato	126.25	175	250
12	Guerrero	184	247	300
13	Hidalgo	90	148	200
14	Jalisco	96	143.5	200
15	Estado de Mexico	63.5	143	249.5
16	Michoacan	55	90	150
17	Morelos	92.5	188	259.75
18	Nayarit	98	152	260
19	Nuevo Leon	150	284	323
20	Oaxaca	80	120	160
21	Puebla	115	120	310
22	Queretaro	110	180	260
23	Quintana Roo	146	210	300
24	San Luis Potosi	150	178	261.5
25	Sinaloa	115	157	328
26	Sonora	147	240	488.75
27	Tabasco	148.75	250	420.5
28	Tamaulipas	130	200	400
29	Tlaxcala	65	124	170
30	Veracruz	139	220	285
31	Yucatan	129.5	233	491.25
32	Zacatecas	59.25	103.5	145

Appendix B. Mexico's Climate Characteristics

Table A2. Statistics considered to analyze the additional variables for Mexico.

No.	State	Climate Region	Poverty (%)	Median ($)	RH (%)	Min °C	Max °C
1	Aguascalientes	Temperate	26.3	151.5	58%	4	30
2	Baja California	Very Hot	23.6	267	75%	5	30
3	Baja California Sur	Very Hot	18.6	200	60%	9	35

4	Campeche	Humid Tropic	49	265	72%	18	30
5	Coahuila	Very Hot	25.5	97.5	65%	4	30
6	Colima	Temperate	30.4	215	78%	18	30
7	Chiapas	Humid Tropic	78	150	78%	17.5	30
8	Chihuahua	Very Hot	26.6	220	47%	−5	40
9	Mexico City (CDMX)	Temperate	30	161	56%	5	25
10	Durango	Very Hot	38.8	120	62%	1.7	31
11	Guanajuato	Temperate	41.5	143	71%	5.2	30
12	Guerrero	Humid Tropic	67.9	175	75%	18	32
13	Hidalgo	Temperate	49.9	247	62%	4	27
14	Jalisco	Temperate	27.8	148	62%	7	23
15	Estado de Mexico	Temperate	41.8	143.5	68%	3	25
16	Michoacan	Temperate	46.2	90	58%	8	31
17	Morelos	Temperate	48.5	188	56%	10	32
18	Nayarit	Temperate	35.7	152	68%	12	35
19	Nuevo Leon	Very Hot	19.4	284	65%	5	32
20	Oaxaca	Humid Tropic	64.3	120	63%	12.5	31
21	Puebla	Temperate	58	120	72%	6.5	28.5
22	Queretaro	Temperate	26.4	180	54%	6	28
23	Quintana Roo	Humid Tropic	30.2	210	78%	17	33
24	San Luis Potosi	Temperate	42.1	178	58%	8.4	32
25	Sinaloa	Very Hot	31	157	65%	10.5	36
26	Sonora	Very Hot	26.7	240	38%	5.5	38
27	Tabasco	Humid Tropic	56.4	250	75%	18.5	36
28	Tamaulipas	Very Hot	34.5	200	79%	10	22
29	Tlaxcala	Temperate	51	124	72%	1.5	25
30	Veracruz	Humid Tropic	60.2	220	85%	13	32
31	Yucatan	Humid Tropic	44	233	71%	16	36
32	Zacatecas	Temperate	49.2	103.5	73%	3	30
Overall Statistics	Min	-	18.6	90	38	−5	22
	First Quartile	-	27.5	143.4	59.5	4.8	29.6
	Median	-	40.2	176.5	66.5	7.5	30.5
	Mean	-	40.6	179.8	66.2	8.7	30.8
	Third Quartile	-	49.4	220	73.5	12.6	32.3
	Max	-	78	284	85	18.5	40
	Standard Deviation	-	15	53.7	10.1	6	4.2

References

1. EIA U.S. Energy Information Administration—EIA—Table 7.6 Electricity End Use 2021. Available online: https://www.eia.gov/totalenergy/data/browser/index.php?tbl=T07.06#/?f=A&start=2020&end=2021&charted=5-6-7 (accessed on 9 May 2022).
2. Méndez, J.I.; Peffer, T.; Ponce, P.; Meier, A.; Molina, A. Empowering Saving Energy at Home through Serious Games on Thermostat Interfaces. *Energy Build.* **2022**, *263*, 112026. https://doi.org/10.1016/j.enbuild.2022.112026.
3. Tomat, V.; Ramallo-González, A.P.; Skarmeta Gómez, A.F. A Comprehensive Survey about Thermal Comfort under the IoT Paradigm: Is Crowdsensing the New Horizon? *Sensors* **2020**, *20*, 4647. https://doi.org/10.3390/s20164647.
4. Chaudhuri, T.; Soh, Y.C.; Li, H.; Xie, L. A Feedforward Neural Network Based Indoor-Climate Control Framework for Thermal Comfort and Energy Saving in Buildings. *Appl. Energy* **2019**, *248*, 44–53. https://doi.org/10.1016/j.apenergy.2019.04.065.
5. Bienvenido-Huertas, D.; Sánchez-García, D.; Rubio-Bellido, C.; Pulido-Arcas, J.A. Influence of the Improvement in Thermal Expectation Levels with Adaptive Setpoint Temperatures on Energy Consumption. *Appl. Sci.* **2020**, *10*, 5282. https://doi.org/10.3390/app10155282.

6. Huchuk, B.; O'Brien, W.; Sanner, S. A Longitudinal Study of Thermostat Behaviors Based on Climate, Seasonal, and Energy Price Considerations Using Connected Thermostat Data. *Build. Environ.* **2018**, *139*, 199–210. https://doi.org/10.1016/j.buildenv.2018.05.003.
7. Cetin, K.S.; O'Neill, Z. Smart Meters and Smart Devices in Buildings: A Review of Recent Progress and Influence on Electricity Use and Peak Demand. *Curr. Sustain. Renew. Energy Rep.* **2017**, *4*, 1–7. https://doi.org/10.1007/s40518-017-0063-7.
8. Fanghella, V.; Della Valle, N. A Behavioral Model for In-Home Displays Usage in Social Housing Districts. In *Smart and Sustainable Planning for Cities and Regions: Results of SSPCR 2019*; Bisello, A., Vettorato, D., Haarstad, H., Borsboom-van Beurden, J., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 511–524, ISBN 978-3-030-57332-4.
9. Chatzigeorgiou, I.M.; Andreou, G.T. A Systematic Review on Feedback Research for Residential Energy Behavior Change through Mobile and Web Interfaces. *Renew. Sustain. Energy Rev.* **2021**, *135*, 110187. https://doi.org/10.1016/j.rser.2020.110187.
10. Shen, M.; Lu, Y.; Wei, K.H.; Cui, Q. Prediction of Household Electricity Consumption and Effectiveness of Concerted Intervention Strategies Based on Occupant Behaviour and Personality Traits. *Renew. Sustain. Energy Rev.* **2020**, *127*, 109839. https://doi.org/10.1016/j.rser.2020.109839.
11. Shen, M.; Lu, Y.; Tan, K.Y. Big Five Personality Traits, Demographics and Energy Conservation Behaviour: A Preliminary Study of Their Associations in Singapore. *Energy Procedia* **2019**, *158*, 3458–3463. https://doi.org/10.1016/j.egypro.2019.01.927.
12. Csoknyai, T.; Legardeur, J.; Akle, A.A.; Horváth, M. Analysis of Energy Consumption Profiles in Residential Buildings and Impact Assessment of a Serious Game on Occupants' Behavior. *Energy Build.* **2019**, *196*, 1–20. https://doi.org/10.1016/j.enbuild.2019.05.009.
13. Iweka, O.; Liu, S.; Shukla, A.; Yan, D. Energy and Behaviour at Home: A Review of Intervention Methods and Practices. *Energy Res. Soc. Sci.* **2019**, *57*, 101238. https://doi.org/10.1016/j.erss.2019.101238.
14. Paone, A.; Bacher, J.-P. The Impact of Building Occupant Behavior on Energy Efficiency and Methods to Influence It: A Review of the State of the Art. *Energies* **2018**, *11*, 953. https://doi.org/10.3390/en11040953.
15. Peffer, T.; Perry, D.; Pritoni, M.; Aragon, C.; Meier, A. Facilitating Energy Savings with Programmable Thermostats: Evaluation and Guidelines for the Thermostat User Interface. *Ergonomics* **2013**, *56*, 463–479. https://doi.org/10.1080/00140139.2012.718370.
16. Bednar, D.J.; Reames, T.G. Recognition of and Response to Energy Poverty in the United States. *Nat. Energy* **2020**, *5*, 432–439. https://doi.org/10.1038/s41560-020-0582-0.
17. Morganti, L.; Pallavicini, F.; Cadel, E.; Candelieri, A.; Archetti, F.; Mantovani, F. Gaming for Earth: Serious Games and Gamification to Engage Consumers in pro-Environmental Behaviours for Energy Efficiency. *Energy Res. Soc. Sci.* **2017**, *29*, 95–102. https://doi.org/10.1016/j.erss.2017.05.001.
18. de Leeuw, A.; Valois, P.; Ajzen, I.; Schmidt, P. Using the Theory of Planned Behavior to Identify Key Beliefs Underlying Pro-Environmental Behavior in High-School Students: Implications for Educational Interventions. *J. Environ. Psychol.* **2015**, *42*, 128–138. https://doi.org/10.1016/j.jenvp.2015.03.005.
19. Ponce, P.; Meier, A.; Mendez, J.; Peffer, T.; Molina, A.; Mata, O. Tailored Gamification and Serious Game Framework Based on Fuzzy Logic for Saving Energy in Smart Thermostats. *J. Clean. Prod.* **2020**, *262*, 121167. https://doi.org/10.1016/j.jclepro.2020.121167.
20. Prochaska, J.O.; Velicer, W.F. The Transtheoretical Model of Health Behavior Change. *Am. J. Health Promot.* **1997**, *12*, 38–48. https://doi.org/10.4278/0890-1171-12.1.38.
21. Ajzen, I. From Intentions to Actions: A Theory of Planned Behavior. In *Action Control: From Cognition to Behavior*; Kuhl, J., Beckmann, J., Eds.; Springer: Berlin/Heidelberg, Germany, 1985; pp. 11–39, ISBN 978-3-642-69746-3.
22. Ryan, R.; Deci, E. Self-Determination Theory and the Facilitation of Intrinsic Motivation, Social Development, and Well-Being. *Am. Psychol.* **2000**, *55*, 68–78. https://doi.org/10.1037/0003-066X.55.1.68.
23. Lu, Q.; Zhang, Z.; Lü, S. Home Energy Management in Smart Households: Optimal Appliance Scheduling Model with Photovoltaic Energy Storage System. *Energy Rep.* **2020**, *6*, 2450–2462. https://doi.org/10.1016/j.egyr.2020.09.001.
24. Nielsen, J. 10 Heuristics for User Interface Design: Article by Jakob Nielsen. Available online: https://www.nngroup.com/articles/ten-usability-heuristics/ (accessed on 7 April 2020).
25. AlSkaif, T.; Lampropoulos, I.; van den Broek, M.; van Sark, W. Gamification-Based Framework for Engagement of Residential Customers in Energy Applications. *Energy Res. Soc. Sci.* **2018**, *44*, 187–195. https://doi.org/10.1016/j.erss.2018.04.043.
26. Lacey, M. *Usability Matters: Mobile-First UX for Developers and Other Accidental Designers*, 1st ed.; Manning Publications Co.: Shelter Island, NY, USA, 2018; ISBN 978-1-61729-393-1.
27. Chen, S.Y.; Macredie, R.D. The Assessment of Usability of Electronic Shopping: A Heuristic Evaluation. *Int. J. Inf. Manag.* **2005**, *25*, 516–532. https://doi.org/10.1016/j.ijinfomgt.2005.08.008.
28. Quiñones, D.; Rusu, C. Applying a Methodology to Develop User EXperience Heuristics. *Comput. Stand. Interfaces* **2019**, *66*, 103345. https://doi.org/10.1016/j.csi.2019.04.004.
29. Muller, M.J.; Matheson, L.; Page, C.; Gallup, R. Methods & Tools: Participatory Heuristic Evaluation. *Interactions* **1998**, *5*, 13–18. https://doi.org/10.1145/285213.285219.
30. Nielsen, J.; Molich, R. Heuristic Evaluation of User Interfaces. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems Empowering People—CHI '90, Seattle, WA, USA, 1–5 April 1990; ACM Press: Seattle, WA, USA, 1990; pp. 249–256.

31. Nielsen, J. Enhancing the Explanatory Power of Usability Heuristics. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Boston, MA, USA, 24–28 April 1994; Association for Computing Machinery: New York, NY, USA, 1994; pp. 152–158.
32. Greenberg, S.; Fitzpatrick, G.; Gutwin, C.; Kaplan, S. Adapting the Locales Framework for Heuristic Evaluation of Groupware. *AJIS* **2000**, *7* , 102–108. https://doi.org/10.3127/ajis.v7i2.267.
33. Harper, R. (Ed.) *Inside the Smart Home*; Springer: London, UK ; New York, NY, USA, 2003; ISBN 978-1-85233-688-2.
34. Marikyan, D.; Papagiannidis, S.; Alamanos, E. A Systematic Review of the Smart Home Literature: A User Perspective. *Technol. Forecast. Soc. Change* **2019**, *138*, 139–154. https://doi.org/10.1016/j.techfore.2018.08.015.
35. Méndez, J.I.; Meza-Sánchez, A.V.; Ponce, P.; McDaniel, T.; Peffer, T.; Meier, A.; Molina, A. Smart Homes as Enablers for Depression Pre-Diagnosis Using PHQ-9 on HMI through Fuzzy Logic Decision System. *Sensors* **2021**, *21*, 7864. https://doi.org/10.3390/s21237864.
36. Méndez, J.I.; Mata, O.; Ponce, P.; Meier, A.; Peffer, T.; Molina, A. Multi-Sensor System, Gamification, and Artificial Intelligence for Benefit Elderly People. In *Challenges and Trends in Multimodal Fall Detection for Healthcare*; Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E., Eds.; Springer International Publishing: Cham, Switzerland, 2020; Volume 273, pp. 207–235, ISBN 978-3-030-38747-1.
37. Avila, M.; Méndez, J.I.; Ponce, P.; Peffer, T.; Meier, A.; Molina, A. Energy Management System Based on a Gamified Application for Households. *Energies* **2021**, *14*, 3445. https://doi.org/10.3390/en14123445.
38. Huotari, K.; Hamari, J. Defining Gamification: A Service Marketing Perspective. In Proceedings of the 16th International Academic MindTrek Conference on—MindTrek '12, Tampere, Finland, 3–5 October 2012; ACM Press: Tampere, Finland, 2012; p. 17.
39. Méndez, J.I.; Ponce, P.; Meier, A.; Peffer, T.; Mata, O.; Molina, A. S4 Product Design Framework: A Gamification Strategy Based on Type 1 and 2 Fuzzy Logic. In Proceedings of the Smart Multimedia: Methodologies and Algorithms, San Diego, CA, USA, 16 December 2019; p. 15.
40. Hargreaves, T.; Wilson, C. *Smart Homes and Their Users*; Human–Computer Interaction Series; Springer International Publishing: Cham, Switzerland, 2017; ISBN 978-3-319-68017-0.
41. Méndez, J.I.; Ponce, P.; Medina, A.; Meier, A.; Peffer, T.; McDaniel, T.; Molina, A. Human-Machine Interfaces for Socially Connected Devices: From Smart Households to Smart Cities. In *Multimedia for Accessible Human Computer Interfaces*; McDaniel, T., Liu, X., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 253–289, ISBN 978-3-030-70715-6.
42. Li, X.; Lu, R.; Liang, X.; Shen, X.; Chen, J.; Lin, X. Smart Community: An Internet of Things Application. *IEEE Commun. Mag.* **2011**, *49*, 68–75. https://doi.org/10.1109/MCOM.2011.6069711.
43. Azahara. Smart Cities vs. Smart Communities | Blog Geographica. Available online: https://geographica.com/en/blog/smart-community (accessed on 05 July 2022).
44. Ceglia, F.; Esposito, P.; Marrasso, E.; Sasso, M. From Smart Energy Community to Smart Energy Municipalities: Literature Review, Agendas and Pathways. *J. Clean. Prod.* **2020**, *254*, 120118. https://doi.org/10.1016/j.jclepro.2020.120118.
45. Fingerman, A. Smart Homes Need Smart Communities. Available online: https://social.techcrunch.com/2015/09/28/smart-homes-need-smart-communities (accessed on 08 April 2022)..
46. Urbytus. Smart Communities, Somewhere between Smart Homes and Smart Cities. Available online: https://www.urbytus.com/smart-communities-somewhere-between-smart-homes-and-smart-cities (accessed on 18 May 2022)..
47. Nishi, H.; Nakamura, Y. IoT-Based Monitoring for Smart Community. In *Urban Systems Design*; Elsevier: Amsterdam, The Netherlands, 2020; pp. 335–344, ISBN 978-0-12-816055-8.
48. Qi, L.; Guo, J. Development of Smart City Community Service Integrated Management Platform. *Int. J. Distrib. Sens. Netw.* **2019**, *15*, 155014771985197. https://doi.org/10.1177/1550147719851975.
49. Méndez, J.I.; Ponce, P.; Peffer, T.; Meier, A.; Molina, A. A Gamified HMI as a Response for Implementing a Smart-Sustainable University Campus. In Proceedings of the Smart and Sustainable Collaborative Networks 4.0, Saint-Étienne, France, 22–24 November 2021; Camarinha-Matos, L.M., Boucher, X., Afsarmanesh, H., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 683–691.
50. Mendez, J.I.; Ponce, P.; Medina, A.; Peffer, T.; Meier, A.; Molina, A. A Smooth and Accepted Transition to the Future of Cities Based on the Standard ISO 37120, Artificial Intelligence, and Gamification Constructors. In Proceedings of the 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), Dortmund, Germany, 18–20 March 2021; IEEE: Dortmund, Germany, 18 March 2021; pp. 65–71.
51. Verstaevel, N.; Boes, J.; Gleizes, M.-P. From Smart Campus to Smart Cities Issues of the Smart Revolution. In Proceedings of the 2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), San Francisco, CA, USA, 4–8 August 2017; IEEE: San Francisco, CA, USA, August 2017; pp. 1–6.
52. da Silva, L.C.P.; Villalva, M.G.; de Almeida, M.C.; Brittes, J.L.P.; Yasuoka, J.; Cypriano, J.G.I.; Dotta, D.; Pereira, J.T.V.; Salles, M.B.C.; Archilli, G.B.; et al. Sustainable Campus Model at the University of Campinas—Brazil: An Integrated Living Lab for Renewable Generation, Electric Mobility, Energy Efficiency, Monitoring and Energy Demand Management. In *Towards Green Campus Operations: Energy, Climate and Sustainable Development Initiatives at Universities*; Leal Filho, W., Frankenberger, F.,

Iglecias, P., Mülfarth, R.C.K., Eds.; World Sustainability Series; Springer International Publishing: Cham, Switzerland, 2018; pp. 457–472, ISBN 978-3-319-76885-4.
53. Bi, T. The Design and Implementation of Smart Campus System. *JCP* **2017**, *12*, 527–533. https://doi.org/10.17706/jcp.12.6.527-533.
54. KPMG Smart Cities en México: Factores de éxito—KPMG México. Available online: https://home.kpmg/mx/es/home/tendencias/2021/10/ao-smart-cities-en-mexico-factores-de-exito.html (accessed on 14 July 2022).
55. Flores, L. Ciudad de México, Puebla, Guadalajara y Monterrey, Con Mayor Necesidad de Crear Soluciones Inteligentes: KPMG. Available online: https://www.eleconomista.com.mx/empresas/Ciudad-de-Mexico-Puebla-Guadalajara-y-Monterrey-con-mayor-necesidad-de-crear-soluciones-inteligentes-KPMG-en-Mexico-20211025-0074.html (accessed on 14 July 2022).
56. Concamin Emite Concamin Lista de 13 Ciudades Que Serán Promovidas Como "Smart Cities". Available online: https://www.concamin.org.mx/prensa/sala/concamin/noticias/60d5f9647c9e64003b83726e (accessed on 14 July 2022).
57. Medina, A.; Méndez, J.I.; Ponce, P.; Peffer, T.; Meier, A.; Molina, A. Using Deep Learning in Real-Time for Clothing Classification with Connected Thermostats. *Energies* **2022**, *15*, 1811. https://doi.org/10.3390/en15051811.
58. Quiroz, J.C.; Bongolan, T.; Ijaz, K. Alexa Depression and Anxiety Self-Tests: A Preliminary Analysis of User Experience and Trust. In Proceedings of the Adjunct Proceedings of the 2020 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2020 ACM International Symposium on Wearable Computers, Virtual Event, Mexico, 12–17 September 2020; ACM: Virtual Event Mexico, 10 September 2020; pp. 494–496.
59. INEGI Encuesta Nacional Sobre Consumo de Energéticos En Viviendas Particulares (ENCEVI) 2018. Available online: https://www.inegi.org.mx/programas/encevi/2018/#Microdatos (accessed on 16 May 2022).
60. Tunguz, B. Big Five Personality Test. Available online: https://www.kaggle.com/tunguz/big-five-personality-test (accessed on 15 June 2022).
61. Marczewski, A. *Even Ninja Monkeys Like to Play: Gamification, Game Thinking and Motivational Design*; CreateSpace Independent Publishing Platform: Scotts Valley, CA, USA, 2015; ISBN 978-1-5147-4566-3.
62. McCrae, R.R.; Costa, P.T. Personality Trait Structure as a Human Universal. *Am. Psychol.* **1997**, *52*, 509–516. https://doi.org/10.1037/0003-066X.52.5.509.
63. John, O.P.; Srivastava, S. The Big Five Trait Taxonomy: History, Measurement, and Theoretical Perspectives. In *Handbook of Personality: Theory and Research*, 2nd ed.; Guilford Press: New York, NY, USA, 1999; pp. 102–138, ISBN 1-57230-483-9.
64. Paunonen, S.V. Big Five Factors of Personality and Replicated Predictions of Behavior. *J. Personal. Soc. Psychol.* **2003**, *84*, 411–424. https://doi.org/10.1037/0022-3514.84.2.411.
65. Brick, C.; Lewis, G.J. Unearthing the "Green" Personality: Core Traits Predict Environmentally Friendly Behavior. *Environ. Behav.* **2016**, *48*, 635–658. https://doi.org/10.1177/0013916514554695.
66. Hirsh, J.B. Personality and Environmental Concern. *J. Environ. Psychol.* **2010**, *30*, 245–248. https://doi.org/10.1016/j.jenvp.2010.01.004.
67. Milfont, T.L.; Sibley, C.G. The Big Five Personality Traits and Environmental Engagement: Associations at the Individual and Societal Level. *J. Environ. Psychol.* **2012**, *32*, 187–195. https://doi.org/10.1016/j.jenvp.2011.12.006.
68. Komarraju, M.; Karau, S.J.; Schmeck, R.R.; Avdic, A. The Big Five Personality Traits, Learning Styles, and Academic Achievement. *Personal. Individ. Differ.* **2011**, *51*, 472–477. https://doi.org/10.1016/j.paid.2011.04.019.
69. Paunonen, S.V.; Ashton, M.C. Big Five Predictors of Academic Achievement. *J. Res. Personal.* **2001**, *35*, 78–90. https://doi.org/10.1006/jrpe.2000.2309.
70. Judge, T.A.; Higgins, C.A.; Thoresen, C.J.; Barrick, M.R. The Big Five Personality Traits, General Mental Ability, and Career Success across the Life Span. *Pers. Psychol.* **1999**, *52*, 621–652. https://doi.org/10.1111/j.1744-6570.1999.tb00174.x.
71. Tomšik, R. Impact of Big Five Personality Traits on Academic Performance of University Students. 9 *Nekonečno v Psychologii* **2018**, *8*, 53-61. Available online: https://psych.upol.cz/fileadmin/userdata/FF/katedry/pch/verejnosti/sbornik_020818.pdf#page=34 (accessed on 25 July 2022).
72. Roos, J.M.; Kazemi, A. Personality Traits and Internet Usage across Generation Cohorts: Insights from a Nationally Representative Study. *Curr. Psychol.* **2018**, *40*, 1287–1297. https://doi.org/10.1007/s12144-018-0033-2.
73. Rammstedt, B.; John, O.P. Measuring Personality in One Minute or Less: A 10-Item Short Version of the Big Five Inventory in English and German. *J. Res. Personal.* **2007**, *41*, 203–212. https://doi.org/10.1016/j.jrp.2006.02.001.
74. IPIP Administering IPIP Measures, with a 50-Item Sample Questionnaire. Available online: https://ipip.ori.org/new_ipip-50-item-scale.htm (accessed on 25 July 2022).
75. Frankel, D.; Heck, S.; Tai, H. *Using a Consumer-Segmentation Approach to Make Energy-Efficiency Gains in the Residential Market*; McKinsey and Company: Chicago, IL, USA, 2013; pp. 1–9.
76. Ponce, P.; Peffer, T.; Molina, A.; Barcena, S. Social Creation Networks for Designing Low Income Interfaces in Programmable Thermostats. *Technol. Soc.* **2020**, *62*, 101299. https://doi.org/10.1016/j.techsoc.2020.101299.
77. Peham, M.; Breitfuss, G.; Michalczuk, R. The "EcoGator" App: Gamification for Enhanced Energy Efficiency in Europe. In Proceedings of the Second International Conference on Technological Ecosystems for Enhancing Multiculturality—TEEM '14, Salamanca, Spain, 1–3 October 2014; ACM Press: Salamanca, Spain, 2014; pp. 179–183.

78. Tondello, G.F.; Wehbe, R.R.; Diamond, L.; Busch, M.; Marczewski, A.; Nacke, L.E. The Gamification User Types Hexad Scale. In Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play–CHI PLAY '16, Austin, TX, USA, 16–19 October 2016; ACM Press: Austin, TX, USA, 2016; pp. 229–243.
79. Shen, M.; Li, X.; Song, X.; Lu, Y. Linking Personality Traits to Behavior-Based Intervention: Empirical Evidence from Hangzhou, China. *Environ. Impact Assess. Rev.* **2022**, *95*, 106796. https://doi.org/10.1016/j.eiar.2022.106796.
80. Liu, X.; Wang, Q.-C.; Jian, I.Y.; Chi, H.-L.; Yang, D.; Chan, E.H.-W. Are You an Energy Saver at Home? The Personality Insights of Household Energy Conservation Behaviors Based on Theory of Planned Behavior. *Resour. Conserv. Recycl.* **2021**, *174*, 105823. https://doi.org/10.1016/j.resconrec.2021.105823.
81. McCulloch, W.S.; Pitts, W. A Logical Calculus of the Ideas Immanent in Nervous Activity. *Bull. Math. Biophys.* **1943**, *5*, 115–133. https://doi.org/10.1007/BF02478259.
82. Ponce, P. *Inteligencia Artificial con Aplicaciones a la Ingeniería*, 1st ed.; Alfaomega: Morelos, Mexico, 2011; ISBN 978-607-7854-83-8.
83. Remaida, A.; Abdellaoui, B.; Moumen, A.; Idrissi, Y.E.B.E. Personality Traits Analysis Using Artificial Neural Networks: A Literature Survey. In Proceedings of the 2020 1st International Conference on Innovative Research in Applied Science, Engineering and Technology (IRASET), Meknes, Morocco, 19–20 March 2020; IEEE: Meknes, Morocco, April 2020; pp. 1–6.
84. Méndez, J.I.; Ponce, P.; Pecina, M.; Schroeder, G.; Castellanos, S.; Peffer, T.; Meier, A.; Molina, A. A Rapid HMI Prototyping Based on Personality Traits and AI for Social Connected Thermostats. In *Advances in Soft Computing*; Batyrshin, I., Gelbukh, A., Sidorov, G., Eds.; Springer International Publishing: Cham, Switzerland, 2021; pp. 216–227.
85. Automoto. Automoto/Big-Five-Data 2021. Available online: https://github.com/automoto/big-five-data (accessed on 15 June 2022).
86. Méndez, J.I. RPubs—Mexico Personality Traits Mexican Map. Available online: https://rpubs.com/IsabelMendezG/917072 (accessed on 21 June 2022).
87. Méndez, J.I. Datasets Built for the ANN Models, Boxplots, and Interactive Map. Available online: https://github.com/IsabelMendezG/MexicanGamifiedTailoredInterfaces (accessed on 25 July 2022).
88. George What Is a Comfortable Humidity Level Outside? 2019. Available online: HumidityCheck.Com (accessed on 14 July 2022).
89. Sensitive Choice. Indoor Humidity Levels. Available online: https://www.sensitivechoice.com/resource/indoor-humidity-levels (accessed on 14 July 2022).
90. CONEVAL Pobreza 2018. Available online: https://www.coneval.org.mx/Medicion/MP/Paginas/Pobreza-2018.aspx (accessed on 14 July 2022).

Chapter 5

A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part I and II

5.1 Summary of the Chapter

This chapter is divided into two parts. The first part analyzes energy consumption and thermal comfort in three locations, Mexico City (Mexico), Concord (California), and Ontario (Canada). Thus, three energy models of a community of twelve houses were simulated, and the energy consumption values were normalized to determine which home had the most energy consumption and which had the least energy consumption. This chapter obtains an adaptive comfort model for measuring these three features through energy simulations to compare them during the year. An interactive online platform is deployed to determine what further actions are required to improve the quality of life of householders without losing thermal comfort and maximizing energy savings. Besides, this platform allows worldwide users to interact with the platform and learn how clothing insulation, activity, and location affect energy consumption and thermal comfort.

The second part proposes a dynamic calculation of thermal comfort. Adaptive methods require integrating dynamic models that predict clothing properties to provide accurate thermal comfort to the householder and understand how an individual adapts to indoor environments rather than the conventional thermal comfort analysis. Thus, a 24-h simulation is performed considering three scenarios: (1) typical 0.5 clo value and 1.0 metabolic rate; (2) dynamic clo values with activities; and (3) dynamic values adding the underwear clo values. Hence, thermal comfort analysis results are included in an interactively connected thermostat mock-up. This mock-up and interaction are available online.

A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part I

Juana Isabel Méndez[1( )], Adán Medina[1], Pedro Ponce[1], Therese Peffer[2], Alan Meier[3], and Arturo Molina[1]

[1] Institute of Advanced Materials for Sustainable Manufacturing, Tecnologico de Monterrey, Monterrey, MX 64849, USA
{isabelmendez,A01331840,pedro.ponce,armolina}@tec.mx

[2] Institute for Energy and Environment, University of California, Berkeley, CA 94720, USA
tpeffer@berkeley.edu

[3] Energy and Efficiency Institute, University of California, Davis, CA 95616, USA
akmeier@ucdavis.edu

Abstract. A successful smart city implementation needs to efficiently use natural and human resources. This can be achieved by dividing the smart city into smaller modules, such as a smart community, and even smaller such as a smart home, to allow energy management systems to monitor the city's behavior. The electricity end-user sector is often divided into the residential, commercial, and public transport, industrial, and agricultural sectors. On the other hand, HVAC systems constitute from 40% up to 60% of energy consumption in buildings. Nevertheless, householders do not entirely accept connected devices due to complex interfaces, lack of interest, or acquired habits of thermostat usage that affect thermal comfort, hence, usability and behavioral problems. Thermal comfort is widely defined as that state of mind which conveys satisfaction with the thermal surroundings. This paper obtains an adaptive comfort model for measuring these three features through energy simulations to compare them during the year. This paper analyzes three energy model scenarios to review the adaptive behavior of a community of twelve houses. Three energy models were simulated for Mexico City, Concord (California), and Ontario (Canada) and later deployed into an interactive online platform to determine what further actions are required to improve the quality of life of householders without losing thermal comfort and maximizing energy savings. Besides, this platform allows worldwide users to interact with the platform and learn how clothing insulation, activity, and location affect energy consumption and thermal comfort.

Keywords: Energy simulations · Interactive platform · Thermal comfort · Gamification · Communities

1 Introduction

Energy measures the electricity consumption needed to manage generation, consumption, and electricity conservation. The electricity end-user sector is often divided into

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the residential, commercial, and public transport, industrial, and agricultural sectors. For instance, in the US, consumption was about 27.238 trillion kWh, with 22%, 18%, 28%, and 35%, respectively. According to the last record in SENER, in 2019, the Mexican electricity consumption was about 284 billion kWh, with 22.7%, 12.3%, 0.4%, 60%, and 4.6% respectively [1]. In other countries such as Canada, electricity consumption is much higher, reaching 3606.38 billion kWh, with 12%, 8%, 20%, 28%, and 2%, respectively [2]. Therefore, reducing electrical consumption without being invasive or losing quality of life is challenging. Moreover, citizens represent the linkage, the main actor, and the sensor to the smart city as they interact with it.

Consequently, users' interaction plays a primary role in understanding and knowing the city to reduce electrical consumption. However, teaching them how to reduce electrical consumption is a challenge as sometimes they have other interests than lowering their consumption. In that regard, a smart home environment seems the ideal place, to begin with, as they provide the interaction between the user and the city to become energy aware.

Gamification, or the use of game elements in real contexts or for real purposes applied to platforms or interfaces, teaches, motivates, and engages the householders in reducing energy consumption or becoming energy aware [3–7]. In that sense, research suggests including ludic elements, for instance, within interfaces or through platforms to teach individuals how energy consumption affects [3–5]. Energy awareness campaigns or comparisons between individuals or homes sensitize citizens about how their consumption affects the environment or community [6, 8–10]. In [9], they suggest including interactive and visual models to engage citizens to adapt to learn new topics.

2 Thermal Comfort

The standard definition of thermal comfort is "*That condition of mind which expresses satisfaction with the thermal environment*" [11, 12]. In 1970, Fanger [13] proposed a comfort model considering physically based determinism and comfort equations. This model is commonly known as the Predicted Mean Vote/ Predicted Percentage of Dissatisfied (PMV/PPD) and considers six mandatory parameters [11]:

- Metabolic rate → related to the occupant
- Clothing insulation → related to the occupant
- Air temperature → related to the surrounding environment
- Radiant temperature → related to the surrounding environment
- Air speed → related to the surrounding environment
- Humidity → related to the surrounding environment

In 1998, Brager and de Dear [14] proposed the adaptive method based on human behavior through three categories of thermal adaptation:

- Behavioral adaptation → related to personal, technological, and cultural responses.
- Clothing insulation → related to genetic and acclimatization
- Air temperature → related to expectations and experiences derived from self-perception and sensory information.

Thus, thermal comfort not only implicates energy saving but also has a personal benefit not only in the perception of well-being but also profitable in a working environment. Therefore, its benefits go beyond a simple energy-saving thing. Moreover, the World Health Organization (WHO) proposed a healthy indoor temperature range between 18 °C and 24 °C [15]. Moreover, increasing 1 °C in a thermostat setpoint during summer can save at least 5% of the electricity [16].

2.1 Metabolic Rate

It is the rate of energy transformation into heat and mechanical work expressed in met units. The metabolic rate depends on the surface skin. Typically, the metabolic rate considers 1.8 m^2 of surface skin. This surface belonged to a man with a height of 1.70 m and 68 kg. Table 1 shows some of the household activities.

Table 1. Typical activities at home.

Activity	Met = 58.1 W/m^2	W/m^2	W/person
Sleeping	0.7	40	72
Sitting	1	60	108
Typing	1.1	65	117
Standing	1.2	70	126
Cooking	1.8	105	189

2.2 Clothing Insulation

As mentioned before, human thermal comfort depends on several factors, such as climate factors and physical activity or clothes worn. These last two are part of the human body's heat loss; since the human being converts food into work and heat. The amount of this heat lost depends intensely on the amount of physical activity being performed and the cloth insulation that affects how much heat is produced by the human body is transferred into the ambient [17].

The main factor that the cloth insulation helps control is the air velocity across the body and controls the exchange of heat between the body and the ambient. Most exchanges are when the body transfers heat into the ambient. However, it can also be the other way around, and the ambient can transfer heat to the body; clothing insulation controls both transfers.

The thermal insulation factor is determined in standards ASHRAE 55 and others like ISO 7730 with the use of thermal manikins to assess the clothing insulation value of each garment, with a measuring unit called clo or m^2K/W when using SI units, and then produce tables such as Table 2 [18]. This table shows different clothing insulation values for various clothing ensembles, and these values are obtained by adding up all the clothing insulation values of each garment.

Table 2. Clothing insulation values for everyday clothing ensembles

Clothing ensemble	Icl (clo)	Rcl (m^2K/W)
Warm socks, briefs, shoes, woven shirt, cool trousers	0.42	0.065
Cool socks, briefs, undershirt, shoes, woven shirt, cool trousers	0.51	0.113
Cool socks, briefs, undershirt, shoes, woven shirt, warm jacket, warm trousers	0.77	0.119
Warm dress, pantyhose, bra and panties, shoes	0.49	0.076
Warm sweater, warm skirt, warm blouse, pantyhose, bra and panties, shoes	0.64	0.099
Warm sweater, warm slacks, warm blouse, pantyhose, bra, and panties, shoes	0.77	0.119

2.3 Behavior

Adaptive behavior requires considering the conditions to which an individual is exposed. These conditions include clothing insulation or activities that increase or reduce heat production. For instance, the individual should require turning on the fans or the Heating, Ventilation, and Air-Conditioning (HVAC) system to feel comfortable [12]. A higher rate of metabolic heat or insulation could rely on indoor thermal comfort. Householders use several strategies to achieve thermal comfort; these strategies lead to choices as [19]:

- Building site: areas shaded by trees, near a pond, or can shelter from wind or dust.
- Architectural design and construction materials: shape, orientation, thermal insulation, glazed areas, open areas, floors.
- Rooms' occupancy is based on the season.
- Type of HVAC system
- Type of controls: programmable or connected thermostat, ceiling fans, openable windows.
- Garments are based on the climate, season, indoor temperature, and fashion style.
- Different activities or postures based on the season.
- Attitude toward the indoor operative temperature: if the individual prefers to save or spend money by accepting wider ranges of indoor temperatures.

Behavioral measures provide insights into individuals' thermal comfort; however, it is complex to measure their satisfaction because their comfort is related to perception [18, 20, 21]. It is possible to identify adaptive opportunities by, for instance, measuring through cameras or voice individuals' reactions [22–24], habits, and garments can help identify adaptive opportunities that can impact comfort while saving energy.

2.4 Determining Acceptable Thermal Comfort in Occupied Spaces

The Graphical Comfort Zone Method considers representative households with metabolic rates between 1.0 and 1.3 met (sitting, typing, and standing activities) and

clothing insulation Icl between 0.5 and 1.0 clo who are not exposed to direct-beam solar radiation and average air speed up to 0.2 m/s. Moreover, this method is limited to a humidity ratio at or below 0.012 kg*H2O/kg dry air, the water pressure of 1.91 kPa at standard pressure, or a dew-point temperature (tdp) of 16.8 °C. Equation 1 describes the comfort zone values for intermediate values of Icl. These values are determined by linear interpolation between the limits for 0.5 and 1.0 clo using the following criteria:

$$t_{min,}I_{cl,\ active} = \left[(I_{cl} - 0.5\ clo)t_{min,1.0\ clo} + (1.0\ clo - I_{cl})t_{min,\ 0.5\ clo}\right]/0.5\ clo \quad (1)$$

$$t_{max,}I_{cl,\ active} = \left[(I_{cl} - 0.5\ clo)t_{max,1.0\ clo} + (1.0\ clo - I_{cl})t_{max,\ 0.5\ clo}\right]/0.5\ clo$$

where:

$t_{min,}\ I_{cl,\ active}$ = lower operative temperature t0 limit for clothing insulation I_{cl}.
$t_{max,}\ I_{cl,\ active}$ = upper operative temperature t0 limit for clothing insulation I_{cl}.
Icl = thermal insulation of the clothing in clo.

2.5 Energy Models for Analyzing Thermal Comfort

Energy model simulators provide information about thermal comfort and energy savings. One of the most common energy simulators is EnergyPlus [25]. This software simulates and predicts the overall energy consumption in the building. Some of the studies performed for thermal comfort analysis include:

- Thermal comfort models in African households improved comfort by 76%.
- Effects on thermal sensation when individuals have a higher level of perceived control and allow energy savings up to 9% [26].
- Improve thermal performance and comfort by replacing glazings or insulation [27].

This paper analyses the adaptive behavior in communities based on clothing insulation, metabolic rate, and behavioral action to promote energy reductions while achieving thermal comfort. The thermal comfort is depicted using the Graphical Comfort Zone Method for 0.5 clo and 1.0 clo during summer and winter, and a metabolic rate up to 1.2 met. These variables are only considered because both the PMV/PPD model and the adaptive model have in common. Besides, these variables are related to the occupant. Hence, this paper proposes feedback to the householder about their clothes or activities and how they relate to electrical consumption. It compares their house with other householders to engage them and promote energy reductions.

3 Proposal

This paper proposes three energy model scenarios to analyze the adaptive behavior of a community of twelve houses. Three energy models were simulated for Mexico City, Concord (California), and Ontario (Canada). Besides, as a result of the energy models, an interactive platform with thermal comfort analysis, HVAC usage, and indoor and outdoor temperature is deployed on the Genial.ly webpage [28].

Figure 1 depicts the community distribution plan view created in Rhinoceros v7 + Grasshopper. The energy model was developed using LadybugTools 1.3.0 from Grasshopper 1.0.0007 [29]. Thus, Table 3 describes the characteristics considered for the energy model input values. These values come from the EnergyPlus templates for the Mid-Rise Apartment Building Program with the following considerations [30]:

- People per area: 0.028309 people/m^2
- Equipment loads per area: 6.7 W/m^2
- Lighting density: 6.5 W/m^2
- Number of people per area: 0.025 ppl/m^2
- Setpoint: Heating: 21.7 °C; Cooling: 24.4 °C

3.1 Graphical Comfort Zone Method Analysis

Once the energy simulation results were obtained, the Graphical Comfort Zone method was interpreted considering 1.0 and 0.5 clo with a metabolic rate of 1.0 to determine the thermal comfort of these communities. Then, based on the thermal comfort, further examination was performed by analyzing the clo and metabolic rate to determine which activities and clothing insulation deliver a higher percentage of thermal comfort.

3.2 Energy Consumption by Community and Household

The energy consumption by community and household was analyzed to determine which location and whether the heating or ventilation wastes more energy than the other. Besides, the surface was obtained to determine the relationship between the area, thermal comfort, and energy depletion.

Table 3. Households' characteristics

Building characteristics	Description
Location	Mexico City, Mexico (ASHRAE Climate zone 3) Concord, California (ASHRAE Climate zone 3) Ontario, Canada (ASHRAE Climate zone 6)
Construction Type	Wood Framed
% Occupancy	9 pm to 6 am: 100% 7 am: 85% 8 am: 39% 9 am a 3 pm: 25% 4 pm: 30% 5 pm: 52% 6 pm to 8 pm: 87%

(*continued*)

Table 3. (*continued*)

Building characteristics	Description
Metabolic rate	95 W/m^2
Construction materials Climate Zone 3	
External wall mass: Typical Insulated Wood Framed Exterior Wall-R12	Construction layers: 25 mm Stucco, 5/8 in. Gypsum Board, Typical Insulation-R10, 5/8 in. Gypsum Board
External window	U 0.42 SHGC 0.25 Simple Glazing Window,
Exterior Roof: Typical Wood Joist Attic Floor-R38	Construction layers: 5/8 in. Gypsum Board, Typical Insulation-R37;
Floor: Typical Insulated Carpeted 8in Slab Floor	Construction layers: Typical Insulation, 8 in. Normal weight Concrete Floor, Typical Carpet Pad
Construction materials Climate Zone 6	
External wall mass: Typical Insulated Wood Framed Exterior Wall-R20	Construction layers: 25mm Stucco, 5/8 in. Gypsum Board, Typical Insulation-R19, 5/8 in. Gypsum Board
External window	U 0.34 SHGC 0.38 Simple Glazing Window,
Exterior Roof: Typical Wood Joist Attic Floor-R48	Construction layers: 5/8 in. Gypsum Board, Typical Insulation-R47
Floor: Typical Insulated Carpeted 8in Slab Floor-R5	Construction layers: Typical Insulation-R4, 8 in. Normal weight Concrete Floor, Typical Carpet Pad

4 Results

Figure 2 depicts the Graphical Comfort Zone Method for 0.5 clo, and 1.0 clo with a metabolic rate of 1 met or for a sitting activity at Mexico City, Concord, and Ontario indoors for Home 1. The three graphics indicate that with 1.0 clo, the individuals feel comfortable during a significant part of the year; on the contrary, with 0.5 clo, there is lesser comfort than with the other clo. The Ontario community reflects that it requires more insulation than 1.0 to feel comfortable. As a complement, Fig. 3 depicted the percentage of comfortable time for the three communities during the year and displayed it by home. It considers the following clo values from Table 2: 0.51, 0.77, and includes a 1.0 clo value. The activities considered were sitting (1 met), typing (1.1 met), and standing (1.2 met). The other values were not considered due to being lower than 0.5, and the Graphical Comfort Zone Method indicates that lower than 0.5 will not be comfortable.

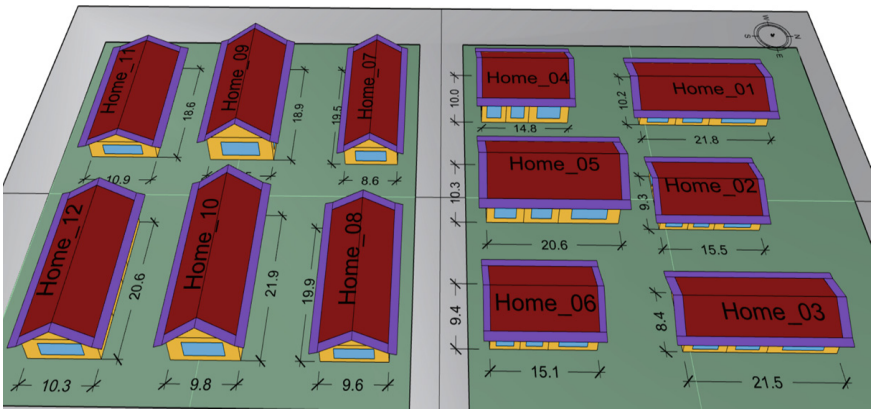


Fig. 1. Community distribution of the twelve houses.

Table 4 displays the area of each household and the percentage of annual HVAC energy consumption compared with the other households. Homes 5, 9, and 10 consumed more than the other homes, although home 1 had more area than these homes. Figure 4 shows the HVAC annual breakdown consumption by home and location. The significant differences relied on the heating; as Ontario is in a cold zone, it required more heating than the other locations located in warmer zones. On the other hand, homes 5, 9, and 10 required more heating than the other homes. However, to propose, for instance, energy reduction alternatives to these types of homes, thermal comfort analysis must be performed. Thus, analyzing Fig. 3 revealed that the householders were most comfortable with 1.0 during the typing activity (1.1 met) for the case of Mexico and the USA. For Ontario, it showed that standing activities (1.2 met) were more comfortable than the other activities; however, it did not increase more than 74% due to Ontario requiring higher insulation of clothes or higher metabolic rates. These results confirm what the Graphical Comfort Zone Method exposed in Fig. 2.

Table 4. Square meters and percentage of annual energy consumption by households.

Household	1	2	3	4	**5**	6
Square meters (area)	222.4	144.2	180.6	148	**212.2**	141.9
% HVAC consumption (kWh)	7%	5%	6%	9%	**11%**	6%
Household	7	8	**9**	**10**	11	12
Square meters (area)	167.7	191	**198.5**	**214.6**	202.7	212.2
% HVAC consumption (kWh)	7%	8%	**11%**	**12%**	8%	10%

		Sitting (1.0 met)			Typing (1.1 met)			Standing (1.2 met)		
clo	Home	Mexico City	Concord	Ontario	Mexico City	Concord	Ontario	Mexico City	Concord	Ontario
0.51 clo	1	1.1%	5.4%	15.7%	20.0%	18.5%	25.5%	32.3%	27.2%	31.3%
	2	2.4%	6.6%	16.2%	21.3%	19.5%	25.2%	33.0%	27.6%	30.8%
	3	3.1%	7.2%	17.7%	23.0%	21.5%	26.5%	35.4%	29.8%	32.1%
	4	11.7%	12.9%	19.1%	26.8%	23.4%	25.4%	36.6%	30.7%	29.7%
	5	6.0%	9.3%	17.3%	23.3%	20.9%	24.3%	33.9%	28.4%	29.2%
	6	5.6%	8.9%	17.9%	24.4%	22.1%	25.7%	35.3%	30.1%	31.2%
	7	4.7%	8.2%	16.6%	23.2%	21.3%	24.5%	33.5%	29.2%	29.7%
	8	3.2%	7.2%	16.4%	22.1%	20.2%	24.3%	33.0%	28.4%	29.5%
	9	8.6%	10.5%	16.7%	24.1%	21.6%	23.6%	33.8%	28.8%	28.0%
	10	7.7%	9.7%	16.5%	23.5%	21.2%	23.5%	33.0%	28.9%	28.4%
	11	1.4%	6.0%	15.7%	20.6%	19.0%	24.1%	32.1%	27.4%	29.7%
	12	5.1%	8.3%	16.6%	22.9%	20.6%	24.0%	33.2%	28.7%	29.0%
0.77 clo	1	33.1%	27.6%	31.7%	47.6%	38.5%	37.3%	79.0%	68.9%	47.6%
	2	33.7%	27.9%	31.1%	47.4%	37.5%	35.1%	77.8%	64.8%	44.5%
	3	36.0%	30.3%	32.2%	48.7%	39.8%	34.9%	77.5%	65.3%	44.7%
	4	36.8%	30.9%	28.6%	47.3%	38.2%	29.2%	65.8%	52.1%	37.5%
	5	34.5%	28.7%	28.7%	46.2%	37.8%	30.7%	70.0%	56.1%	39.1%
	6	35.8%	30.4%	31.1%	47.9%	39.7%	32.9%	74.1%	61.2%	41.9%
	7	34.1%	29.5%	29.9%	46.0%	38.8%	33.8%	73.4%	60.8%	43.3%
	8	33.5%	28.7%	29.7%	45.8%	38.4%	33.9%	74.1%	62.1%	43.9%
	9	34.2%	28.9%	28.1%	45.1%	37.9%	30.6%	68.4%	54.3%	40.1%
	10	33.4%	29.0%	28.2%	44.6%	38.1%	31.1%	69.1%	55.7%	40.2%
	11	32.7%	27.8%	30.1%	45.6%	37.8%	34.7%	75.6%	64.2%	46.2%
	12	33.6%	29.0%	29.0%	45.4%	38.4%	32.3%	72.2%	59.1%	42.5%
1.0 clo	1	61.4%	49.8%	38.9%	92.9%	84.5%	58.3%	80.1%	81.4%	72.8%
	2	60.5%	46.8%	36.7%	90.2%	82.1%	53.5%	79.1%	80.4%	72.3%
	3	60.9%	48.4%	36.7%	88.6%	80.5%	53.7%	77.2%	78.6%	71.2%
	4	53.5%	40.6%	30.6%	75.9%	68.6%	44.3%	73.8%	76.8%	67.7%
	5	55.6%	42.5%	32.2%	83.1%	73.8%	46.4%	77.3%	79.4%	70.3%
	6	58.8%	46.1%	34.6%	84.5%	76.9%	49.9%	75.9%	78.0%	70.7%
	7	57.2%	46.0%	35.5%	85.1%	77.2%	51.2%	77.1%	79.1%	72.2%
	8	57.7%	46.6%	36.0%	87.2%	78.9%	52.1%	78.3%	80.1%	72.6%
	9	53.9%	41.9%	32.4%	79.4%	72.1%	47.5%	76.3%	78.8%	70.5%
	10	54.0%	43.2%	32.9%	80.4%	72.9%	47.6%	77.1%	79.3%	70.7%
	11	58.3%	47.4%	37.5%	90.3%	81.6%	55.5%	79.6%	81.1%	73.6%
	12	56.0%	45.1%	34.9%	84.1%	76.4%	50.2%	77.7%	79.7%	72.2%

Fig. 2. Percentage of comfortable time for three activities and three clothing insulations. Clo = 0.51, 0.77, and 1.0. Met = 1.0, 1.1, 1.2 (sitting, typing, and standing postures).

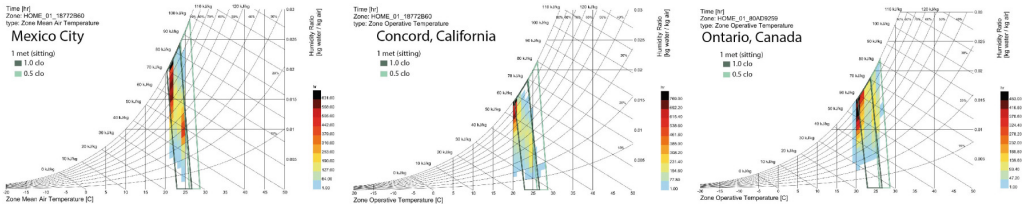
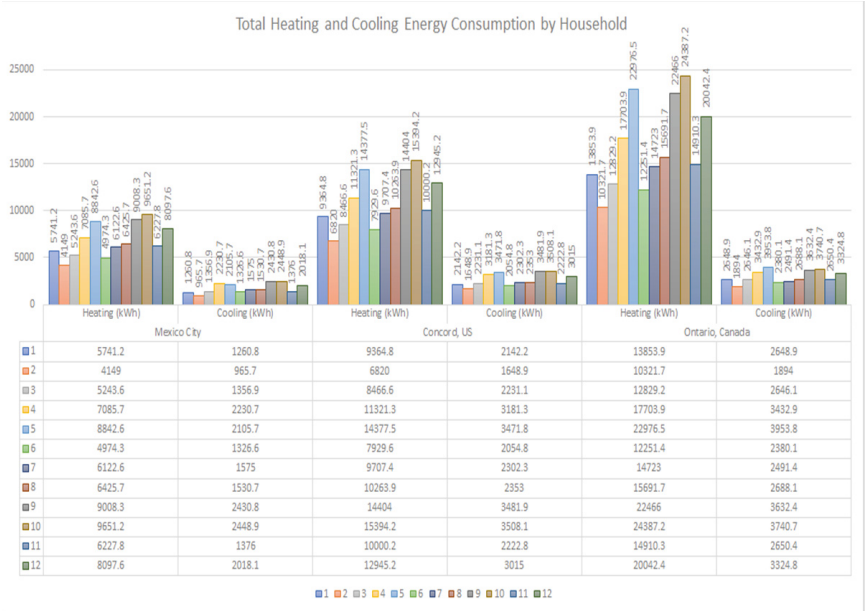


Fig. 3. Graphical Comfort Zone Method for 0.5 clo and 1.0 clo, with a metabolic rate of 1.0 (sitting activity).



	Mexico City Heating (kWh)	Mexico City Cooling (kWh)	Concord, US Heating (kWh)	Concord, US Cooling (kWh)	Ontario, Canada Heating (kWh)	Ontario, Canada Cooling (kWh)
1	5741.2	1260.8	9364.8	2142.2	13853.9	2648.9
2	4149	965.7	6820	1648.9	10321.7	1894
3	5243.6	1356.9	8466.6	2231.1	12829.2	2646.1
4	7085.7	2230.7	11321.3	3181.3	17703.9	3432.9
5	8842.6	2105.7	14377.5	3471.8	22976.5	3953.8
6	4974.3	1326.6	7929.6	2054.8	12251.4	2380.1
7	6122.6	1575	9707.4	2302.3	14723	2491.4
8	6425.7	1530.7	10263.9	2353	15691.7	2688.1
9	9008.3	2430.8	14404	3481.9	22466	3632.4
10	9651.2	2448.9	15394.2	3508.1	24387.2	3740.7
11	6227.8	1376	10000.2	2222.8	14910.3	2650.4
12	8097.6	2018.1	12945.2	3015	20042.4	3324.8

Fig. 4. HVAC Annual breakdown consumption by home and location.

4.1 Interactive Community Platform

Figure 5 depicts the community interactive platform and the number of homes available at Genial.ly [28]. This platform shows three views and a 360 view. Each 360 view deploys a central view from Mexico City, MEX, Concord, CA, and Ontario, CAN. The objective of each view is to show the player or householder how the location affects and how the shadow changes, having the same characteristics in terms of date and hour.

Figure 6 depicts the energy consumption, the indoor and outdoor temperature of the community, and the comparison between locations. The information came from Table 2, Figs. 2 and 4. The interactive views allow the community members can review each consumption, compare the HVAC usage between homes, and how the thermal comfort changes depending on the clothing, activity, and location. Figure 6(a) shows the energy use intensity by home and location. Thus, Figs. 6(b) to (e) show the case for home 1. Figure 6(b) depicts the indoor and outdoor temperature monthly graph for each location and the monthly HVAC consumption. Figures 6(c) to (e) illustrate the percentage of thermal comfort for three activities and the clothing insulation.

Fig. 5. Community platform deployed at Genially. (a) General plan view; (b) A View; (c) B View; (d) C View; (e) 360 Mexico City View's community; (f) 360 Concord View's community; (g) 360 Ontario View's community.

Fig. 6. Community platform deployed at genially. (a) Overall Energy Use Intensity by home and location; home 1 platforms; (b) indoor and outdoor temperature and HVAC usage; thermal comfort and different clothing for these activities; (c) sitting; (d) typing; and (e) standing.

5 Discussion

The results showed that three homes consumed more energy during winter periods and that the thermal comfort was like the other homes that consumed less energy. Therefore, in terms of comfort, if a proposal regarding saving energy is made, there should not be a major problem for homes 5, 9, and 10, as they are within the range of comfort. However, an interesting finding is that, for instance, home 4 consumes less energy than the other homes and is less comfortable than the other homes; thus, proposals that include higher metabolic rates or have more cloth insulation should be suggested.

This leads to a system proposal that evaluates the user's thermal comfort and shows them in interactive platforms or interfaces how to become energy aware and compare their consumption with the other homes. Future work includes personalizing the platforms. For instance, Méndez et al. [3, 16, 31] proposed to employ gamification elements

based on personality traits, energy end-user segments, and gamified user types to show tailored interfaces that engage householders. Moreover, suggestions such as clothing element changes can help the user to maintain a thermal comfort sensation that helps not only the energy consumption of his environment but also helps him stay in a healthier environment that reduces stress and negative emotions. For instance, an interface proposal could include the thermal sensation scale, where the end-user can vote based on their preference.

This paper proposes an interactive online platform where worldwide users can play with the platform, analyze the difference between each location, and get their conclusions based on this usage. Besides, thermal comfort awareness is deployed by providing graphics that show how clothing and activity affect thermal comfort. However, this proposal could be improved by adding features such as changing the location or the number of homes. Nevertheless, further research is required, for instance, by providing Artificial Intelligence techniques that, based on the location, predict the energy consumption to speed up the process in which EnergyPlus is required. Therefore, more time is needed to run the simulation.

Conventional energy model simulators such as Ladybug Tools [29] allow personalization in terms of energy usage, schedules, activities, and clothes; however, this personalization has its limits when analyzing thermal comfort in real-time to provide strategies or solutions based on daily activities.

Thus, research should include, for instance, the use of computer vision for predicting clothing insulation and continuously updating the thermal comfort ranges in real-time. Moreover, thermal comfort methods associate activities with clothing insulation; thus, computer vision could even predict the thermal comfort based on the clothing insulation and then infer the type of activity that the householders will do. Besides, this research can be extended and implemented for every home by providing this information, for instance, in thermostat interfaces or smart homes interfaces [3, 22].

Providing interactive interfaces and access to compare the energy consumption of the other householders lets the community and the citizens or individuals know more about their environment and how their decisions may affect the environment, their spending money, or their thermal comfort.

6 Conclusion

This paper compared three communities in Mexico City, Concord, California, and Ontario, Canada, to analyze thermal comfort and HVAC energy consumption. The community comprises twelve homes in different areas; besides measuring the energy impacts and thermal comfort between cities, the occupancy remained the same, and the construction type and metabolic rate. The changes occurred in the climate zone. Mexico and Concord are warmer, whereas Ontario is in a colder climate.

Graphical Comfort Zone Method provides insights about the thermal comfort ranges within the home; if using clothing values of 1.0 or 0.5, the people would feel comfortable. Then, based on that analysis, propose decisions that improve the quality of life of householders and consider their thermal preferences. These communities showed that three homes consumed greater amounts of heating and remained within the thermal

comfort ranges. In addition, homes like the fourth had lesser thermal comfort and lower energy consumption than the other three homes. Homes 5, 9, and 10 represented 34% of the total energy consumption in the community; thus, efforts require understanding their habits and how small changes could benefit the total amount of consumption and that it would not affect their thermal comfort.

Nevertheless, due to the increase of dynamic models, adaptive methods that predict, for instance, clothing properties are needed to understand how an individual could adapt to indoor environments. Moreover, those predictions could go further by predicting environmental impacts that lead to energy waste; thus, strategies must be addressed to promote energy reduction while achieving thermal comfort.

Therefore, efforts require focusing on how they can increase thermal comfort without increasing energy consumption and, if possible, decrease consumption. Thus, attempts can be targeted into clothing insulation, and real-time feedback can help householders improve their comfort without wasting more energy or money.

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References

1. SENER | Sistema de Información Energética | Usuarios de energía eléctrica por entidad federativa, https://sie.energia.gob.mx/bdiController.do?action=cuadro&subAction=applyOptions. Accessed 20 June 2021
2. Natural Resources Canada: Energy Fact Book 2020–2021. Natural Resources Canada (2020)
3. Méndez, J.I., Peffer, T., Ponce, P., Meier, A., Molina, A.: Empowering saving energy at home through serious games on thermostat interfaces. Energy Build. **263**, 112026 (2022). https://doi.org/10.1016/j.enbuild.2022.112026
4. Ponce, P., Meier, A., Mendez, J., Peffer, T., Molina, A., Mata, O.: Tailored gamification and serious game framework based on fuzzy logic for saving energy in smart thermostats. J. Clean. Prod. **262**, 121167 (2020). https://doi.org/10.1016/j.jclepro.2020.121167
5. Chou, Y.: Actionable Gamification: Beyond Points, Badges, and Leaderboards. Packt Publishing Ltd, Fremont, CA (2019)
6. Schiele, K.: Utilizing gamification to promote sustainable practices. In: Marques, J. (ed.) Handbook of Engaged Sustainability, pp. 427–444. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-71312-0_16
7. AlSkaif, T., Lampropoulos, I., van den Broek, M., van Sark, W.: Gamification-based framework for engagement of residential customers in energy applications. Energy Res. Soc. Sci. **44**, 187–195 (2018). https://doi.org/10.1016/j.erss.2018.04.043
8. Mendez, J.I., Ponce, P., Medina, A., Peffer, T., Meier, A., Molina, A.: A smooth and accepted transition to the future of cities based on the Standard ISO 37120, Artificial Intelligence, and gamification constructors. In: 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), pp. 65–71, IEEE, Dortmund, Germany (2021). https://doi.org/10.1109/E-TEMS51171.2021.9524900
9. Méndez, J.I., Ponce, P., Peffer, T., Meier, A., Molina, A.: A gamified HMI as a response for implementing a smart-sustainable university campus. In: Camarinha-Matos, L.M., Boucher, X., Afsarmanesh, H. (eds.) PRO-VE 2021. IAICT, vol. 629, pp. 683–691. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-85969-5_64

10. Fraternali, P., et al.: A socio-technical system based on gamification towards energy savings. In: 2018 IEEE International Conference on Pervasive Computing and Communications Workshops (PerCom Workshops), pp. 59–64, IEEE, Athens (2018). https://doi.org/10.1109/PERCOMW.2018.8480405
11. Jenkins, M.: Thermal Comfort Basics: What is ASHRAE 55? | SimScale Blog. https://www.simscale.com/blog/2019/08/what-is-ashrae-55-thermal-comfort/. Accessed 3 June 2021
12. Parsons, K.C.: Human Thermal Comfort. CRC Press, Boca Raton, FL (2020)
13. Fanger, P.O., et al.: Thermal Comfort. Analysis and Applications in Environmental Engineering (1970)
14. de Dear, R.J., Brager, G.S.: Developing an Adaptive Model of Thermal Comfort and Preference. Center for the Built Environment, Berkeley (1998)
15. High Indoor Temperatures. World Health Organization (2018)
16. Méndez, J.I., et al.: Designing a consumer framework for social products within a gamified smart home context. In: Antona, M., Stephanidis, C. (eds.) HCII 2021. LNCS, vol. 12768, pp. 429–443. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-78092-0_29
17. Nicol, F., Humphreys, M.A., Roaf, S.: Adaptive Thermal Comfort: Principles and Practice. Routledge, London (2012)
18. Fergus Nicol, J., Humphreys, M.A.: Principles of adaptive behaviours. In: Kubota, T., Rijal, H.B., Takaguchi, H. (eds.) Sustainable Houses and Living in the Hot-Humid Climates of Asia, pp. 209–217. Springer, Singapore (2018). https://doi.org/10.1007/978-981-10-8465-2_20
19. Humphreys, M., Nicol, F., Roaf, S.: Adaptive Thermal Comfort: Foundations and Analysis. Routledge (2015). https://doi.org/10.4324/9781315765815
20. de Dear, R., Xiong, J., Kim, J., Cao, B.: A review of adaptive thermal comfort research since 1998. Energy Build. **214**, 109893 (2020). https://doi.org/10.1016/j.enbuild.2020.109893
21. Yang, L., Fu, R., He, W., He, Q., Liu, Y.: Adaptive thermal comfort and climate responsive building design strategies in dry–hot and dry–cold areas: Case study in Turpan, China. Energy Build. **209**, 109678 (2020). https://doi.org/10.1016/j.enbuild.2019.109678
22. Medina, A., Méndez, J.I., Ponce, P., Peffer, T., Meier, A., Molina, A.: Using deep learning in real-time for clothing classification with connected thermostats. Energies **15**, 1811 (2022). https://doi.org/10.3390/en15051811
23. Méndez, J.I., Mata, O., Ponce, P., Meier, A., Peffer, T., Molina, A.: Multi-sensor system, gamification, and artificial intelligence for benefit elderly people. In: Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E. (eds.) Challenges and Trends in Multimodal Fall Detection for Healthcare. SSDC, vol. 273, pp. 207–235. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-38748-8_9
24. Méndez, J.I., et al.: Smart homes as enablers for depression pre-diagnosis using PHQ-9 on HMI through fuzzy logic decision system. Sensors **21**, 7864 (2021). https://doi.org/10.3390/s21237864
25. EnergyPlus | EnergyPlus. https://energyplus.net/. Accessed 3 June 2021
26. Yun, G.Y.: Influences of perceived control on thermal comfort and energy use in buildings. Energy Build. **158**, 822–830 (2018). https://doi.org/10.1016/j.enbuild.2017.10.044
27. Shabunko, V., Lim, C.M., Mathew, S.: EnergyPlus models for the benchmarking of residential buildings in Brunei Darussalam. Energy Build. **169**, 507–516 (2018). https://doi.org/10.1016/j.enbuild.2016.03.039
28. Méndez, J.I.: Know Your Community – Thermal Comfort. https://view.genial.ly/6286e8f6ec1be60019eec51d/interactive-content-community-thermal-comfort. Accessed 27 May 2022
29. Ladybug Tools: Ladybug Tools | Home Page. https://www.ladybug.tools/. Accessed 2 May 2021

30. U.S. Department of Energy: EnergyPlus^{TM} Version 9.5.0 Documentation: Input Output Reference (2021)
31. Méndez, J.I., et al.: A rapid HMI prototyping based on personality traits and AI for social connected thermostats. In: Batyrshin, I., Gelbukh, A., Sidorov, G. (eds.) MICAI 2021. LNCS (LNAI), vol. 13068, pp. 216–227. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-89820-5_18

A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part II

Adán Medina[1], Juana Isabel Méndez[1], Pedro Ponce[1(✉)], Therese Peffer[2], Alan Meier[3], and Arturo Molina[1]

[1] Institute of Advanced Materials for Sustainable Manufacturing, Tecnologico de Monterrey, Monterrey, MX 64849, USA
{A01331840isabelmendez,pedro.ponce,armolina}@tec.mx

[2] Institute for Energy and Environment, University of California, Berkeley, CA 94720, USA
tpeffer@berkeley.edu

[3] Energy and Efficiency Institute, University of California, Davis, CA 95616, USA
akmeier@ucdavis.edu

Abstract. Clothing garments directly affect the human body's thermal balance and thermal comfort. The ideal thermal balance is when the body's temperature remains neutral and the environment is not affecting it. Nevertheless, achieving that thermal balance is very unlikely due to other variables, such as humidity, that need consideration. Therefore, these variables affect the human body's perception of the environment's temperature leading to behavioral problems and a lack of thermal comfort. Besides, adaptive methods require integrating dynamic models that predict clothing properties to provide accurate thermal comfort to the householder and understand how an individual adapts to indoor environments rather than the conventional thermal comfort analysis. Therefore, a computer vision system integrated into camera recognition is needed to implement an online clothing insulation recognition system to get feedback on thermal comfort and provide information to the householders about how the clothes and activities affect their thermal comfort. Besides, this recognition needs to be considered in dynamic interfaces such as connected thermostat interfaces. Furthermore, this vision system needs to detect the clothing worn by the user and infer possible metabolic activities based on the clothes. Hence, this paper proposes classifying the garments through a Deep Neural Network (DNN) using the YOLOv3 in which available external sources, such as cameras, gather the householder's clothes and postures to classify the type of cloth and activity and provide information to the householder through a dynamic interface in order to continue their thermal comfort. Thus, a 24-h simulation is performed considering three scenarios: (1) typical 0.5 clo value and 1.0 metabolic rate; (2) dynamic clo values with activities; and (3) dynamic values adding the underwear clo values. Hence, thermal comfort analysis results are included in an interactively connected thermostat mock-up. This mock-up and interaction are available online.

Keywords: Clothing insulation · Online monitoring · Yolov3 · Behavioral clothing and activities · Connected thermostat mock-up · Online platform · Interactive interface

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1 Introduction

The worn clothing influences the Human body's thermal balance in different temperature environments. According to the laws of thermodynamics, the heat exchange between the human body and the environment depends on which is warmer than the other [1–5]. Thus, if the environment is warmer than the human body, it transfers heat into the body, and if the human body is warmer than the environment, it transfers heat to the surroundings. In the case of equal temperature, there would be a thermal balance between the environment and the body; hence, there would be no heat transfer. However, achieving that thermal balance is very unlikely due to other variables, such as humidity, that need consideration. Therefore, these variables affect the human body's perception of the environment's temperature leading to behavioral problems and a lack of thermal comfort [6].

Clothing garments act as a thermal insulator that affects the heat transfer in two aspects regarding the human body's perception and the environment's temperature [7]:

It prevents the human body from exchanging heat with the environment.

It acts on the evaporative resistance of the skin, which influences how the body.

Standards such as ASHRAE 55 [1, 8] provide clothing insulation values (clo value) tables for both clothing ensembles and individual clothing garments; the measurements were obtained from a standing thermal manikin [8]. Other methods like direct measurement while the clothing garments are worn, employing tables using thermal manikin values, or through regression methods on the physical characteristics of clothes to determine the clothing insulation are mentioned by Lotens and Hanevith [9]. However, the most accepted method is the thermal manikin method [8, 10].

In addition, metabolic rate influences the blood flow in the body and determines the body's temperature affecting the thermal comfort and thermal sensation of the clothes worn [11, 12]. Thus, Table 1 displays a list of actions regarding clothing, garments, and activities responding to cold or heat [13, 14].

Table 1. List of actions as a response to warm or cool environments.

Heat responses	Cold responses
Adopt an open posture to increase the area available for heat loss	Increase muscle tension and shivering to generate more heat in the muscles
Take off some garments to increase heat loss	Curling up or cuddling up to reduce the surface area available for heat loss
Reduce the level of activity to decrease body heat production	Increase the activity level to promote body heat
Adopt the siesta routine to avoid more heat production	Add clothes that reduce the rate of heat loss per unit area
Going for a swim	Go to bed to increase the heat

Nevertheless, due to the increase in dynamic models, adaptive methods that predict clothing properties need to understand how an individual adapts to indoor environments.

Matsumoto, Iwai, and Ishiguro [15] used a computer vision system and a combination of Histogram of Oriented Objects (HOG) and Support Vector Machines (SVM) to recognize clothing garments. Bouskill and Havenith [16] used a thermal manikin to determine the relationship between clothing insulation and clothing ventilation with different activities known as metabolic rates. They concluded that clothing insulation affects less than the design and fabric of the clothing garment; thus, they recommended analyzing the clothing garments worn in specific places during specific activities to determine the best outfit that avoids colder or warmer thermal sensations.

Using computer vision to detect clothing may seem expensive when thinking about the implementation of the camera system and the computer needed to process the information and run the solution. However, suppose cameras are being spread to different uses such as telecare [10, 17–19] or personal assistants like Alexa [18, 20]. In that case, the idea that cameras are part of the smart home infrastructure needs to be considered. Thus, there would be no need to invest in a camera system and only think about the processing part of the problem. Figure 1. Displays some household devices that can track end-user activities, moods, and garments. For example, through smart TV, camera detection can monitor householder reactions or postures; voice detection can analyze the householders' speech to detect if any possible disease or affection may affect the individual. Méndez et al. [21] proposed using cameras and Alexa to track householders' moods and as a tool for depression pre-diagnosis. In [20], they proposed using Alexa and a camera to track seniors' moods and emotions to prevent social isolation and depression. Besides, Medina et al. presented a detailed example of using online analysis to detect clothing insulation and show messages to the householder to suggest how to save energy while keeping thermal comfort. Thus, this picture shows the integration of household appliances that can help track householders' daily activities and moods; therefore, this paper considers cameras to classify the garment and infer daily activities.

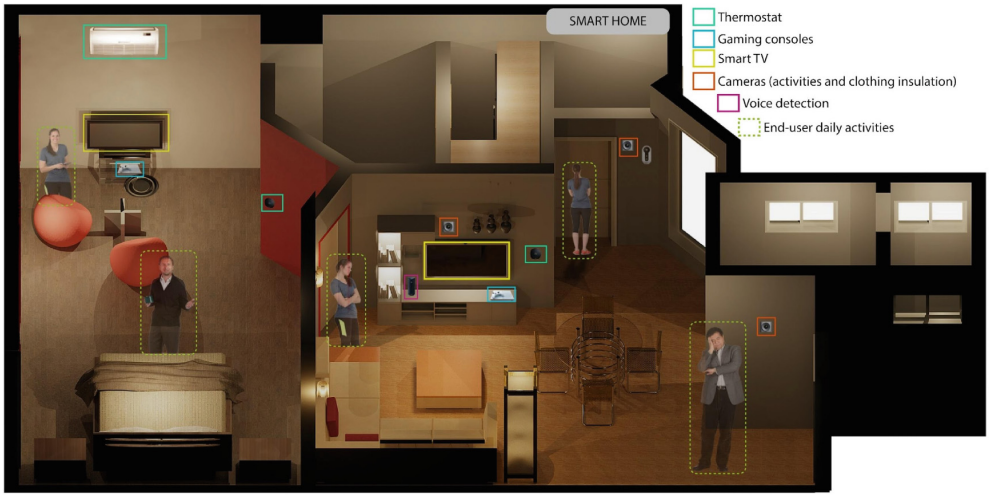


Fig. 1. Household devices integration in Smart Homes: cameras to classify householders' garments and activities.

1.1 Determining Acceptable Thermal Comfort in Occupied Spaces

ASHRAE 55 proposes three methods for determining thermal comfort during occupancy hours [22]:

- Graphic Comfort Zone Method: This method is limited to representative households with metabolic rates between 1.0 and 1.3 met (sitting, typing, and standing activities) and clothing insulation I_{cl} between 0.5 and 1.0 clo who are not exposed to direct-beam solar radiation and average air speed up to 0.2 m/s. Moreover, this method is limited to a humidity ratio at ro below 0.012 kg*H2O/kg dry air, a water pressure of 1.91 kPa at standard pressure or a dew-point temperature tdp of 16.8 °C.
- Analytical Comfort Zone Method: This method considers average metabolic rates between 1.0 and 2.0 met (sitting, typing, standing, and cooking activities) and clo up to 1.5. This method uses the ASHRAE thermal sensation scale and the PMV/PPD model. Acceptable indoor thermal comfort considers a 10% percentage of dissatisfied people in a range of predicted mean vote between −0.5 and 0.5.
- Elevated Air Speed Comfort Zone Method: this method considers activity levels with average metabolic rates between 1.0 and 2.0 met, clothing insulation up to 1.5, and average air speeds greater than 0.20 m/s. For instance, an increase of 0.1 clo or met reduces up to 0.8 °C the operative temperature, whereas a decrease of 0.1 clo or met increases the operative temperature to 0.8 °C or 0.5 °C

1.2 Interactive Connected Thermostat Interfaces

About 86% of the residential buildings have thermostats that control the Heating Ventilation and Air-Conditioning systems (HVAC) [6, 23]. Besides, studies revealed that connected thermostats reduce energy consumption by up to 35%, and with a behavioral change up to 5% can be reduced [6, 24]. Thus, these behavioral factors explain up to half of the variance of overall HVAC consumption. In that sense, in [6, 25] indicated that interfaces should teach, engage, and motivate the householder in performing activities that reduce energy consumption and ideally without losing thermal comfort [6].

Thus, they stated that an interface needs to provide information about their thermal comfort and not only the electricity bill or information about the energy consumption [6, 26]. This information can be provided through interactive platforms or through the use of game elements that engage the householder [6, 25, 26]. Moreover, in [27] they suggested using strategies that feedback to the user about how their garments affect their thermal comfort and possible activities that can improve their thermal comfort as exemplified in Table 1.

In that sense, a computer vision system integrated into camera recognition is needed to implement an online clothing insulation recognition system to get feedback on thermal comfort. Furthermore, this vision system needs to detect the clothing worn by the user and infer possible metabolic activities based on the body pose. Besides, using game elements in real contexts or for educational purposes help individuals understand better their products or how to take advantage of them. For instance, Méndez et al. [6] proposed a serious gamified interface for connected thermostats and proposed to use game elements as tips, feedback, rewards, or social communities to engage householders in energy

activities [25]. Besides, Medina et al. [27] suggest including messages about the garments on the thermostat interfaces to show the householders how they can reduce energy while maintaining comfort by wearing the same clothes, lighter or heavier clothes.

Nevertheless, none of these proposals are available on online platforms or shows, for instance, how clothing and activities impact thermal comfort. Thus, this paper proposes to include an online platform as a result of the online analysis and show how the thermal comfort affects depending on the type of thermal comfort analysis, how it affects by analyzing in a conventional method or by using the methodology proposed in this research. In other words, the differences between the conventional model and online analysis.

2 Proposal

Figure 2 depicts the proposal divided into five steps. This proposal aims to determine if the householders are comfortable by comparing the conventional thermal comfort analysis and the DNN clothing and activity thermal comfort analysis. Thus, clothing recommendation feedback is provided if the householders are not comfortable.

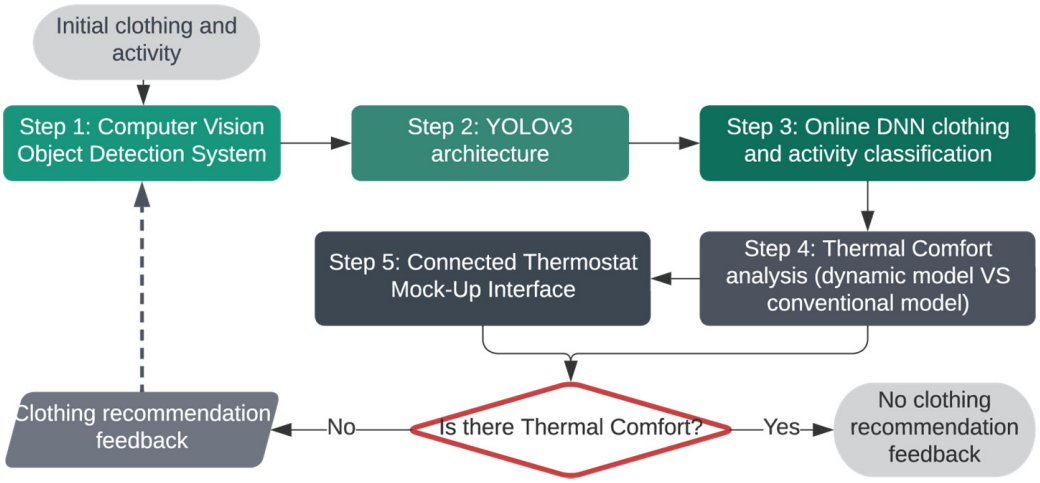


Fig. 2. General proposal for detecting clothing insulation and inferring activities using the YOLOv3.

- Step 1: it proposes a computer vision object detection system using a Deep Neural Network (DNN). The camera gathers the clothes and postures of the householder to classify the type of clothes.
- Step 2: The desired architecture needs to be fast due to the online complexity and accuracy; hence, Fig. 3 shows the YOLOv3 architecture chosen for this proposal. A single-stage object detection neural network presents results as the fastest algorithm. This accurate model is the You Only Look Once Version 3 algorithm (YOLOv3) [25].

  a. Since YOLOv3 uses a DarkNet53 backbone, the difference relies on the last three layers and eliminates the softmax connected layer with convolutional layers. The

last one depends on the number of classes to be predicted (N); the architecture mentioned is listed in Table 2. This algorithm has a pre-trained model so we can apply transfer learning to be able to reuse the weights of the model trained for image classification and spend less time in the training steps, and have more free time to tweak the datasets used to train and test the model, specifically the labeled images that are discussed next.

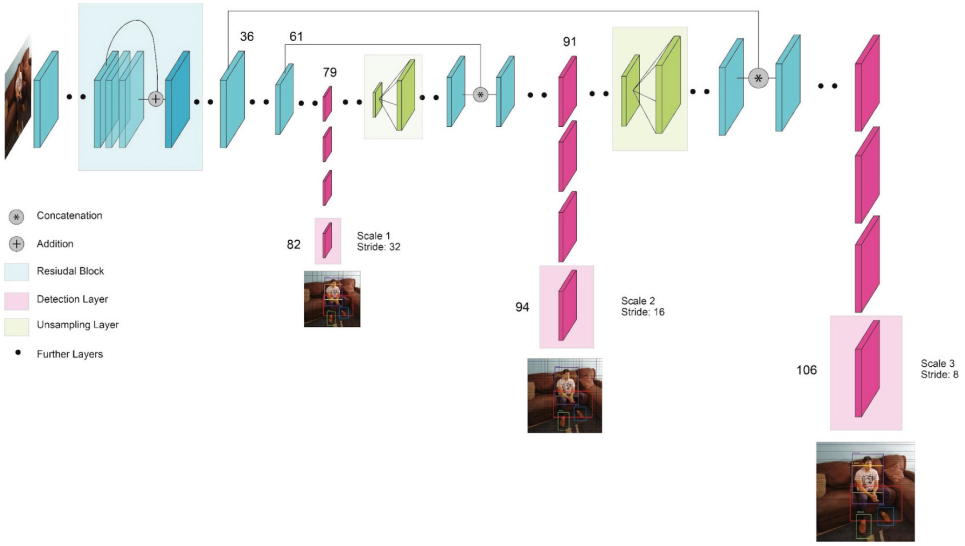


Fig. 3. DNN architecture: You only look once version 3 structure (YOLOv3).

- Step 3: The DNN was obtained, and an online analysis was performed. The DNN classifies the clothes based on the Modified National Institute of Standards and Technology Fashion database (FMNIST), containing 60,000 labeled images of different clothing garments. However, as this database was oriented toward the fashion industry, the images lack the background and people information; therefore, 1,000 images are manually labeled using VIA Image Annotator Software to cover this lack of information. These images were taken from free image databases and contained people with different clothing outfits in other locations and with an entire clothing ensemble instead of the individual clothing garment as presented in the FMNIST images. Table 3 describes the classes used for the data labeling; those classes were: Highly Insulating Jacket, Highly Insulating Shoes, Highly Insulating Trousers, Jacket, Trousers, Shoes, Socks, Hat, Gloves, Scarf, and Person so the network could recognize the individual wearing the jacket.
- Step 4: Once obtained from the DNN, the percentage of comfortable time was analyzed for three locations: Mexico City, Concord, and Ontario. Daily activity was analyzed to review the differences between static and dynamic thermal comfort. Thus, three scenarios were considered:

  a. Conventional values from thermal comfort analysis: 0.5 clo and 1 met.

b. DNN clo value: A 24-h activity with four activities: sleeping, sitting, standing, reading, and typing. The DNN determined the clo values.
c. DNN + underwear: A 24-h activity considering four activities: sleeping, sitting, standing, reading, and typing. The clo values were determined by the DNN plus the underwear clo values.

- Step 5: A mock-up interface was deployed, considering a thermostat interface. Heating Ventilation and Air-Conditioning (HVAC) consume most of the energy at home, and thermostats are present in more than 86% of HVAC systems [6, 23, 26, 29]. Thus, a connected thermostat interface is proposed. In [6, 25], they suggested including in a thermostat interface tips or messages that teach the householder how specific actions affect, for instance, thermal comfort. Thus, using the information for step 4, an interactive platform was deployed to encapsulate the results into six activities: sitting, reading, standing, typing, sleeping, and reclining.

Moreover, this research aimed to determine if there was any difference between considering conventional clo values and metabolic rates and analyzing the end-users hourly activities in online. Besides, the percentage of time during each hour was analyzed for each location; the outdoor temperature was considered to not deal with indoor variables such as mean radiant temperature, building materials, or other heat sources that may affect this analysis.

Table 2. Deep neural network architecture (YOLOv3 architecture) [28].

Repetitions	Type	Filters	Size/stride	Output
	Convolutional	32	3 × 3	256 × 256
	Convolutional	64	3 × 3	112 × 112
1	Convolutional	32	1 × 1	
	Convolutional	64	3 × 3	
	Residual			128 × 128
	Convolutional	128	3 × 3/2	64 × 64
4	Convolutional	64	1 × 1	
	Convolutional	128	3 × 3	
	Residual			64 × 64
	Convolutional	256	3 × 3/2	32 × 32
8	Convolutional	128	1 × 1	
	Convolutional	256	3 × 3	
	Residual			32 × 32

(*continued*)

Table 2. (*continued*)

Repetitions	Type	Filters	Size/stride	Output
	Convolutional	512	3 × 3/2	16 × 16
8	Convolutional	256	1 × 1	
	Convolutional	512	3 × 3	
	Residual			16 × 16
	Convolutional	1024	3 × 3/2	8 × 8
8	Convolutional	512	1 × 1	
	Convolutional	1024	3 × 3	
	Residual			8 × 8
	Convolutional	1024	3 × 3	8 × 8
	Convolutional	1024	3 × 3	8 × 8
	Convolutional	1024	3 × 3	8 × 8
	Convolutional	N	1 × 1	8 × 8

Table 3. Clothing insulation values for the classes included in FMNIST and VIA images [6].

Class	Clo	$m^2 * °C/W$
Ankle boot	0.1	0.016
T-shirt/top	0.08	0.012
Dress	0.15	0.023
Pullover	0.28	0.043
Sneaker	0.04	0.006
Sandal	0.02	0.0032
Trouser	0.19	0.0304
Coat	0.6	0.096
Shirt	0.09	0.0144
Bag	0	0
Highly insulated jacket	0.4	0.064
Highly insulated trousers	0.35	0.056
Highly insulated shoes	0.1	0.016
Jacket	0.26	0.0416

(*continued*)

Table 3. (*continued*)

Class	Clo	$m^2 * °C/W$
Shoes	0.04	0.0064
Trousers	0.19	0.0304
Scarf	0.04	0.0064
Hat	0.04	0.0064
Gloves	0.05	0.008
Socks	0.02	0.0032

3 Results

This section presents the results of each step proposed in Fig. 2. Thus, the six activities with different clothing insulation were analyzed for the first step. Therefore, for the second step, the FMNIST dataset was considered. Figure 4(a) shows examples of the images in the FMNIST dataset; the main problem with this dataset is that it has no images containing human beings or background information; therefore, it could present problems with the implementation. Consequently, Fig. 4(b) displays a set of images gathered to create additional training examples by labeling the images with the VGG Image Annotator (VIA). Figure 5 shows the FMNIST dataset class samples. These classes were classified to follow ASHRAE 55 and recognize and validate the different clothing insulation values and their effects on thermal comfort calculations.

(a) (b)

Fig. 4. FMNIST dataset (a); and (b) additional images using VGG Image Annotator labelling.

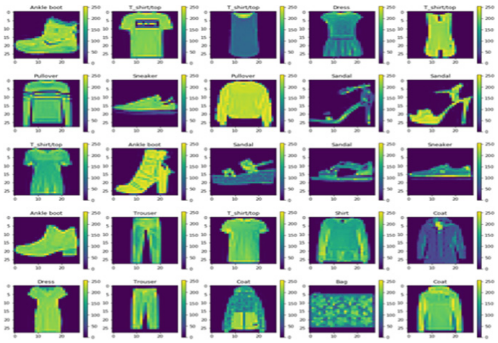


Fig. 5. FMNIST dataset classes.

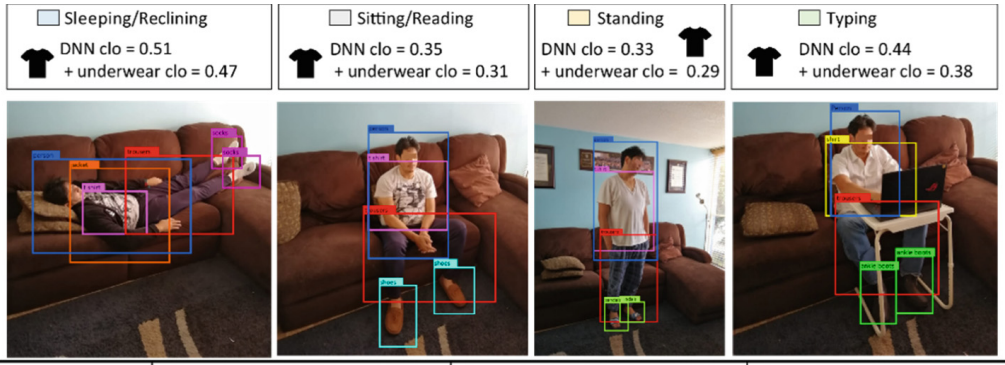
Thus, Table 4 depicts the clothing insulation values considered for the analysis and the activity and metabolic rate for the third and fourth steps. The bold words were the garments that the DNN analyzed. Figure 6 depicts the results considering the three scenarios stated in the previous section. The first scenario shows that just for Mexico, there were hours where the conventional values had a higher percentage of comfortable time during each hour during sleeping activities or a metabolic rate of 0.8; for activities with 1.1 met, the percentage of comfortability remains the same in the three cases. The second scenario revealed that the comfortable percentage of time increased or remained the same as the conventional scenario; just for Mexico during 10 pm and 11 pm, it was comfortable with the first scenario. Finally, the third scenario was the one that had higher values where the householder had more percentage during each hour of comfortability. The difference relies on the underwear's value. The DNN cannot classify the underwear; it had lower clo values; nevertheless, it had a higher percentage of comfortable time than the conventional. However, it had a lower rate and no greater than 25% in terms of time comfortable because the analysis performed only considered the outdoor temperature.

Table 4. Clothing insulation values for common clothing ensembles

Clothing ensemble	DNN clo value	DNN + underwear	Activity	Met
Men's underwear, **shoes, trousers, t-shirt**	0.35	0.31	Sitting	1
Men's underwear, **jacket, socks, trousers, t-shirt**	0.51	0.47	Reclining	0.8
Men's underwear, **sandals, trousers, t-shirt**	0.33	0.29	Standing	1.2
Men's underwear, socks, **ankle boots, trousers, shirt**	0.44	0.38	Typing	1.1

The fifth step is explained in Fig. 7. This figure depicts a mock-up of a connected thermostat interface that mainly focus on the results presented in Fig. 6 for the three types of thermal comfort analysis: conventional, DNN clo value, and DNN + underwear clo value). The thermostat mock-up is available at [29]. Figure 7(a) shows the connected

thermostat home view, and a message or tip is deployed as suggested in [6]. This message explains how the activity, location, and clothing insulation affect thermal comfort percentage. The messages invite the reader to interact with each activity and visualize the percentage of thermal comfort. These percentages are based on the results shown in Fig. 6 and consider just the clothing insulation scenarios with the associated activity. Figure (b) displays the activities the player can interact with. Figure 7(c) to (d) show the values for the sitting or reading, standing, typing, and sleeping or reclining activities with different clo values. It shows the differences between conventional analysis, the DNN clo value analysis, and underwear consideration for three locations (Mexico City, Concord, and Ontario).



Hour	Activity	met	Mexico City, Mexico: Conventional (0.5 clo, 1 met)	Mexico City, Mexico: DNN clo value	Mexico City, Mexico: DNN + underwear	Concord, California: Conventional (0.5 clo, 1 met)	Concord, California: DNN clo value	Concord, California: DNN + underwear	Ontario, Canada: Conventional (0.5 clo, 1 met)	Ontario, Canada: DNN clo value	Ontario, Canada: DNN + underwear
0	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
1	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
2	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
3	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
4	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
5	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
6	Sleeping	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
7	Sitting	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
8	Sitting	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
9	Sitting	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
10	Standing	1.2	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	16.7%	16.7%
11	Typing	1.1	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	12.5%	12.5%
12	Typing	1.1	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	12.5%	12.5%
13	Typing	1.1	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	12.5%	12.5%
14	Reading	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
15	Reclining	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
16	Reclining	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
17	Reclining	0.8	16.7%	12.5%	12.5%	8.3%	16.7%	20.8%	12.5%	25.0%	25.0%
18	Standing	1.2	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	16.7%	16.7%
19	Standing	1.2	16.7%	16.7%	16.7%	8.3%	8.3%	8.3%	12.5%	16.7%	16.7%
20	Reading	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
21	Reading	1	16.7%	20.8%	20.8%	8.3%	16.7%	12.5%	12.5%	20.8%	25.0%
22	Sleeping	0.8	16.7%	0.0%	4.2%	8.3%	20.8%	20.8%	12.5%	12.5%	12.5%
23	Sleeping	0.8	16.7%	0.0%	4.2%	8.3%	20.8%	20.8%	12.5%	12.5%	12.5%

Fig. 6. Comparison between scenarios, clo and daily activities with traditional values.

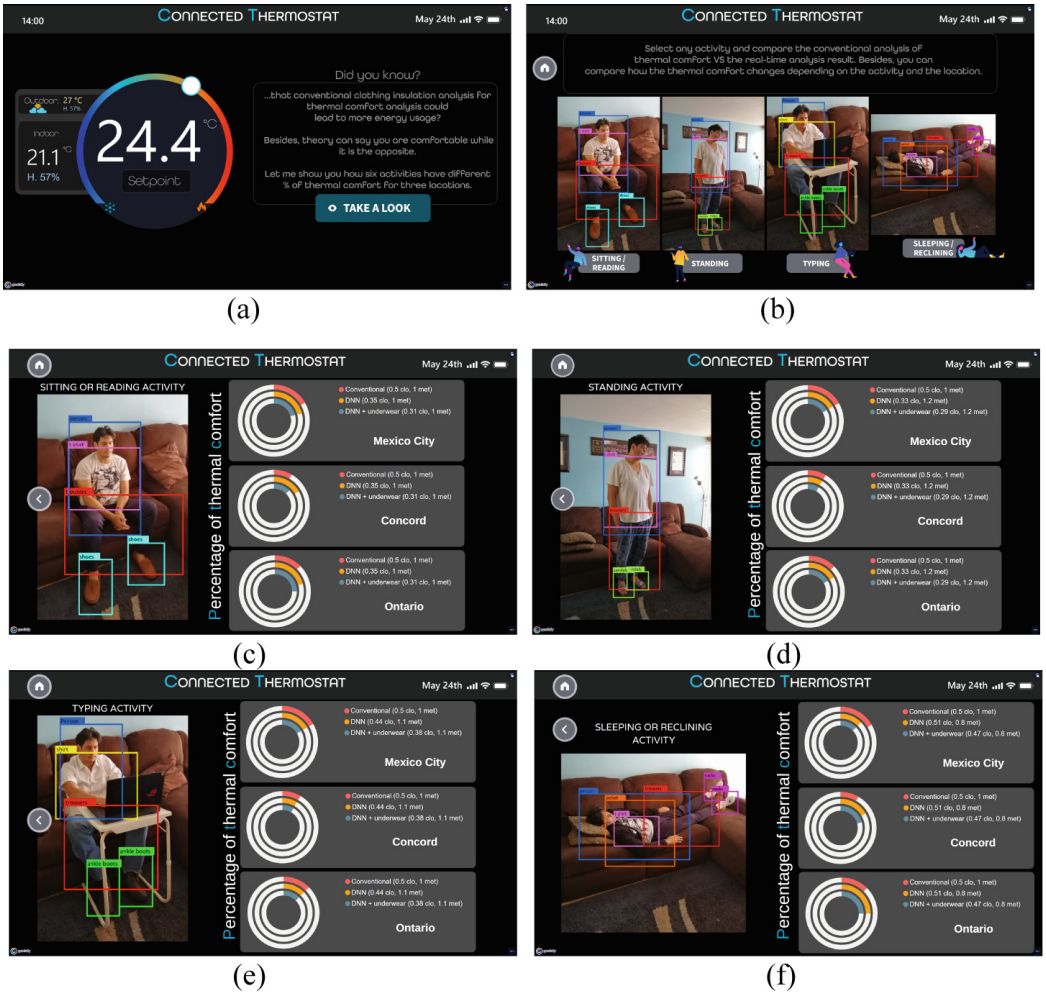


Fig. 7. Connected thermostat mock-up deployed at genially. The thermal comfort depends on the clothing insulation, activities, and location: (a) Home view; (b) activities selection view; (c) sitting or reading activity; (d) standing activity; (e) typing activity; (f) sleeping or reclining activity.

4 Discussion

Part I of these two papers shows a conventional thermal comfort analysis for a community of twelve homes and depicts an online interactive platform. However, this part states that online implementation of clothing insulation recognition could reveal the end-user's comfort. State of the art found that Histogram of Oriented Objects (HOG) and color histogram with the help of a Support Vector Machine (SVM) was implemented to determine which class the cloth garment detected belongs to [8]. Unfortunately, this approach can be used only on static images and not on video or dynamic interfaces.

After the obtention of the clothing garments of the user obtained by the DNN, standards as ASHRAE 55 or ISO help as a guideline for getting the clo value, nevertheless, a problem arises, as it was presented for the second scenario, the DNN cannot consider the underwear clo values, as the camera cannot detect it. However, the underwear can be considered as a constant, so at the end of the garment analysis, an additional 0.04 clo

value could be added. That affected the overall score of the clothing insulation value, as it was compared with the third scenario.

Online feedback and monitoring allow integrating these into dynamic interfaces where the end-user can interact directly with, for instance, gamified interfaces. Thus, as Table 1 indicates, the end-user can make recommendations to increase comfort. Besides, a connected thermostat mock-up was also deployed to show the differences between conventional thermal comfort analysis and online analysis.

Furthermore, this research provides insights into possible recommendations for including messages in the thermostat interface. For example, one of the recommendations that can be given inside the interface is the change of the clothing garments worn by the user. These recommendations can be either to change to garments with lower clothing insulation values as proposed by Medina et al. [27] or alternatives such as those proposed by Wang and Cao [8]. They concluded that it was better to have a higher insulation clothing garment in the lower part of the body to avoid feeling cold. Besides, people are expected to be more accustomed to using more clothing garments in the upper body and fewer in the lower part of the body, having an unbalanced clothing insulation value across the different body sections.

5 Conclusion

This paper proposes a system that detects and promotes thermal comfort considering the type of clothing and activity. This system uses a computer system with a deep neural network for online clothing insulation value detection. Once obtained the analysis, a connected thermostat mock-up is deployed.

Three communities in three different countries, Mexico City in Mexico, Concord in California, and Ontario in Canada, were used to demonstrate the difference between an online clothing insulation value and the current approach using constant values. As shown in Fig. 5, there are cases where the percentage varies as little as 8.3% and others that vary as much as 12.5% of the comfortable time, reaching a peak of 25.0% of time spent in the thermal comfort zone. In contrast, the constant value only reaches 16.7% of the time in the thermal comfort zone. However, the variation between the communities can be explained because the temperature used to perform the thermal comfort calculation was the outdoor temperature. Besides, communities located far north from the Equator, such as Ontario, can reach a thermal comfort time of a community closer to the Equator, such as the Mexico City community.

Another measurement is proposed in an indoor enclosure where all the other variables are kept constant to analyze better how the online clothing insulation value calculation affects the overall thermal comfort time. However since in our proposal we talk about a gamified interface where it can make suggestions to the user the presented results seem sufficient to denote the difference between constant values and online calculations and this allows the interface to be able to offer both short term solutions such as the change of a clothing garment in order to avoid entering a cycle of the user entering and leaving the thermal comfort zone, and long term solutions such as recommendations on change of wardrobe garments in order to have a balanced clothing insulation values across the entire body and even in further stages train the model for a specific season

so the recommendations take into account if it's winter or summer and the location so there is no thermal stress from the changes between outdoor and indoor temperatures, also trying to make a more efficient use of an HVAC system by better controlling the clothing insulation and therefore reducing the need of alteration of settings in the HVAC system and finally achieving both a higher quality of life for the user and a more efficient energy use for the building.

Future work includes enhancing this platform by providing more scenarios to analyze and adding a feature where the user can scan their outfit so the platform displays the thermal insulation. Besides, depending on the user location, include the percentage of thermal comfort based on the location, considering that this percentage is based only on the outdoor temperature available on climate files and not on the indoor temperature. Thus, the ranges of thermal comfort may vary.

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References

1. Nagashima, K., Tokizawa, K., Marui, S.: Thermal comfort. In: Handbook of Clinical Neurology, pp. 249–260. Elsevier (2018). https://doi.org/10.1016/B978-0-444-63912-7.00015-1
2. Romanovsky, A.A.: The thermoregulation system and how it works. In: Handbook of Clinical Neurology, pp. 3–43. Elsevier (2018). https://doi.org/10.1016/B978-0-444-63912-7.00001-1
3. Székely, M., Garai, J.: Thermoregulation and age. In: Handbook of Clinical Neurology, pp. 377–395. Elsevier (2018). https://doi.org/10.1016/B978-0-444-63912-7.00023-0
4. Te Lindert, B.H.W., Van Someren, E.J.W.: Skin temperature, sleep, and vigilance. In: Handbook of Clinical Neurology, pp. 353–365. Elsevier (2018). https://doi.org/10.1016/B978-0-444-63912-7.00021-7
5. Appenheimer, M.M., Evans, S.S.: Temperature and adaptive immunity. In: Handbook of Clinical Neurology, pp. 397–415. Elsevier (2018). https://doi.org/10.1016/B978-0-444-63912-7.00024-2
6. Méndez, J.I., Peffer, T., Ponce, P., Meier, A., Molina, A.: Empowering saving energy at home through serious games on thermostat interfaces. Energy Build. **263**, 112026 (2022). https://doi.org/10.1016/j.enbuild.2022.112026
7. Hudie, L.-A.: Ergonomics of the thermal environment: Determination of metabolic rate (2016)
8. Clothing Thermal Insulation During Sweating – Y.S. Chen, J. Fan, W. Zhang, 2003. https://journals.sagepub.com/doi/abs/https://doi.org/10.1177/004051750307300210. Accessed 2 Feb 2021
9. Lotens, W.A., Havenith, G.: Calculation of clothing insulation and vapour resistance. Ergonomics **34**, 233–254 (1991). https://doi.org/10.1080/00140139108967309
10. Caine, K.E., et al.: DigiSwitch: a device to allow older adults to monitor and direct the collection and transmission of health information collected at home. J Med Syst. **35**, 1181–1195 (2011). https://doi.org/10.1007/s10916-011-9722-1
11. Parsons, K.C.: Human Thermal Comfort. CRC Press, Boca Raton, FL (2020)
12. Luo, M., Wang, Z., Ke, K., Cao, B., Zhai, Y., Zhou, X.: Human metabolic rate and thermal comfort in buildings: The problem and challenge. Build. Environ. **131**, 44–52 (2018). https://doi.org/10.1016/j.buildenv.2018.01.005

13. Nicol, F., Humphreys, M.A., Roaf, S.: Adaptive Thermal Comfort: Principles and Practice. Routledge, London (2012)
14. de Dear, R.J., Brager, G.S.: Developing an Adaptive Model of Thermal Comfort and Preference. Center for the Built Environment, UC Berkeley (1998)
15. Matsumoto, H., Iwai, Y., Ishiguro, H.: Estimation of thermal comfort by measuring clo value without contact. In: MVA, pp. 491–494. Citeseer (2011)
16. Bouskill, L.M., Havenith, G., Kuklane, K., Parsons, K.C., Withey, W.R.: Relationship between clothing ventilation and thermal insulation. AIHA J. **63**, 262–268 (2002). https://doi.org/10.1080/15428110208984712
17. Solli, H., Hvalvik, S., Bjørk, I.T., Hellesø, R.: Characteristics of the relationship that develops from nurse-caregiver communication during telecare. J. Clin. Nurs. **24**, 1995–2004 (2015). https://doi.org/10.1111/jocn.12786
18. Sudharsan, B., Corcoran, P., Ali, M.I.: Smart speaker design and implementation with biometric authentication and advanced voice interaction capability, p. 12
19. Maharjan, R., Bækgaard, P., Bardram, J.E.: "Hear me out": Smart speaker based conversational agent to monitor symptoms in mental health. In: Adjunct proceedings of the 2019 ACM international joint conference on pervasive and ubiquitous computing and proceedings of the 2019 ACM international symposium on wearable computers, pp. 929–933. Association for Computing Machinery, New York, NY, USA (2019). https://doi.org/10.1145/3341162.3346270
20. Méndez, J.I., Mata, O., Ponce, P., Meier, A., Peffer, T., Molina, A.: Multi-sensor System, Gamification, and Artificial Intelligence for Benefit Elderly People. In: Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E. (eds.) Challenges and Trends in Multimodal Fall Detection for Healthcare. SSDC, vol. 273, pp. 207–235. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-38748-8_9
21. Méndez, J.I., Meza-Sánchez, A.V., Ponce, P., McDaniel, T., Peffer, T., Meier, A., Molina, A.: Smart homes as enablers for depression pre-diagnosis using PHQ-9 on HMI through fuzzy logic decision system. Sensors **21** (2021). https://doi.org/10.3390/s21237864
22. ANSI/ASHRAE: Standard 55-2017, Thermal environmental conditions for human occupancy (2017)
23. Peffer, T., Pritoni, M., Meier, A., Aragon, C., Perry, D.: How people use thermostats in homes: A review. Build. Environ. **46**, 2529–2541 (2011). https://doi.org/10.1016/j.buildenv.2011.06.002
24. Huchuk, B., O'Brien, W., Sanner, S.: A longitudinal study of thermostat behaviors based on climate, seasonal, and energy price considerations using connected thermostat data. Build. Environ. **139**, 199–210 (2018). https://doi.org/10.1016/j.buildenv.2018.05.003
25. Ponce, P., Meier, A., Mendez, J., Peffer, T., Molina, A., Mata, O.: Tailored gamification and serious game framework based on fuzzy logic for saving energy in smart thermostats. J. Clean. Prod. 121167 (2020). https://doi.org/10.1016/j.jclepro.2020.121167
26. Méndez, J.I., et al.: Designing a consumer framework for social products within a gamified smart home context. In: Antona, M., Stephanidis, C. (eds.) HCII 2021. LNCS, vol. 12768, pp. 429–443. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-78092-0_29
27. Medina, A., Méndez, J.I., Ponce, P., Peffer, T., Meier, A., Molina, A.: Using deep learning in real-time for clothing classification with connected thermostats. Energies **15**, 1811 (2022). https://doi.org/10.3390/en15051811
28. Redmon, J., Farhadi, A.: YOLOv3: An Incremental Improvement. arXiv:1804.02767 [cs]. (2018)
29. Meier, A., Ueno, T., Pritoni, M.: Using data from connected thermostats to track large power outages in the United States. Appl. Ener. **256**, 113940 (2019). https://doi.org/10.1016/j.apenergy.2019.113940

Chapter 6

Human-Machine Interfaces for Socially Connected Devices: From Smart Households to Smart Cities

6.1 Summary of the Chapter

This chapter exemplifies how product platforms through connected devices help in the transition from smart households to smart cities. Thus, this chapter defines a smart community as a set of smart homes, commercial buildings, public spaces, and transportation with boundaries based on walking distance located in a physical region. This smart community uses socially connected platforms and provides community public services, smart water management, and smart mobility management to promote social interaction.

The communication uses a tailored Human Machine Interface (HMI) within a gamification structure that provides feedback and adjustments based on user profiles and behavior to teach, motivate, and engage end-users in achieving specific goals, such as energy reduction. Hence, gamification builds strategies to make engaging applications by triggering internal and external motivations in end-users. A smart home gathers and analyzes data from its sensors, then delivers analytics and predictions to end users and service providers, as well as strives to improve the management of its various subsystems through social products. In that regard, the multi-sensor system allows experts to know more about the needs of homes to propose actions that reduce energy consumption and improve the home and community quality of life by enhancing individuals to read, analyze, and act upon their energy consumption through sensor profile patterns.

Thus, this chapter discusses the use of an adaptive neural network fuzzy inference and a fuzzy logic decision system to evaluate the level of energy consumption in households and the type of environmental home.

Human-Machine Interfaces for Socially Connected Devices: From Smart Households to Smart Cities

Juana Isabel Méndez, Pedro Ponce, Adán Medina, Alan Meier, Therese Peffer, Troy McDaniel, and Arturo Molina

Abstract This chapter defines a smart community as a set of smart homes, commercial buildings, public spaces, and transportation with boundaries based on walking distance, located in a physical region. This smart community uses social products and provides community public services, smart water management, smart mobility management to promote social interaction. The communication uses a tailored Human Machine Interface (HMI) within a gamification structure that provides feedback and adjustments based on user profiles and behavior to teach, motivate, and engage end-users in achieving specific goals, such as energy reduction. Hence, gamification builds strategies to make engaging applications by triggering internal and external motivations in end-users. A smart home gathers and analyzes data from its sensors, then delivers analytics and predictions to end-users and service provides as well as strives to improve the management of its various subsystems through social products. In that regard, the multi-sensor system allows experts to know more about the needs of homes to propose actions that reduce energy consumption and improve the home and community quality of life by galvanizing individuals to read, analyze, and act upon their energy consumption through sensor profile patterns. Thus, this chapter discusses the use of an adaptive neural network fuzzy inference and a fuzzy logic decision system to evaluate the level of energy consumption in households and the type of environmental home.

J. I. Méndez · P. Ponce (✉) · A. Medina · A. Molina
School of Engineering and Sciences, Tecnológico de Monterrey, México City, Mexico
e-mail: A01165549@itesm.mx; pedro.ponce@tec.mx; A01331840@itesm.mx; armolina@tec.mx

A. Meier
Lawrence Berkeley National Laboratory, University of California, Berkeley, CA, USA
e-mail: akmeier@ucdavis.edu

T. Peffer
Institute for Energy and Environment, University of California, Berkeley, CA, USA
e-mail: tpeffer@berkeley.edu

T. McDaniel
Arizona State University, Mesa, AZ, USA
e-mail: troy.mcdaniel@asu.edu

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These decision systems give insights to propose an interactive and tailored HMI for each kind of home and community interaction. Finally, this chapter discusses improving the quality of life of people who are elderly using connected devices that transmit and receive information inside households or public spaces via an HMI.

Keywords Smart community · Smart home · Social products · Socially connected products · Multi-sensor system · ANFIS · Gamification · HMI

1 Introduction

This chapter introduces a multi-sensor system for use in a smart community environment composed of a set of smart homes, commercial buildings, public spaces, and transportation with boundaries based on the walking distance, located in the same geographical space. This multi-sensor system enables connectivity of sensors in a smart home toward understanding the neighborhoods' requirements, specifically, for promoting pro-environmental attitudes among neighbors to achieve a reduction in energy consumption and improve quality of life.

Figure 1 shows the proposed multi-sensor structure focused on decision fusion where the home behavior (local point of view) and the community behavior (global point of view) provide information into the system throughout the social products. The adaptive neural network fuzzy inference (ANFIS) analyzes and evaluates this information to propose actions to perform regarding energy, quality of life, and the

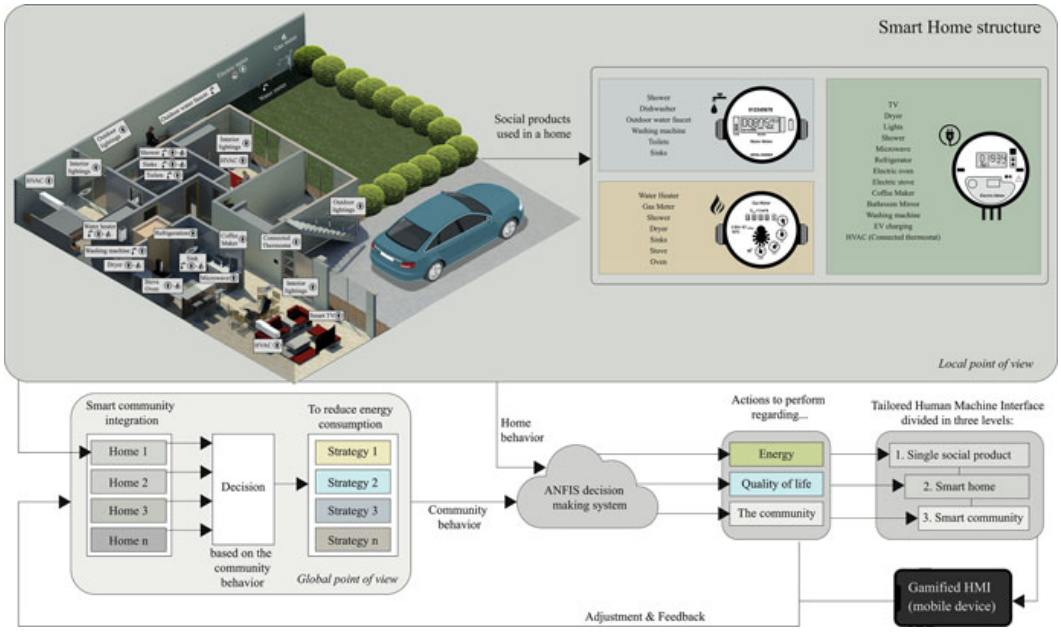


Fig. 1 General proposal for data fusion and HMI in smart homes and the smart community

community. Finally, a Human Machine Interface (HMI) uses a gamification strategy with a fuzzy logic decision system to run on a tailored interface in three levels:

1. A single social product, for instance, a connected thermostat,
2. The smart home, which is the set of social products within the home,
3. The smart community.

1.1 Smart Community

Although the concept of a smart community is nascent, it is still not yet well defined as there is no clear separation between a smart community and a smart city. This section considers that it is necessary to determine the single concept of a community first without considering its smartness. Thus, in [24], Łucka believes that a community should have these characteristics:

- Be self-sustaining and dense to enable residents short commutes by bicycle or walking rather than by automobile.
- Layout should support a normal walking distance, which is typically a radius of 0.25–0.5 miles.
- Be organized around public transportation.
- Promote social relationships by interconnected networks of streets and public spaces.
- Be safe by making strangers fell noticed and potentially unwelcomed if they plan to commit a crime. This safety is provided by promoting "eyes on the street" in the neighborhoods.
- Besides housing, there are places of work, leisure, and shopping near the community.

Thus, a community in terms of energy is composed of not only residential sectors, but also industrial, commercial, and transport sectors. Figure 2 depicts the total energy consumption by sector in the U.S. from January 2019 to February 2020 obtained from the database *Energy consumption estimates by sector* of the U.S. Energy Information Administration [11]. According to this information, residential buildings, commercial sectors, and transportation represent 21.69%, 18.22%, and 27.84%, respectively. Communities therefore belong to 67.75% of the total U.S energy consumption in the last year. An essential task for communities is to promote a reduction in energy consumption without being obtrusive or losing the quality of life by transitioning the community into a smart community. An essential task for smart communities is to promote pro-environmental attitudes.

Several authors have defined their concept of the Smart Community. Li et al. [21] describe it as a set of smart homes, amenities, and green areas where residents have social interaction and relationships with their neighborhoods. Homes are virtually connected in the same geographic region by powerline communication, wireless

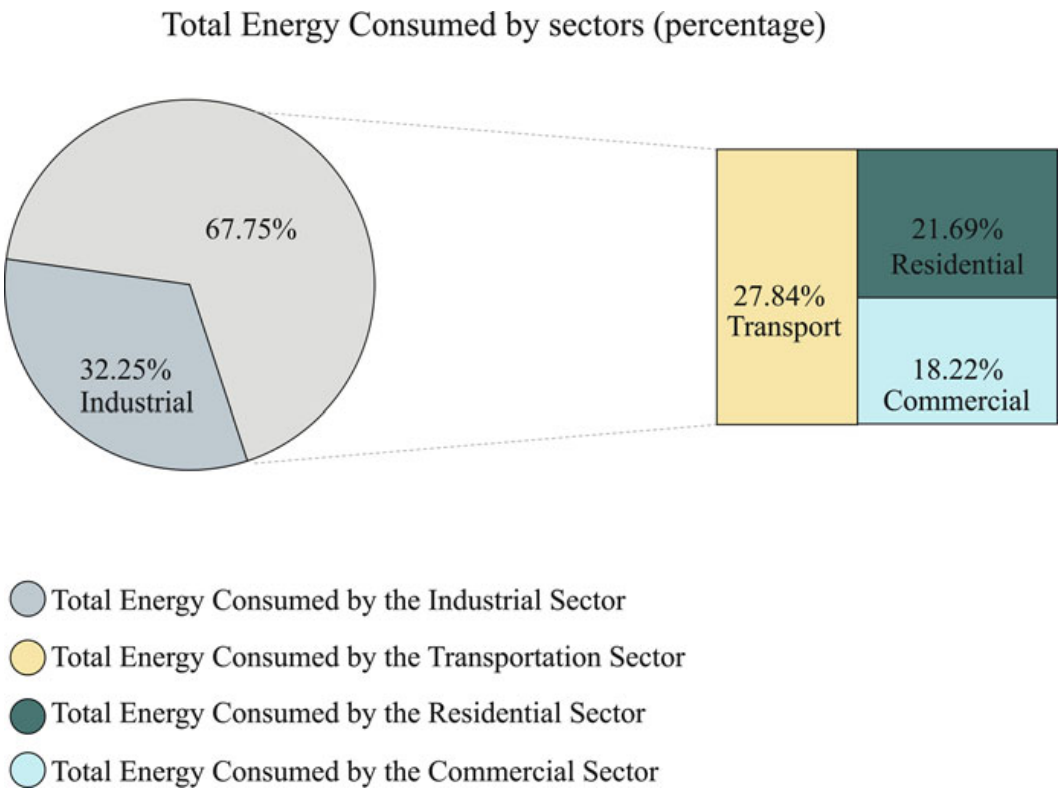


Fig. 2 Total energy consumed by industrial, transportation, residential and commercial sector in percentage from January 2019 to February 2020 [11]

communication, such as Bluetooth or Wi-Fi, phone line communication, and/or technologies that require dedicated wiring such as Ethernet.

Eltoweissy et al. [12], indicate that a smart community has four key characteristics:

- Sustainability: the community is self-sufficient regarding services offered and the resources needed to enable those services.
- Resilience: the community changes dynamically; for instance, the smart community can react in a precise and timely way in response to incipient emergencies.
- Empathy-driven proactive intelligence: the community can predict future needs using artificial intelligence algorithms within smart products.
- Emergent behavior: the community evolves based on current needs as profiled by smart products.

Wang [48] emphasizes that the smart community should use smart products, a management method, and a community philosophy featured with multinetwork integration. He mentions that there is a lack of standardization due to a miss in the unified local region. This author describes three development stages for a smart community:

- Initial stage: community uses smart products and provides management, e-commerce services, and health services within the smart community and the smart home.
- Development stage: A smart platform application reaches the community. This application gathers multiple mobile apps to enhance the community.
- Improvement stage: A standardized service system should be initiated for the smart community. This stage focuses on continuous improvement and development.

London [49], Oslo [52], and Copenhagen [16] have launched smart community initiatives where there is a continuous interaction between the citizen and the communities (government, agency, company, and institutions) and user-centered designs by encouraging the digital engagement of the populace. A key component for a smart community is the smart home. There is an interaction between the building, user, and the software and hardware technology within the smart home through smart household appliances, or social products. Ponce et al. [40] define a social product as a product that modifies the behavior of the end-user by observing, registering, and analyzing her or his consumption patterns. This product can adapt its characteristics online or offiline to improve its performance and acceptability. Thus, a smart product, or an intelligent household appliance, can be considered a social product for tracking and understanding users [8, 14, 29].

Social interaction plays a primary role in understanding users' patterns [30, 31]. A way to shape occupants' habits is by sending stimuli through gamification strategies [29–32, 39, 40]. Gamification, in this context, is defined as a process to improve services through gameful experiences to augment value creation for users [15].

We therefore define smart community as a creative community located in a physical region by a set of smart homes, commercial buildings, public spaces, and transportation with boundaries based on walking distance. A smart community uses social products to provide community public services, smart water management, and smart mobility management to promote social interaction. Communication uses a tailored HMI within a gamification structure that includes feedback and adjustments based on user profiles and behavior to teach, motivate, and engage end-users to perform specific tasks and achieve certain goals, as energy reduction (Fig. 3). For this chapter, the set of homes is used as a fundamental part of smart community integration.

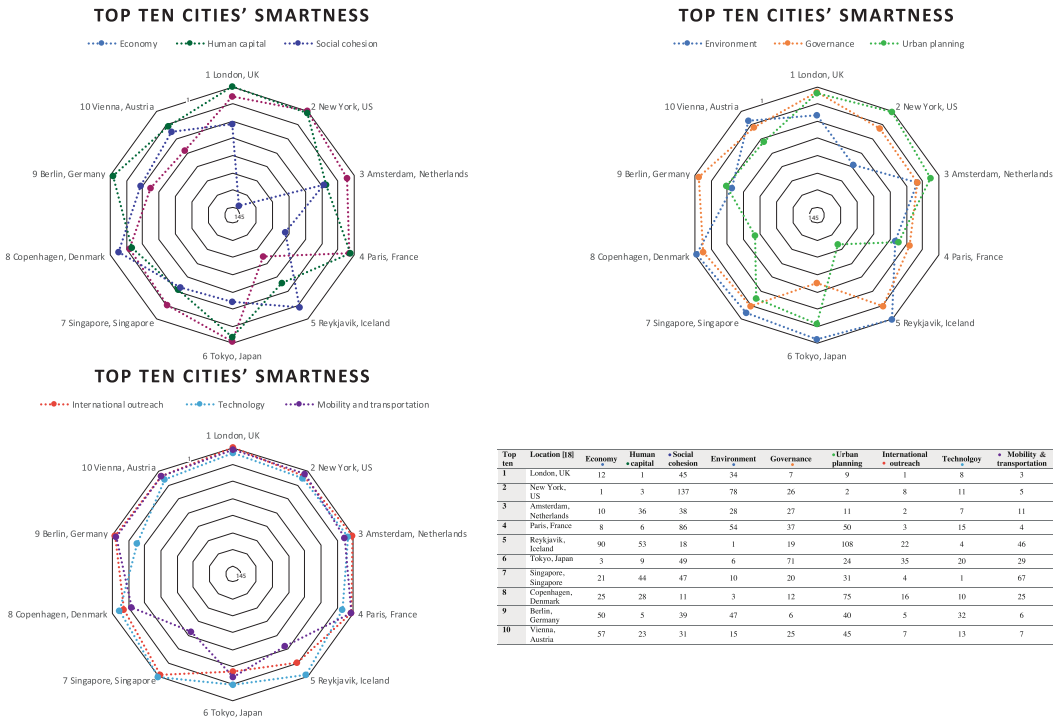
Currently, the *IESE Cities in Motion Index* [5] presented a report on 147 cities' smartness. Figure 4 shows the top 10 smart cities around the world based on nine dimensions described below. Note that each of the top cities has strengths and weakness based on these dimensions.

- Economy: this dimension measures 13 indicators that promote the economic development of a territory: productivity, the time required to start a business, ease of starting a business, headquarters, motivation to start early-stage entrepreneurial activity, estimated annual GDP growth, GDP in millions of dol-

Fig. 3 Smart community integration

lars, GDP per capita, mortgage, Glovo and Uber services, salary, and purchasing power.

- Human capital: this dimension measures 10 indicators to promote education accessibility at different levels, as well as promote arts and recreation activities.
- Social cohesion: this dimension measures 16 indicators to determine how happy citizens are and how much equality exists among city's population; also how other factors may alter these levels, such as crime, death, homicide, terrorism, and suicide rates.
- Environment: this dimension measures 11 indicators that take into account the amount of pollution a city produces, such as air pollution, garbage or emissions, as well as environmental performance, future climate estimations, and public water access.



Top ten	Location [18]	Economy	Human capital	Social cohesion	Environment	Governance	Urban planning	International outreach	Technolgoy	Mobility & transportation
1	London, UK	12	1	45	34	7	9	1	8	3
2	New York, US	1	3	137	78	26	2	8	11	5
3	Amsterdam, Netherlands	10	36	38	28	27	11	2	7	11
4	Paris, France	8	6	86	54	37	50	3	15	4
5	Reykjavik, Iceland	90	53	18	1	19	108	22	4	46
6	Tokyo, Japan	3	9	49	6	71	24	35	20	29
7	Singapore, Singapore	21	44	47	10	20	31	4	1	67
8	Copenhagen, Denmark	25	28	11	3	12	75	16	10	25
9	Berlin, Germany	50	5	39	47	6	40	5	32	6
10	Vienna, Austria	57	23	31	15	25	45	7	13	7

Fig. 4 Top 10 smart cities around the world and their place regarding each dimension [5]

- Governance: this dimension measures 12 indicators to determine how well prepared a city is to confront economic problems, incentivize investments, legal strength, international presence, democracy, corruption rankings, and how inclusive a government is to its citizens.
- Urban planning: this dimension measures five indicators that take into account the number of bicycle rental or sharing points, percentage of urban population with access to private sanitation services, number of people per household, percentage of high rise buildings, and number of completed buildings, including high rises.
- International outreach: this dimension measures six indicators to assess how prepared a city is to receive outside visitors; this means the number of passengers per airport, number of hotels and restaurants, and how attractive a city is, taking into account the number of international businesses implemented in the city, and the number of photos taken in city locations.
- Technology: this dimension measures 11 indicators to assess how proficient the population is with technology by use of the internet and social networks, also internet quality, and cell phone accessibility.
- Mobility and transportation: this dimension measures 10 indicators that determine the efficiency of the city by means of transportation, either private cars or public transportation, as well as bicycle accessibility.

1.2 Smart Home

A smart home gathers and analyzes data from its sensors, then delivers analytics and predictions to end-users and service provides as well as strives to improve the management of its various subsystems through social products [2]. The system controls home electronics and appliances such as HVAC, telecommunications, A/V, security, lighting, and sprinklers, and provides residents with analytics such as how much electricity they have consumed on specific appliances or system. Moreover, utilities are capability of reading meters from a distance [14]. Furthermore, a smart home interface with a gamification structure provides interactions that make users feel comfortable; for instance, in [29], a gamified smart home structure was proposed that uses social products to promote ecological-saving and money-saving activities to promote energy-saving behavior in end-users (Fig. 5).

Also, a smart home requires an Energy Management System between the home and the household products to track and monitor users' activities to generate profiles [6]. Artificial intelligence enables communication between homes by monitoring and enriching services to end-users, from entertainment, to security, to lighting and temperature access and optimization [44].

There are four categories of smart homes based on the types of services they offer [27]:

1. Assistive homes: this home assists occupants based on their daily actions, providing care for everyone from children to the elderly. These homes are mostly used for healthcare.
2. Detection and multimedia information gathering: this home collects photos and videos of the occupants.
3. Surveillance home: This home processes data that alert users of upcoming natural disasters or invasions of security.
4. Ecological home: this type of home promotes environmental sustainability by providing occupants with capabilities to manage energy supply versus demand.

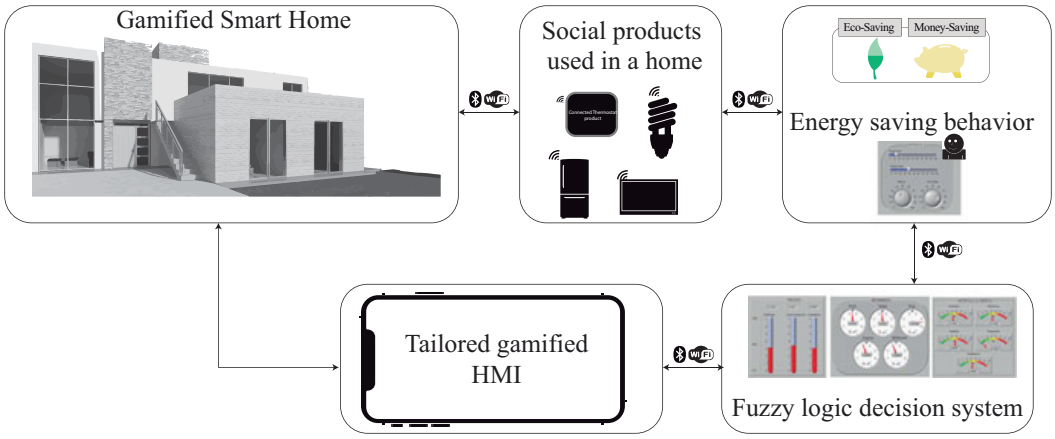


Fig. 5 Examples of a gamified smart home structure presented in [29]

Smart home services can be added to homes by transitioning from a traditional home to a smart home. Thus, smart homes have the potential to improve the quality of living for many families.

1.3 Socially Connected Products

In [34], the S^3 product development reference framework was proposed to implement sensing, smart, and sustainable products:

- *Sensing* is the ability of a system to detect events, obtain information, and measure changes utilizing sensors for observing physical and/or environmental conditions.
- *Smart* is the complementary consolidation of physical parts, components, and connectivity to make a product intelligent and accessible to interface with other gadgets.
- *Sustainable* incorporates social, environmental, and economic elements to produce balanced and optimized performance.

Social products can be promoted by knowing the types of behavior and usability problems in the use of connected devices and involving residential energy users in planning, implementing, and monitoring energy usage.

Figure 6 displays the social products of a smart home, divided by the type of utility consumption (water, gas, and electricity) and needs to be satisfied within the smart community environment to provide safety, transportation, and healthcare. Those elements working together provide a more in-depth insight into the improvement of energy behavior. For instance, if the homeowner knows the weather, the individual could determine the type of clothes to wear; hence, when he or she returns home, with the appropriate outfit, the individual would not need

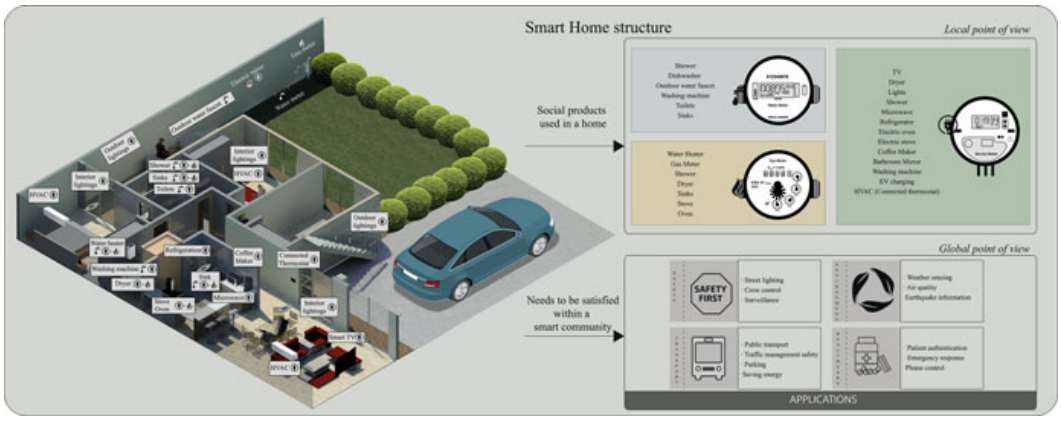


Fig. 6 Social products divided by the type of utility

to increase or decrease the indoor temperature. Thus, the individual could avoid consuming extra electricity as she or he is thermally comfortable.

Social products acceptability has the following characteristics [13]:

- Users know that when they buy a connected product, they can exploit advantages.
- Products fit with the user's current and changing lifestyles.
- Appliances and devices are quick and cheap to obtain.
- Products demonstrate reduced or eliminated physical demands in operation.
- Neither a high degree of background knowledge, nor routine interventions by professionals, is needed for installation, use, and/or maintenance.
- The usability of the product considers end-user skills; the product does not fail or act unpredictability.
- Products interpret user requirements.
- Products have privacy and security features, so users' information is secure and safe.

1.4 Gamification

Several authors have defined gamification:

- For Terrill [50], gamification takes game mechanics and uses them in web properties to increase engagement.
- For Huotari and Hamari [15], gamification is a process to improve services through gameful experiences to augment value creation for users.
- For Deterding et al. [9], it is the employment of game design and elements within non-gaming contexts.
- For Chou [7], it is the art of designing fun, engaging elements found traditionally in games, and employing these features in real-world activities.

For environmental purposes, gamification has the following addresses and considerations:

- Albertalli et al. [1], defined energy gamified applications as traditional software targeting an environmental goal using serious game features.
- An analysis of 25 gamified energy applications suggests three best practices for sustainable applications [43]:

  1. Sustainability should be rewarding and fun.
  2. Leverage positive peer pressure.
  3. Use gamification to galvanize useful action.

- In [3], a variety of game design elements were explored to enhance the engagement of end-users in energy saving and optimization applications. Examples of game design elements ranged from incentives such as discounts and prizes, to competitive aspects such as leaderboards and badges.

1.4.1 Energy Adapted Octalysis Framework

The Octalysis framework proposed by Chou [7] analyzes and builds strategies to make engaging applications. This framework considers extrinsic and intrinsic motivations, among other elements:

- Extrinsic motivation: motivation stems from the desire to attain something for outer recognition or monetary prizes. Encompasses a variety of factors from identification to external regulation.
- Intrinsic motivation: motivation stemming from a source that is rewarding or of value wholly on its own in the absence of a particular objective to accomplish. Following [19], this motivation considers three elements applicable for an energy purpose:
  - Autonomy through customization and independence including control of goals and tasks. Contributes to familiar routines, improved performance, reinforced success, responsibility, and internalized rewards.
  - Competence can relate to task complexity/understanding, execution challenge, and memory, and may be categorized as performance, achievement or engagement based.
  - Relatedness pertains to preferences, sharing, relationships and their interactions. Contributes to forging social relationships, disseminating achievements and milestones, sharing experiences, enhancing empathy, setting examples, exchanging suggestions and feedback, and validation.

In previous research [39], an adaptation for the Octalysis framework was proposed. This adaptation includes the game design elements offered in [3], the Hexad gamified user, the role player, and the end-user in the energy segment and the target group proposed in [4, 7, 26, 36, 38, 45]. Table 1 shows the extrinsic and intrinsic motivations regarding energy applications [3].

Table 1 Gamification elements for extrinsic and intrinsic motivations

Extrinsic motivation	Intrinsic motivation
Offers, coupons	Notifications
Bill discounts	Messages
Challenges	Tips
Levels	Energy community
Dashboard	Collaboration
Statistics	Control over peers
Degree of control	Social comparison
Points, badges, leaderboard	Competition

2 Multisystem: Data Fusion

When multiple sensors collect information, data fusion is often useful for making more robust inferences compared to single modalities, especially when a reference framework is utilized to map attribute or property values to quantitative measurements in a way that is both predictable and consistent. The utility of a multi-sensor data fusion framework is attractive for its functions of information processing, integration, communication, and compensation [18, 23, 47].

Multi-sensor data fusion is a concept based on animals' and humans' fundamental ability to integrate redundant and complementary information across modalities to improve the chance of survival. The primary functions are:

- Compensation: diagnose, calibrate, and adapt in response to environmental variations.
- Information processing: attention, event recognition, and decision-making.
- Communication: standard inference protocol for conveying perceptions and interpretations of sensor data to the external world.
- Integration: seamlessly coupled sensing, processing, and actuator subsystems.
- Decision-making: analyze and make predictions from sensed data to inform decisions.

While data fusion is not novel, we are now able to realize higher performance and more robost systems for data fusion through advancements in sensors, artificial intelligence, digital systems, information processing techniques, and embedded systems.

2.1 ANFIS: Adaptive Neuro-Fuzzy Inference Systems

In the presence of uncertain or vague information, conventional modeling techniques may face challenges. The IF-THEN linguistic rules of fuzzy systems employ human-like reasoning without complete or precise information. The issue arises in transferring human knowledge to that of fuzzy logic systems, and tuning these systems. Many approaches have been proposed, including of fusing fuzzy systems with artificial neural networks (ANNs), which can adapt and learn based on experience. One example is the adaptive neuro-fuzzy inference system (ANFIS) by Jang [18], which automatically produces fuzzy membership functions and IF-THEN rule bases. ANFIS uses adaptive networks, which are a superset of the feed-forward type ANNs [18, 37], in a directionally-connected topology of nodes. Learning takes place through rules that minimize an error criterion as connection parameters are updated. A common learning rule is gradient descent although Jang introduced a hybrid learning rule using least squares estimation. The ANFIS topology [18] is depicted in Fig. 7.

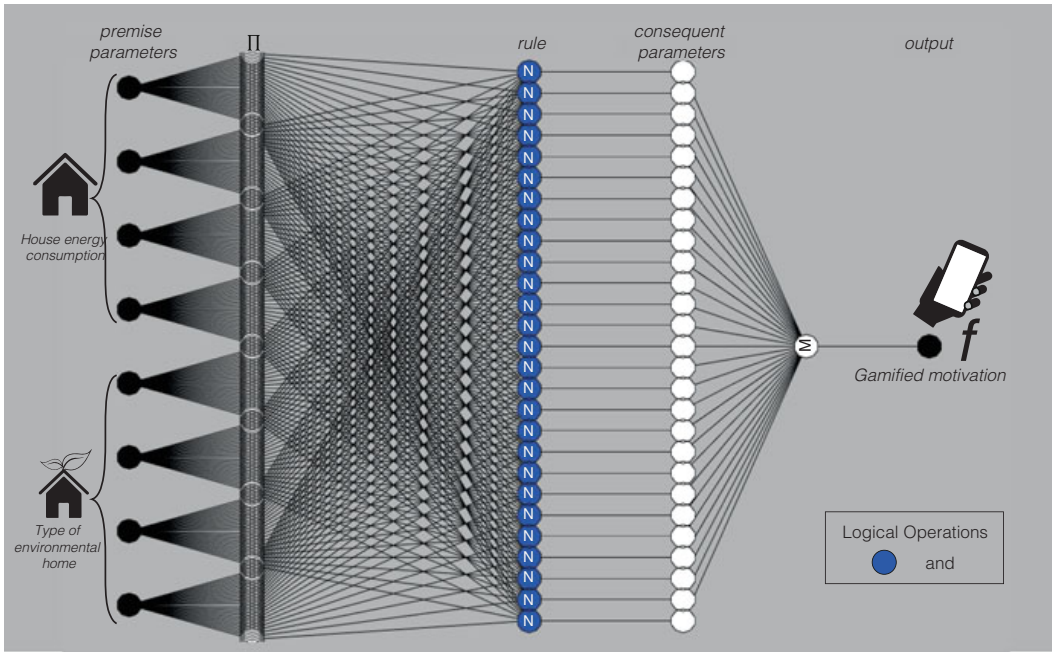


Fig. 7 ANFIS topology

2.2 *Topology Proposed: Detection of Gamified Motivation at Home for Saving Energy*

The proposed system is based on two elements: the level of household energy consumption and the type of ecological behavior.

2.3 *Input 1: Level of Energy Consumption*

The level of energy consumption was obtained from the 2015 Residential Energy Consumption Survey public database [10]. Table 2 depicts the code and characteristics selected to meet the following criteria:

- Single-family house detached from any other home.
- No basement in the housing unit.
- No attic in the housing unit.
- One story.
- Owned by someone in the household.
- 10–15 windows in heated areas.
- Household is responsible for paying incurred electricity costs.
- Members of household are home most weekdays.
- Square footage ranges from 1100 sq. ft. to 1800 sq. ft.
- Located in the Bay Area (California).

Table 2 Code selected from the Residential Energy Consumption Survey public database [10]

CODE	Description	Information
TYPEHUQ	Type of housing unit	2 – single-family house detached from any other house
CELLAR	Basement in the housing unit	0 – no
ATTIC	Attic in the housing unit	0 – no
STORIES	Number of stories in a single-family home	10 – one story
KOWNRENT	A housing unit is owned, rented, or occupied without payment of rent	1 – owned by someone in the household
WINDOWS	Number of windows in heated areas	41 – 10 to 15
ELPAY	Who pays the electricity used in the home?	1 – household is responsible for paying for all electricity used in this home
ATHOME	How many weekdays is someone at home most or all of the day?	5 – 5 days
TOTSQFT_EN	Total square footage (includes heated/cooled garages, all basements, and finished/heated/cooled attics). Used for EIA data tables	The range used between 1100 sq. ft. and 1800 sq. ft.
CLIMATE_REGION_PUB	Building America Climate Region (collapsed for public file)	5 – marine
IECC_CLIMATE_PUB	International Energy Conservation Code (IECC) climate zone (collapsed for public file)	3C IECCC climate zone 3C (California, Bay Area)

Once the kWh energy consumption is obtained during the year, we may estimate the 30-day energy consumption from each type of home to profile the households using (1),

$$\begin{aligned} &Monthly\ house\ energy\ consumption\left(\frac{kWh}{month}\right) \\ &= \frac{kWh}{year} \bullet \frac{year}{8760\ hours} \bullet \frac{24\ hours}{1\ day} \bullet \frac{30\ days}{1\ month} \end{aligned} \tag{1}$$

The house is then profiled, and a 30-day table is generated with random values where the limit value is the monthly house energy consumption. As the database does not present information about months, this calculation has the premise that the total monthly hours should be at least under the monthly average of the household

energy consumption reference. Next, from the 30-day table, the following data is obtained:

- The complete set of types of homes.
- The minimum value of the set.
- The maximum value of the set.
- Mean.
- Standard Deviation.
- House low consumption: Mean – Standard Deviation.
- House high consumption: Mean + Standard Deviation.

Finally, these values are normalized using (2),

$$X1 = \frac{X - (\mathrm{Min}_{set} - 5)}{(\mathrm{Max}_{set} + 5) - (\mathrm{Min}_{set} - 5)} \tag{2}$$

where,

$X1$ = normalized value.
X = value to be normalized.
Min_{set} = Minimum value of the set.
Max_{set} = Maximum value of the set.
$+/-5$ = This value is used to avoid having a maximum normalized number of 1 and a minimum normalized number of 0.

2.4 Input 2: Type of Environmental Home

The type of pro-environmental user is related to the level of energy consumption: *It is assumed that based on the criteria selected from* Table 2*, there is similar home behavior. Hence, there is a lower limit for a home that consumes less energy than the other houses, an average energy consumption, and an upper limit for a home that consumes more power than the other houses.*

A pro-environmental home can be designed a lower limit home as this type of house demonstrates awareness for energy consumption; an average environmental home can be designated for average energy consumption; and a disengaged-environmental home can be designated an upper limit energy consumer, i.e., a lack of awareness for energy consumption. Thus, each type of home is associated with a value from 0 to 1:

- Pro-environmental home: 0.2
- Average environmental home: 0.4
- Disengaged-environmental home: 0.6

A new database was created and associated with the type of pro-environmental home by considering these premises (3),

$$Type\ of\ home \begin{cases} \dfrac{x}{0.20} & if\ x2 > x \quad \rightarrow pro-environmental\ home \\ \dfrac{x}{0.60} & if\ x3 < x \quad \rightarrow disengaged-environmental\ home \\ \dfrac{x}{0.40} & if\ x2 > x < x3. \quad \rightarrow Average\ environmental\ home \end{cases} \tag{3}$$

Finally, these values are normalized using (2).

2.5 *Output: Gamified Motivation (Local Point of View)*

Gamified motivation considers intrinsic and/or extrinsic motivators: *The disengaged-environmental home and the home that consumes more kWh requires extrinsic motivation as they are moved by outer recognition and external rewards. The pro-environmental home and the home that consumes less kWh can be related to intrinsic motivation as the house is using less kWh than others in similar conditions due to this activity being rewarding on its own. On the other hand, the average home in either environmental type and kWh consumed use both motivations as this type of home may be motivated by external recognition or by autonomy, competence, and relatedness elements.*

Thus, a Sugeno Fuzzy Inference System is employed where the input variables are Input 1: Level of energy consumption and Input 2: Type of environmental home, and the output values are the gamified motivators (see Fig. 8).

2.5.1 Community Gamified motivation's Detection (Global Point of View)

Obtaining the output values for each type of home, we may then calculate the mean value of the four output values from each household to get the average. Then, these values are used to create the ANFIS system using backpropagation as an optimization method and subclustering to generate the Fuzzy Inference System.

3 Proposal

From a representational sample of 118,208,250 households around the country, 55,727 houses represented in four groups met the criteria established in Table 2. Table 3 depicts the four types of homes with their characteristics and their household appliances, according to [10]. The ranges of energy consumption are from a house the consumed 4159 kWh to a house that consumed 10,674 kWh. Surprisingly, the second biggest home (home type 3) consumed the most energy during the year,

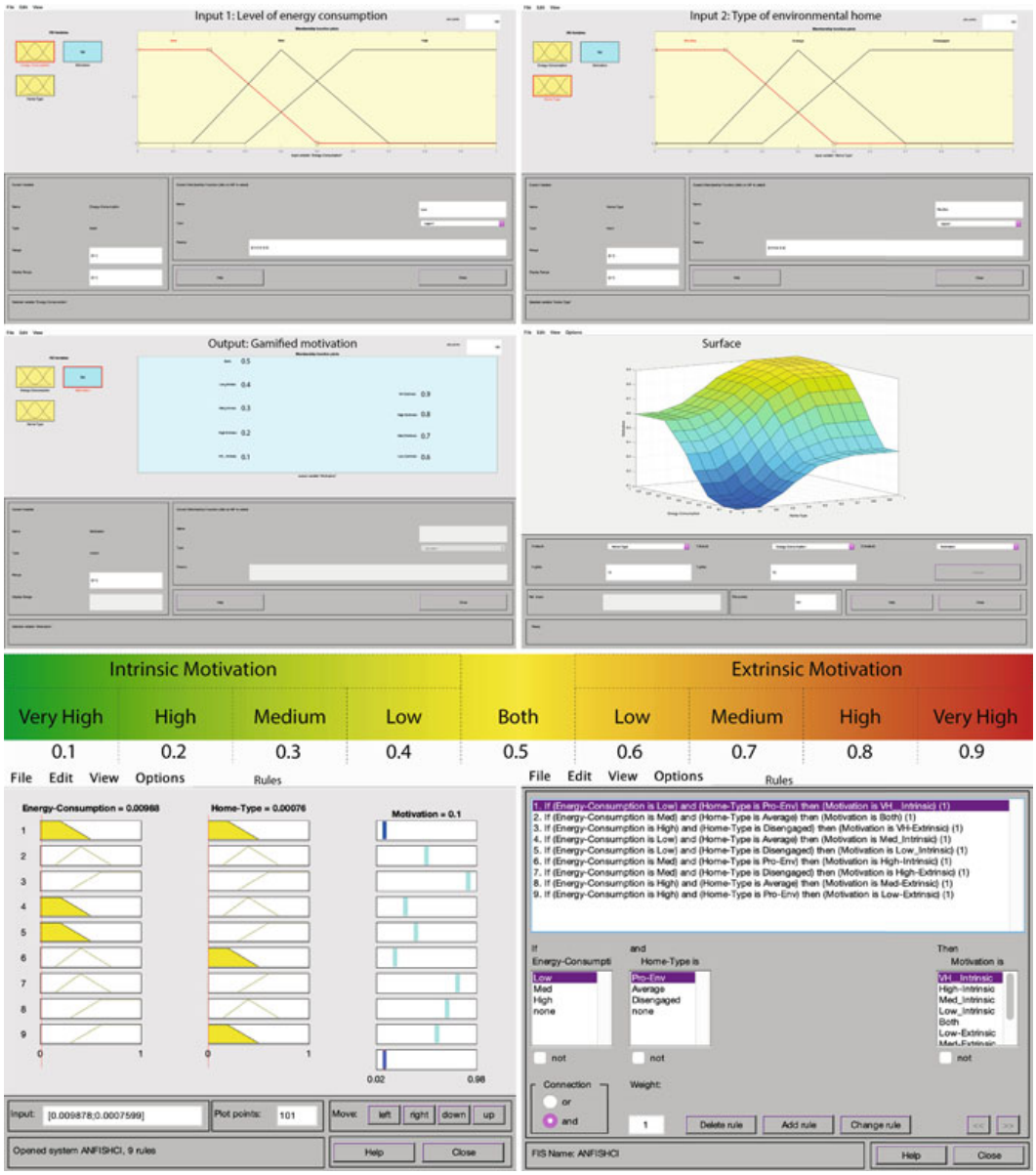


Fig. 8 Sugeno fuzzy logic inference system

likely due to the number of refrigerators (three), and that this home, when compared to home type 4, does not have a smart meter.

3.1 Input 1: Level of Energy Consumption

Based on (1), Table 4 shows the daily kWh consumption per home, and Table 5 depicts the estimated 30-day kWh consumption per household and their normalized values.

Table 3 Four types of households

CODE	Description	Home type 1	Home type 2	Home type 3	Home type 4
DOEID	Unique identifier for each respondent	11,106	12,192	12,834	15,114
NWEIGHT	Final simple weight	17,076	13,385	11,678	13,588
TOTSQFT_EN	Total square footage	1125 (104 m^2)	1550 (144 m^2)	1652 (153 m^2)	1793 (166 m^2)
KWH	Total site electricity usage per household over a year	4159.13 kWh	8920.06 kWh	10,674.33 kWh	6371.80 kWh
HHAGE	Age of the survey responder	36	76	50	79
NHSLDMEM	Number of household members	3	2	4	6
NUMADULT 18 years or older	A housing unit is owned, rented, or occupied without payment of rent	2	2	4	4
NUMCHILD 0–17 years old	Number of windows in heated areas	1	0	0	2
SMARTMETER 0 No 1 Yes	Does your home have a "smart meter"?	1	1	0	1
NUMFRIG	Number of refrigerators used	1	2	3	1
MICRO	How many microwaves are in your home?	1	1	2	1
TOAST 0 No 1 Yes	Is the toaster used at least once a week in your home?	1	1	0	1
COFFEE 0 No 1 Yes	Coffee maker used	1	1	0	1
DISHWASH 0 No 1 Yes	Dishwasher used	1	1	1	0
CWASHER 0 No 1 Yes	Clothes washer used in home	1	1	1	1
DRYER 0 No 1 Yes	Clothes dryer used in home	1	1	1	1
TVCOLOR	Number of televisions used	5	3	1	3

Table 4 Daily energy consumption per house

Home	kWh/year	Year/8760 h	24 h/day
Home type 1	4159.13	0.47	11.39
Home type 2	8920.06	1.02	24.44
Home type 3	10,674.33	1.22	29.24
Home type 4	6371.80	0.73	17.46
Average	7531.33	0.86	20.63

Table 5 Estimated monthly house energy consumption per home

Min set	10.29	Deviation			6.844			
Max set	29.75	**House low consumption <**			13.46			
Average	20.31	**House high consumption >**			27.15			
Monthly house energy consumption per home					**Normalized values**			
Day	**Home 1**	**Home 2**	**Home 3**	**Home 4**	**Home 1**	**Home 2**	**Home 3**	**Home 4**
1	10.93	23.3	29.75	16.88	0.21	0.68	0.92	0.44
2	10.29	24.68	29.36	16.13	0.19	0.73	0.91	0.41
3	10.87	24.35	29.03	17.38	0.21	0.72	0.90	0.46
4	10.87	23.93	28.4	17.17	0.21	0.70	0.87	0.45
5	10.33	24.29	29.08	16.26	0.19	0.72	0.90	0.41
6	11.7	23.5	29.29	17.71	0.24	0.69	0.91	0.47
7	11.1	24.32	28.57	17.03	0.22	0.72	0.88	0.44
8	11.56	23.42	29.67	16.91	0.24	0.69	0.92	0.44
9	11.41	23.58	28.89	17.83	0.23	0.69	0.89	0.47
10	11.61	23.94	28.18	17.38	0.24	0.70	0.87	0.46
11	10.91	23.87	258	16.92	0.21	0.70	0.92	0.44
12	11.2	23.94	29.49	17.03	0.22	0.70	0.91	0.44
13	10.67	23.15	29.33	16.66	0.20	0.67	0.91	0.43
14	11.27	23.63	29	17.19	0.23	0.69	0.90	0.45
15	11.67	24	29.32	17.24	0.24	0.71	0.91	0.45
16	11.57	24.23	28.82	16.6	0.24	0.72	0.89	0.43
17	11.27	24.17	28.94	16.56	0.23	0.71	0.89	0.43
18	11.34	23.52	29.65	17.04	0.23	0.69	0.92	0.44
19	10.99	23.79	28.83	17.06	0.22	0.70	0.89	0.44
20	10.37	23.46	29.31	17.24	0.19	0.69	0.91	0.45
21	11.63	24.24	28.75	17.31	0.24	0.72	0.89	0.45
22	11.52	23.88	29.6	16.78	0.24	0.70	0.92	0.43
23	11.44	24.43	29.46	17.27	0.23	0.72	0.91	0.45
24	11.36	24.29	28.41	16.97	0.23	0.72	0.87	0.44
25	11.14	23.94	29.4	16.42	0.22	0.70	0.91	0.42
26	10.95	24.05	29.01	17.39	0.21	0.71	0.90	0.46
27	10.87	24.25	28.96	17.24	0.21	0.72	0.89	0.45
28	11.66	24.38	28.99	16.31	0.24	0.72	0.90	0.42
29	11.21	24.86	28.48	17.49	0.22	0.74	0.88	0.46
30	10.76	23.87	28.95	17.15	0.21	0.70	0.89	0.45

Table 6 Type of environmental home

Monthly type of environmental home					Normalized values			
Day	Home 1	Home 2	Home 3	Home 4	Home 1	Home 2	Home 3	Home 4
1	2.19	9.32	17.85	6.75	0.22	0.54	0.91	0.43
2	2.06	9.87	17.62	6.45	0.22	0.56	0.90	0.41
3	2.17	9.74	17.42	6.95	0.22	0.56	0.89	0.43
4	2.17	9.57	17.04	6.87	0.22	0.55	0.88	0.43
5	2.07	9.72	17.45	6.50	0.22	0.56	0.89	0.41
6	2.34	9.40	17.57	7.08	0.23	0.54	0.90	0.44
7	2.22	9.73	17.14	6.81	0.23	0.56	0.88	0.43
8	2.31	9.37	17.80	6.76	0.23	0.54	0.91	0.43
9	2.28	9.43	17.33	7.13	0.23	0.54	0.89	0.44
10	2.32	9.58	16.91	6.95	0.23	0.55	0.87	0.43
11	2.18	9.55	17.75	6.77	0.22	0.55	0.91	0.43
12	2.24	9.58	17.69	6.81	0.23	0.55	0.91	0.43
13	2.13	9.26	17.60	6.66	0.22	0.54	0.90	0.42
14	2.25	9.45	17.40	6.88	0.23	0.54	0.89	0.43
15	2.33	9.60	17.59	6.90	0.23	0.55	0.90	0.43
16	2.31	9.69	17.29	6.64	0.23	0.55	0.89	0.42
17	2.25	9.67	17.36	6.62	0.23	0.55	0.89	0.42
18	2.27	9.41	17.79	6.82	0.23	0.54	0.91	0.43
19	2.20	9.52	17.30	6.82	0.23	0.55	0.89	0.43
20	2.07	9.38	17.59	6.90	0.22	0.54	0.90	0.43
21	2.33	9.70	17.25	6.92	0.23	0.55	0.89	0.43
22	2.30	9.55	17.76	6.71	0.23	0.55	0.91	0.42
23	2.29	9.77	17.68	6.91	0.23	0.56	0.90	0.43
24	2.27	9.72	17.05	6.79	0.23	0.56	0.88	0.43
25	2.23	9.58	17.64	6.57	0.23	0.55	0.90	0.42
26	2.19	9.62	17.41	6.96	0.23	0.55	0.89	0.43
27	2.17	9.70	17.38	6.90	0.22	0.55	0.89	0.43
28	2.33	9.75	17.39	6.52	0.23	0.56	0.89	0.42
29	2.24	9.94	17.09	7.00	0.23	0.57	0.88	0.44
30	2.15	9.55	17.37	6.86	0.22	0.55	0.89	0.43

3.2 Input 2: Type of Environmental Home

Table 6 shows the type of environmental home values per home and their normalized values.

3.3 Output: Gamified Motivation (Local Point of View)

Table 7 displays the type of gamified motivation values per home.

Table 7 The gamified motivation for each home

Gamified motivation by home					
Day	Home 1	Home 2	Home 3	Home 4	Mean
1	0.17	0.81	0.90	0.57	0.61
2	0.16	0.83	0.90	0.52	0.60
3	0.17	0.83	0.90	0.59	0.62
4	0.17	0.83	0.90	0.55	0.61
5	0.16	0.83	0.90	0.52	0.60
6	0.19	0.82	0.90	0.61	0.63
7	0.18	0.83	0.90	0.57	0.62
8	0.19	0.82	0.90	0.57	0.62
9	0.19	0.82	0.90	0.61	0.63
10	0.19	0.83	0.90	0.59	0.63
11	0.17	0.83	0.90	0.57	0.62
12	0.18	0.83	0.90	0.57	0.62
13	0.17	0.81	0.90	0.55	0.61
14	0.19	0.82	0.90	0.58	0.62
15	0.19	0.83	0.90	0.55	0.62
16	0.19	0.83	0.90	0.55	0.62
17	0.19	0.83	0.90	0.55	0.61
18	0.19	0.82	0.90	0.57	0.62
19	0.18	0.83	0.90	0.57	0.62
20	0.16	0.82	0.90	0.57	0.61
21	0.19	0.83	0.90	0.55	0.62
22	0.19	0.83	0.90	0.55	0.62
23	0.19	0.83	0.90	0.58	0.62
24	0.19	0.83	0.90	0.57	0.62
25	0.18	0.83	0.90	0.54	0.61
26	0.18	0.83	0.90	0.59	0.62
27	0.17	0.83	0.90	0.55	0.61
28	0.19	0.83	0.90	0.54	0.61
29	0.18	0.84	0.90	0.60	0.63
30	0.17	0.83	0.90	0.55	0.61

Figure 9 presents the ANFIS system for the global community point of view. Figure 9a shows the relationship between each home and its interaction with the other dwellings regarding its level of energy consumption and type of environmental home. Figure 9b displays the ANFIS system structure, the rules, and the surfaces of the community interaction.

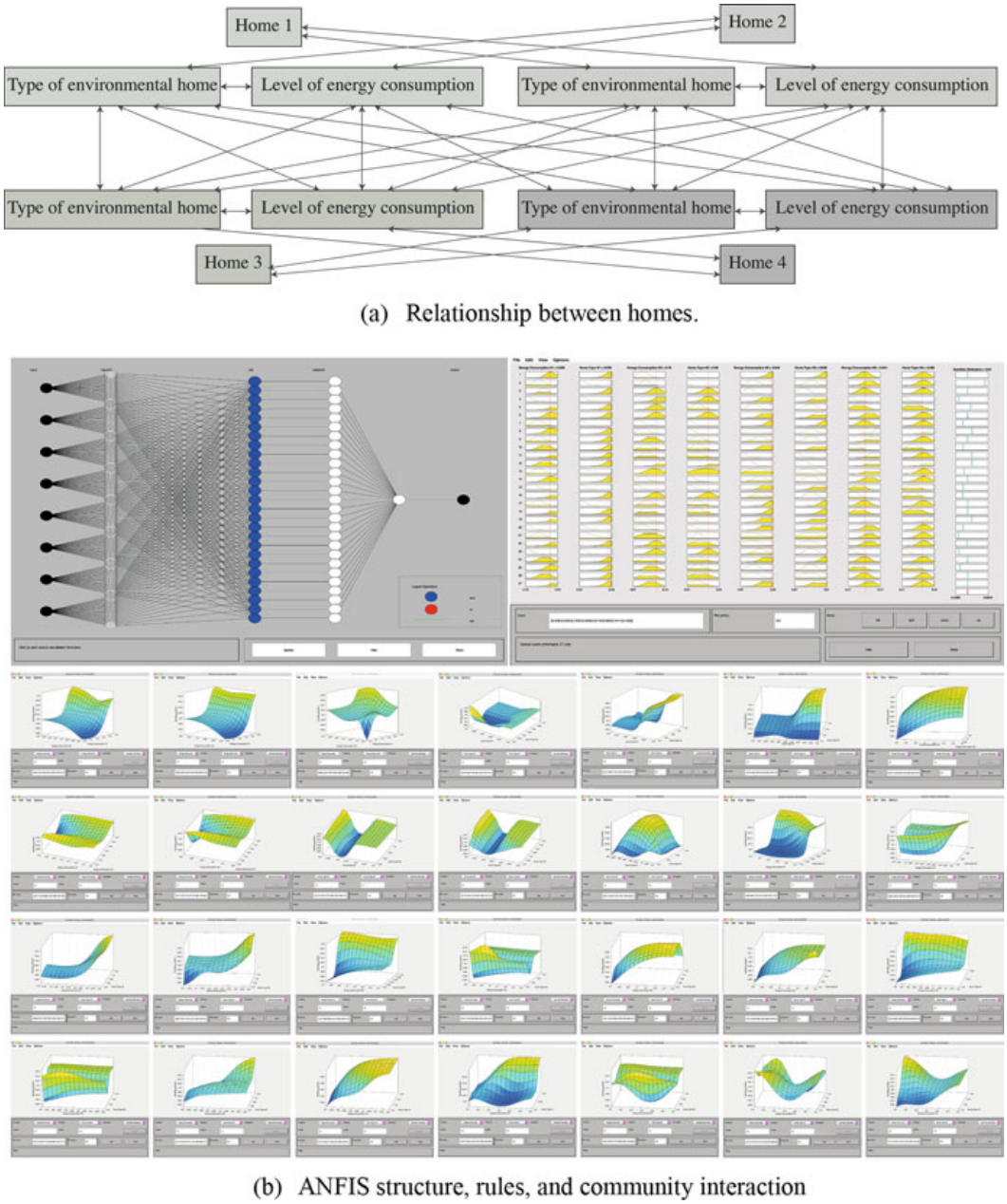


Fig. 9 ANFIS system for the global point of view (set of homes). (**a**) Relationship between homes. (**b**) ANFIS structure, rules, and community interaction

4 Results

From the local point of view, a correlation between the input and output can be seen. From the global point of view, a relationship between the data and the mean output is shown. Figure 10 displays these correlations; for the local location of view, home 1, 2 and 4 have a strong relationship; home 3 shows no correlation due to output values of 0.9, representing a constant value. However, either the fuzzy system or the ANFIS

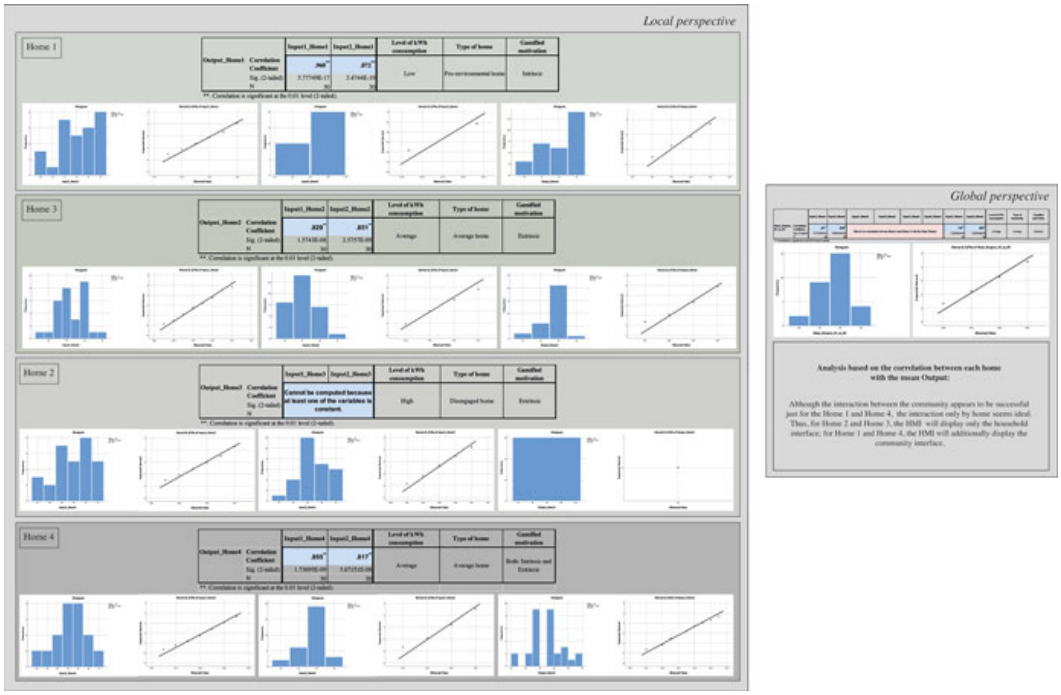


Fig. 10 Correlations between input and output for each home (local point of view) and the community (global point of view)

system demonstrates that home 3 is the home that consumes more electricity than the other houses and is cataloged as a disengaged home. This home should display in the interface extrinsic gamified motivation.

The global point of view presents a strong correlation between home 1 and 4, and the mean output values because home 2 and 3, in a local point of view, require high to very high extrinsic gamified motivation. Therefore, both houses need extrinsic motivation to interact with the community and promote energy reduction; the ANFIS system depicts this interaction between each pair of homes.

Thereby, Figure 11 shows a radar map of the level of energy consumption, type of home, and gamified motivation:

- Home 1: Energy consumption = Low; Type of home = Pro-environmental home; and Motivation: Intrinsic.
- Home 2: Energy consumption = Average; Type of home = Disengaged-environmental home; and Motivation: Extrinsic.
- Home 3: Energy consumption = High; Type of home = Disengaged-environmental home; and Motivation: Extrinsic.
- Home 4: Energy consumption = Average; Type of home = Average home; and Motivation: Intrinsic and Extrinsic (Both).

Thus, considering the gamification elements regarding energy applications and the type of motivation:

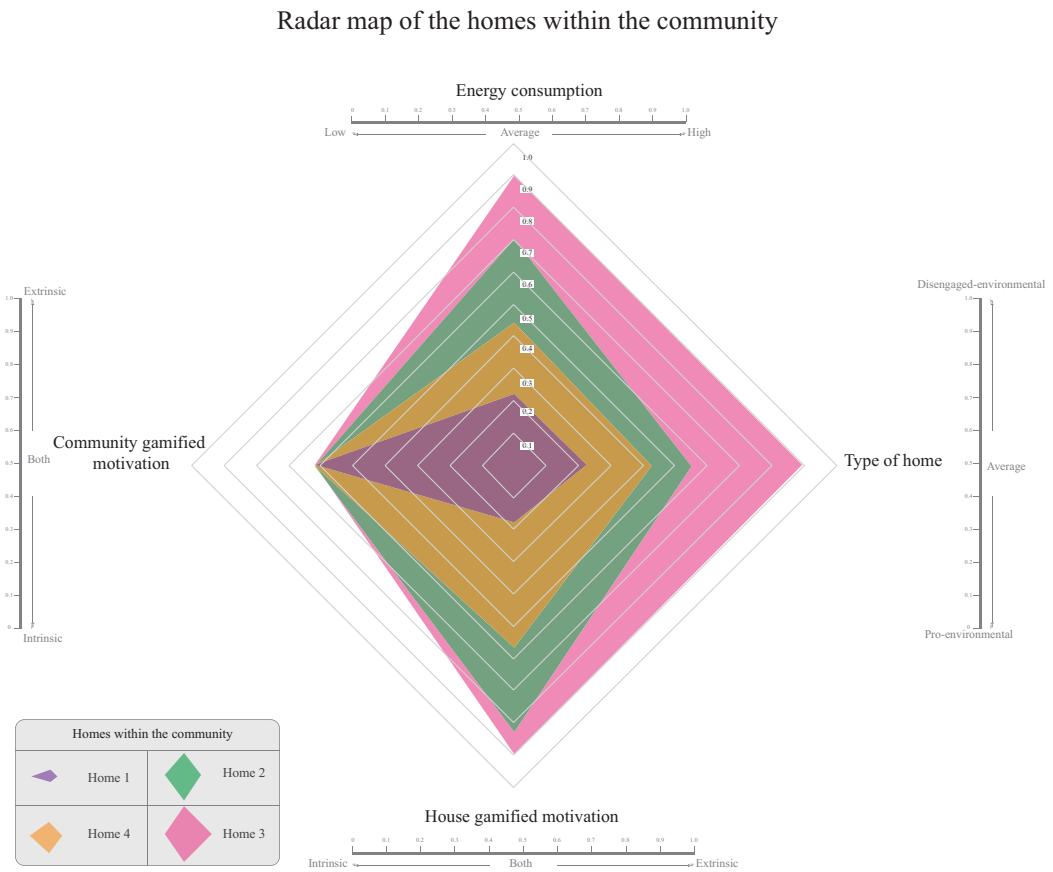
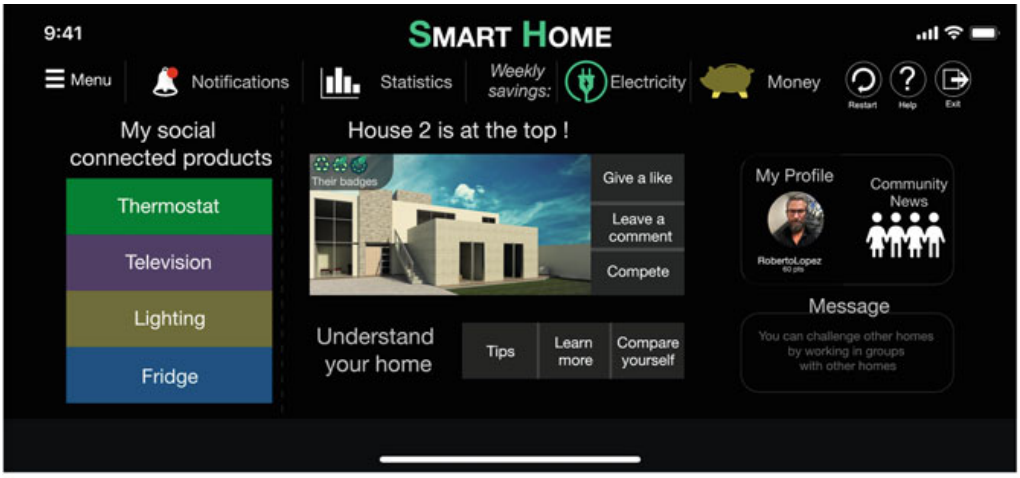


Fig. 11 Level of energy consumption, type of home, and gamified motivation for each home

- Intrinsic motivation: energy community, collaboration, control over peers, social comparison, competition; additional elements from the Octalysis framework are mentorship, community progress.
- Extrinsic motivation: offers, coupons, bill discounts, challenges, levels, dashboards, statistics, degree of control, additional elements to consider are points, badges, progress bar, and leaderboard.
- Therefore, an application with both motivation types should consider gamification elements from the extrinsic and intrinsic motivation.

Figure 12 displays the type of HMI for all home types. Figure 12a is the interface for home 1; this home is considered a pro-environmental home with less consumption. This interface emphasizes the community side by adding the community news, ability to comments and discuss, and compete to reduce energy consumption. Figure 12b is for house 3, the disengaged- environmental home, and the home that consumes more energy. This interface is focused on showing the rewards elements: coupons, prizes and bill discounts; although extrinsic motivation is not interested in challenges, it is included to subtly promote social interaction. HMI changes weekly savings to weekly expenses as a method to push the user to reduce consumption if they are visualizing a loss instead of a win. Figure 12c shows



(a) Human-Machine Interface for Home 1.

(b) Human-Machine Interface for Home 3.

(c) Human-Machine Interface for Home 2 and Home 4.

Fig. 12 Human machine interfaces (HMIs) for each type of home from a local point of view. (**a**) Human-machine interface for home 1. (**b**) Human-machine interface for home 3. (**c**) Human-machine interface for home 2 and home 4

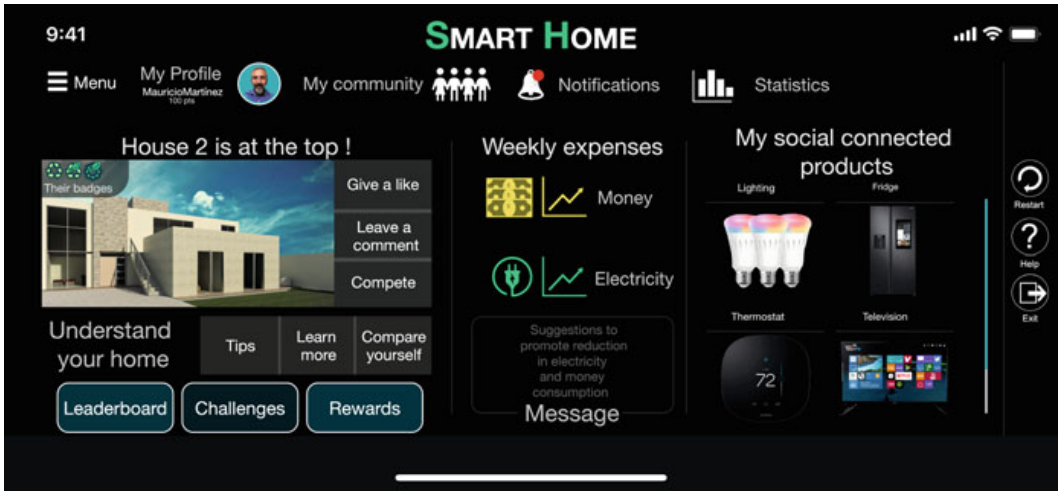


Fig. 13 Human-machine interface for the community from a global point of view

the interface for home 2 and 4, the average home, as this type of home can be motivated either by extrinsic or intrinsic triggers; this first iteration displays both motivational insights to track which of these elements interest the end-user. Finally, Fig. 13 shows the HMI for Home 1 and Home 4 at a global point of view, in smart community integration. Home 2 and Home 3 do not have a tailored global interface. According to the correlation presented from Fig. 10, they may not be interested in interacting with other homes, which is also strongly related to extrinsic motivation.

5 HMI to Improve the Quality of Life of Older People Using the Proposed Structure

Householders from Home type 2 and Home type 4 represent a type of elderly occupant. People who are older can be viewed as individuals who have a wealth of experience and knowledge, along with desires and interests, but also losses and limitations [42]. The aging process consists of biological changes including sensory, physical, and cognitive deterioration as well as social changes, e.g., social isolation and/or loss of loved ones, and potentially psychosocial variations to confidence, purpose, or value [20, 28]. Table 8 depicts the percentage of the elderly population that lives alone in Mexico, the United States, and around the world, and the 10 most common causes of death in each country and worldwide. Understanding the most common causes of death in each country, a tailored HMI can tackle specific needs [17, 41, 51].

Losing autonomy is a challenge for many as they age, often resulting in changes to living situations and environments. Social inclusion aims to provide a channel for social participation and engagement via local services, relationships, civic activities, and financial resources [46]. It is well known that healthy social relationships, and

Table 8 Percentage of older people that live alone and common diseases

Country	Mexico	United States	World
Live alone (% in 2018)	11% [17]	27% [51]	16% [51]
Most common diseases in 2017 [41]	Cardiovascular	Cancer	Cardiovascular
	Cancer	Cardiovascular	Cancer
	Kidney	Digestive	Respiratory
	Digestive	Respiratory	Digestive
	Liver	Liver	Liver
	Respiratory	Drug disorder	Tuberculosis
	Homicide	Kidney	Lower respiratory infection
	Lower respiratory infection	Lower respiratory infection	Kidney
	Road accidents	Suicide	Road accidents
	Alcohol disorder	Road accidents	Diarrheal

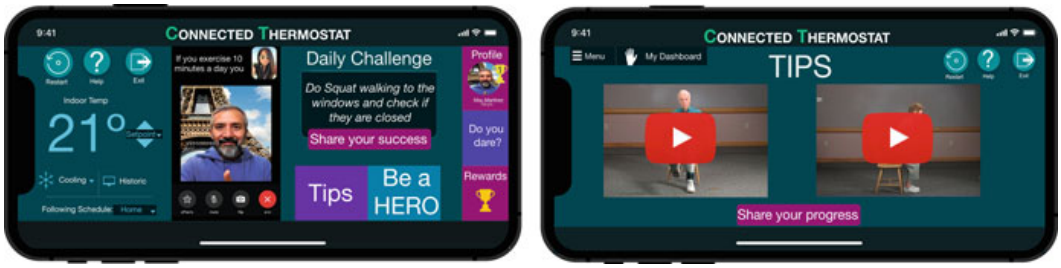
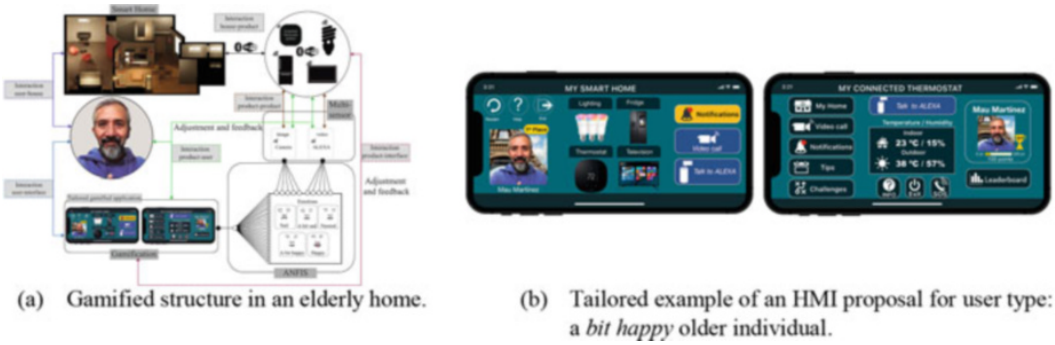


Fig. 14 Tailored HMI presented in [30] for an elderly user. This interface is designed to promote social interaction and physical activity seen at a level 1 social connected product of the local point of view

feelings of belonging and connectedness, reduce stress and promote health and well-being. Nowadays, many older adults use technology within their social context, but psychosocial aspects, such as negative or positive evaluation and opinions of technological solutions, influence use. Gamification is a useful technique for enriching enjoyment, encouraging healthcare, and promoting social participation among the elderly [25]. As rapid advancements in technology and medicine increase our life spans, there is a pronounced and timely need to design novel personalized solutions for older adults that enhance healthcare, cultivate independence, and facilitate social inclusion.

Previous research focused on the elderly using gamified interfaces include the following:

- In [30], a novel tailored gamified HMI is proposed for helping older people (Fig. 14). This interface considers the personality trait of the end-user to choose gamificiation elements for physical activity guidance.



(a) Gamified structure in an elderly home.

(b) Tailored example of an HMI proposal for user type: a *bit happy* older individual.

Fig. 15 Gamified structure and tailored HMI for end-users from a local point of view [31]. (**a**) Gamified structure in an elderly home. (**b**) Tailored example of an HMI proposal for user type: a *bit happy* older individual

- In [31], the inclusion of Alexa and cameras is proposed to track end-users to monitor daily mood and status toward enriching quality of life by encouraging physical activity and social participation. Physical characteristics are identified through the use of the smart home's multi-sensor system. Algorithms for face and voice detection run on the ANFIS system to select and recommend personalized gamification elements that operate on user type-specific HMIs. Figure 15a displays the gamified structure within the local point of view in a home, where Alexa and a camera track the user's mood, and Fig. 15b displays the tailored HMI.

Both proposals aim to change how we use products such that we may leverage household appliances to increase social engagement and participation. Using multi-sensor systems and data fusion techniques, we may leverage sensors and smart household appliances to detect, analyze, and predict end-user behavior, patterns, trends, and propose personalized applications that align well with users.

A limitation of the proposed approach is that individuals who are older as well as their caregivers and family members must adopt and accept automated monitoring in the house. Further, the type of mobile device available to the end-user may be limited or noncompatible due to socioeconomic levels. It is also required that end-users use voice assistants, such as Alexa, as an initial channel of interaction. Another possible limitation is face detection and emotion recognition. Emotions are complex and multilayered, and therefore susceptible to misclassification in certain circumstances, especially in the wild and in situations of limited training data. But technology is becoming more ubiquitous and machine learning models are evolving and developing robustness as data collection efforts ramp up.

With this local perspective and by tackling end-user needs, it is feasible to interact with the community through continuous feedback where end-users needs are satisfied, and the business sector is either in the community or the city. Supportive and fundamental technologies can improve the satisfaction of the individual, community, and city needs. Table 9 shows the characteristics of supportive

Table 9 Supportive and fundamental technologies and their interaction at smart homes, smart community, and smart city

Supportive technologies	Customer journey, 3D printing, energy technology, gamification, voice assistants, health technology, geospatial technology, clean technology, collaborative technology, advanced materials	
Fundamental technologies	Human-computer interaction, artificial intelligence, internet of things, cloud computing, nanotechnology, mobile internet, automation, big data, robots	
Smart home	**Smart community**	**Smart city**
Healthcare: socially connected products track end-user biometrics to detect or track heart attacks, pneumonia, falls, seizures, anxiety attacks, psychosis, respiratory diseases, hearing loss, insulin status, and dementia. These products display medicament schedules, missing pills, and/or fall frequency Environment: during natural disasters, such as earthquakes, detect if all users are safe, e.g., outside the home. Avoid fires by identifying lit candles, or provide weather sensing to promote social interaction and physical activities Groceries: detect missing food or food shortages Household appliances: detect and foresee missing supplies Face-to-face virtual interaction: promote social relationships with other homes, and when possible, promote public interaction at parks	Healthcare: receive from a house its requirements, for instance, assistance with eldery occupants. Schedule medical appointments. If an accident occurs, send an ambulance to the house Environment: provide weather forecasts to inform end-users to support daily planning, such as going outside or staying in. During a pandemic, provide information on how many infected people are near the end-user Groceries: provisioning food to the home Transport: monitoring parking spaces and transportation; managing traffic; and ensuring public transportation is accessible. Establish connection with groceries to supply food to the home	The interactions between communities allow the smart city to track citizens' behavior, understand the trends, and provide accurate feedback, security, and information to the populace Participatory sensing [33]: The end-user through a smartphone becomes a sensor that shares and extracts information to monitor the environment, transportation, mobility, and energy waste

techniques and necessary technologies, and examples of interactions at the three levels: smart home, smart community, and smart city.

6 From Citizen to Smart City: A Future Vision

The *IESE Cities in Motion Index* report [5] gives a clear picture of the elements required to have a transition toward a smart city. The future of smart cities tends to integrate not only the technological aspects of life but also how they combine with and develop the rest of the indicators. Therefore, converging into a city that sees participation from all inhabitants may reduce stress from traffic, legal problems, crime and suicide rates. This may seem Utopian, however with the right planning, partnerships, and public's help, the integration of technology to achieve this ideal is a matter of time.

With the global pandemic COVID-19, at least five areas that artificial intelligence could have contributed to within a smart city were identified [22]:

- Detecting, tracking, and predicting outbreaks using big data.
- Use of face recognition and infrared-based technologies to improve public safety and security.
- Surveillance, sterilization, and supply delivery via drones and autonomous robots.
- Innovations in virus understanding, diagnostics, and treatments.
- Novel tele-communication devices and platforms to promote togetherness and connectedness during times when physical contact must be limited for safety.

Thus, in times of social distancing, the role of the HMIs takes a suitable place as they serve as a social connector between the end-user and the entire community or smart city. It is a new paradigm where end-users partake in a new type of social interaction, leveraging the internet of things, social media, and e-commerce to make a new life.

6.1 Smart City Vision in a COVID-19 Context

Figure 16 depicts a third-layer structure to achieve a smart city. A new concept considered in this roadmap is the COVID-19 global pandemic. With technology and network communications, it is feasible to continue living in a new normal and with new methods of communication where HMIs take the central role as a social connector and interactor between the end-user and the community and smart city. The three-layer topology considers the following:

- The first layer is the individual segment. The home takes advantage of the socially connected products and devices to interact with the house. Some applications

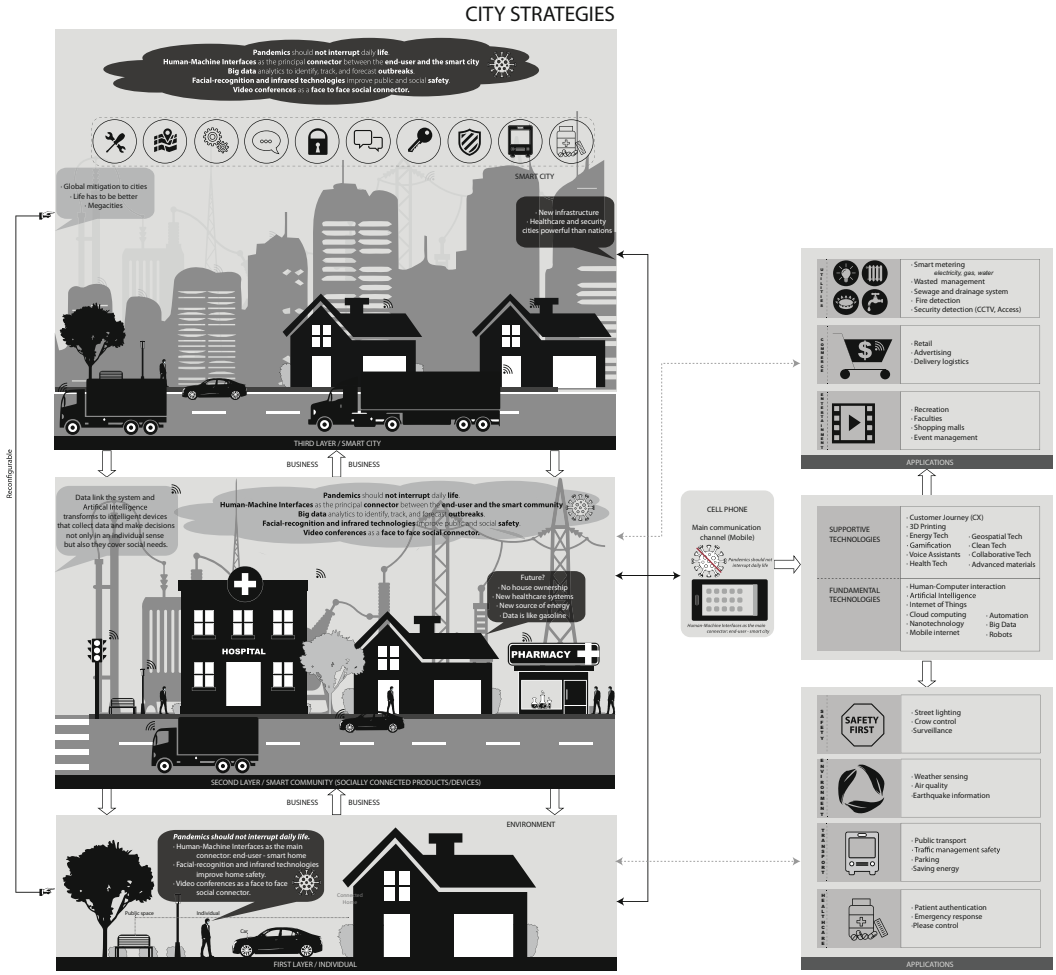


Fig. 16 Smart city vision from an individual layer into a connected smart city

consider healthcare, transportation, environment, and safety in interactions with the smart community and the smart city. HMIs connect with the home to provide new forms of social interaction and foresee if a family member is becoming ill, for instance, with cameras and communication via Alexa by detecting if the user is having fever and presenting COVID-19 symptoms. The smart fridge can identify, based on a dietary list, any food shortages, and contact the market to request provisions.

- The second layer is the smart community. This layer imagines new healthcare systems, new sources of energy, no home ownership, and data is like gasoline in the future. The data link the system, and artificial intelligence transforms devices that collect data and make decisions not only in a personal sense but also from the perspective of social needs. This layer considers applications for utilities, commerce, and entertainment. The HMIs and big data analytics bring new information to identify, track, and forecast outbreaks. The surveillance cameras and infrared technologies can detect users with erratic behavior or with fever to improve public and social safety. Video conferences allow new manners of

business; for instance, physicians assist infected users and avoid physical contact to help prevent the spread of viruses.

- The third layer deepens the smart city concept. It considers that life should be better, with new developments and improvements to infrastructure, healthcare, and security. Cities should be powerful, connected, responsive, and adaptive. The safest and most reliable and convenient way to interact will be through HMIs, video conferencing, conventional calls, or mails; however, new dynamics will be implemented for social and physical interactions, e.g., access to information about a specific location and how many nearby people are infected so that a user can take precaution.

Therefore, considering the elderly sector, by taking advantage of HMIs, smart devices, and household products in the home, the elderly can receive more attention from their family, interact with friends, and monitor their health. For instance, as proposed in [31], the home can track an end-user's mood, and avoid social isolation through interaction. In this way, an elderly user can engage with Alexa through conversation. On the other hand, implementing social connectors such as video conferences in the HMIs could encourage the elderly to be more in touch with friends and family.

7 Discussion

This chapter presented socially connected products within a smart home, and proposed a tailored interface to improve the quality of life of users and the community by promoting a reduction in energy consumption. A Sugeno Fuzzy Logic decision system was used to classify the type of home based on energy consumption level and type of environmental home to propose a gamified structure that runs in a customized HMI. The proposed interface is oriented based on the preferred motivation. Although the level of energy consumption was classified based on the 2015 Residential Energy Consumption Survey public database [10], the fuzzy decision system is designed to organize the level of energy consumption from the household appliances.

This classification uses the following scale: low consumption, average consumption, and high consumption. The average value range comes from the database, by using the standard deviation; the higher consumption comes from the addition of the average value plus the standard deviation. Whereas the lower consumption comes from the subtraction of the average value minus the standard deviation. The type of energy home is classified as either a pro-environmental home, average home, or disengaged-environmental home. The type of home is related to the level of energy consumption of the house. Finally, the gamified motivation is classified in three varieties: intrinsic motivation (Low, Medium, High, and Very High); extrinsic motivation (Low, Medium, High, and Very High); or both motivation types. This interaction is included within the local point of view (see Fig. 1).

Once the decision system classifies the type of home and provides a personalized gamification interface, the multi-sensor system may be utilized inside the smart home setting to detect the level of energy consumption and the environmental type of the home to promote social interaction and energy reduction to improve the quality of life in the community. This interaction is included within the global point of view (see Fig. 1). Therefore, the ANFIS system is designed to propose the type of gamification motivation based on community behavior and a tailored community gamified interface.

Hence, a Human Machine Interface for each type of home is proposed and considers three levels:

- For a single social product, e.g., a connected thermostat. Several approaches to this type of social product have been published in [30, 39].
- For the smart home, which is the set of social products within the home. In [29, 31], saving energy in smart homes was empowered using gamification techniques.
- And lastly, for the smart community. Although there is no limitation, this interface should be included and considered based on the correlation and interaction between homes and the gamified community motivation.

This general proposal is limited in that the home should have a level of automatization and connectivity to provide real-time monitoring and feedback, as well as enable user profile creation to provide personalized interfaces. Moreover, once the community interaction is classified, if there are homes that a community structure will not allow to reduce energy consumption, then perhaps other interactions may be explored. For example, interaction between pairs of homes or groups of three homes may be proposed to offer more types of community awareness and engagement to improve quality of life.

Considering Nielsen's heuristics within the interface may increase the impact for and engagement of the end-user. These heuristics take into account [35]: the visibility of a system's current status; whether the real world matches the system; users' freedom and control; standards and consistency; error prevention; recognition (as opposed to recall); efficiency of use as well as flexibility; minimalist and aesthetic design; error recovery; and user support.

This proposal looks for a change in how connected/social products are used and how a community could interact to enhance social inclusion. It aims to produce new forms of social interaction between users and their homes. This first approach considers only the interaction between homes and the household products within the smart home; nevertheless, with further research, this interaction could include the transportation and commercial sector by taking advantage of the associated communications and promoting more connected community interaction. With a multi-sensor system, we may leverage connected smart home appliances to develop a profile of a house, and propose tailored applications triggered by intrinsic and/or extrinsic motivations that best fit the type of home.

8 Conclusion

In this chapter, a multi-sensor system for improving the quality of life by reducing energy consumption was proposed. A gamification structure triggered by outcome motivations within an HMI for a community was presented based on each home's characteristics. This strategy considers each home's interaction by profiling the level of energy consumption and type of environmental home within a fuzzy logic decision system. Then the interaction between homes to set the community was proposed through an ANFIS system that provides which gamified motivation is required to engage the home in having a reduction in energy consumption and improvement of quality of life in the community. The proposed approach aims to develop a profile of the home and improve our understanding of the type of home and the interaction of the houses in the community toward an accurate application that improves quality of life while promoting energy reduction. This HMI introduces an opportunity to create an ecosystem enabling connected products and homes to interact with the community to help residents feel included.

An example of the relevance of HMIs is the COVID-19 pandemic. HMIs tackle social distancing by taking advantage of social products and connectors such as video conferences, calls, blogs, and social media. Thus, individuals interact with others without concerns of infection; for instance, this interaction works for social relationships, work, healthcare, schools, and religious groups. As Fig. 16 indicates, HMIs work as a critical connector between each smart home, smart community, and smart city with the end-user, where the user provides information and consumption and behavior patterns to each level, improving their quality of life and fostering social synergy with other users.

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References

1. Albertarelli, S., Fraternali, P., Herrera, S., Melenhorst, M., Novak, J., Pasini, C., Rizzoli, A.-E., Rottondi, C.: A survey on the design of gamified systems for energy and water sustainability. Games. **9**, 38 (2018). https://doi.org/10.3390/g9030038
2. Aldrich, F.K.: Smart homes: past, present and future. In: Harper, R. (ed.) Inside the smart home, pp. 17–39. Springer, London (2003)
3. AlSkaif, T., Lampropoulos, I., van den Broek, M., van Sark, W.: Gamification-based framework for engagement of residential customers in energy applications. Energy Res. Soc. Sci. **44**, 187–195 (2018). https://doi.org/10.1016/j.erss.2018.04.043
4. Bartle, R.: Hearts, clubs, diamonds, spades: players who suit MUDs, 28 (1996). https://www.researchgate.net/publication/247190693_Hearts_clubs_diamonds_spades_Players_who_suit_MUDs

5. Berrone, P., Ricart, J.E., Duch, A., Carrasco, C.: IESE cities in motion index 2019. Servicio de Publicaciones de la Universidad de Navarra, Navarra (2019)
6. Bhati, A., Hansen, M., Chan, C.M.: Energy conservation through smart homes in a smart city: a lesson for Singapore households. Energy Policy. **104**, 230–239 (2017). https://doi.org/10.1016/j.enpol.2017.01.032
7. Chou, Y.: Actionable gamification beyond points, badges, and leaderboards. CreateSpace Independent Publishing Platform, Scotts Valley (2015)
8. Csoknyai, T., Legardeur, J., Akle, A.A., Horváth, M.: Analysis of energy consumption profiles in residential buildings and impact assessment of a serious game on occupants' behavior. Energ. Buildings. **196**, 1–20 (2019). https://doi.org/10.1016/j.enbuild.2019.05.009
9. Deterding, S., Dixon, D., Khaled, R., Nacke, L.: From game design elements to gamefulness: defining "gamification", Presented at the MindTrek 11: Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments (2011), https://doi.org/10.1145/2181037.2181040
10. EIA: Residential Energy Consumption Survey (RECS) – Data – U.S. Energy Information Administration (EIA). https://www.eia.gov/consumption/residential/data/2015/index.php?view=microdata
11. EIA: Total Energy Annual Data – U.S. Energy Information Administration (EIA). https://www.eia.gov/totalenergy/data/annual/index.php
12. Eltoweissy, M., Azab, M., Olariu, S., Gracanin, D.: A new paradigm for a marketplace of services: smart communities in the IoT era. In: 2019 international conference on innovation and intelligence for informatics, computing, and technologies (3ICT), pp. 1–6. IEEE, Sakhier (2019)
13. Hargreaves, T., Wilson, C.: Smart homes and their users. Springer, Cham (2017)
14. Harper, R.: Inside the smart home: ideas, possibilities and methods. In: Harper, R. (ed.) Inside the smart home, pp. 1–13. Springer, London (2003)
15. Huotari, K., Hamari, J.: Defining gamification: a service marketing perspective. In: Proceeding of the 16th international academic MindTrek conference on – MindTrek '12, p. 17. ACM Press, Tampere (2012)
16. IBM's Smarter Cities Challenge: Copenhagen report. IBM Corporate Citizenship & Corporate Affairs, Copenhagen (2013)
17. INEGI: Estadísticas a Propósito del Día Internacional de Las Personas de Edad (1o de Octubre)
18. Jang, J.-R.: ANFIS: adaptive-network-based fuzzy inference system. IEEE. Trans. Syst. Man Cybern. **23**, 665–685 (1993). https://doi.org/10.1109/21.256541
19. Kappen DL (2015) Adaptive engagement of older adults' fitness through gamification. http://dl.acm.org/citation.cfm?doid=2793107.2810276
20. Kostopoulos, P., Kyritsis, A.I., Ricard, V., Deriaz, M., Konstantas, D.: Enhance daily live and health of elderly people. Procedia Comput. Sci. **130**, 967–972 (2018). https://doi.org/10.1016/j.procs.2018.04.097
21. Li, X., Lu, R., Liang, X., Shen, X., Chen, J., Lin, X.: Smart community: an internet of things application. IEEE Commun. Mag. **49**, 68–75 (2011). https://doi.org/10.1109/MCOM.2011.6069711
22. Lii Inn, T.: Smart city technologies take on Covid-19. Penang Institute. https://penanginstitute.org/publications/issues/smart-city-technologies-take-on-covid-19/
23. Llinas, J., Waltz, E.: Multisensor data fusion. Artech House, Boston (1990)
24. Łucka, D.: How to build a community. New urbanism and its critics. Urban. Dev. Issues. **59**, 17–26 (2018). https://doi.org/10.2478/udi-2018-0025
25. Malwade, S., Abdul, S.S., Uddin, M., Nursetyo, A.A., Fernandez-Luque, L., Zhu X (Katie), Cilliers L, Wong C-P, Bamidis P, Li Y-C (Jack): Mobile and wearable technologies in healthcare for the ageing population. Comput. Methods Prog. Biomed. **161**, 233–237 (2018). https://doi.org/10.1016/j.cmpb.2018.04.026
26. Marczewski, A.: Even ninja monkeys like to play: gamification, game thinking and motivational design. CreateSpace Independent Publishing Platform, Scotts Valley (2015)

27. Marikyan, D., Papagiannidis, S., Alamanos, E.: A systematic review of the smart home literature: a user perspective. Technol. Forecast. Soc. Chang. **138**, 139–154 (2019). https://doi.org/10.1016/j.techfore.2018.08.015
28. Meiselman, H.L. (ed.): Emotion measurement. Elsevier, Woodhead Publishing, Amsterdam (2016)
29. Méndez, J.I., Ponce, P., Mata, O., Meier, A., Peffer, T., Molina, A., Aguilar, M.: Empower saving energy into smart homes using a gamification structure by social products. In: 2020 IEEE international conference on consumer electronics (ICCE), pp. 1–7. IEEE, Las Vegas (2020)
30. Méndez, J.I., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A.: Framework for promoting social interaction and physical activity in elderly people using gamification and fuzzy logic strategy. In: 2019 IEEE global conference on signal and information processing (GlobalSIP), pp. 1–5. IEEE, Ottawa (2019)
31. Méndez, J.I., Mata, O., Ponce, P., Meier, A., Peffer, T., Molina, A.: Multi-sensor system, gamification, and artificial intelligence for benefit elderly people. In: Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E. (eds.) Challenges and trends in multimodal fall detection for healthcare, pp. 207–235. Springer, Cham (2020)
32. Méndez, J.I., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A.: S4 product design framework: a gamification strategy based on type 1 and 2 fuzzy logic. In: Smart multimedia: methodologies and algorithms, San Diego, California, USA, p. 15 (2019)
33. Middya, A.I., Roy, S., Dutta, J., Das, R.: JUSense: a unified framework for participatory-based urban sensing system. Mobile Netw. Appl. (2020). https://doi.org/10.1007/s11036-020-01539-x
34. Miranda, J., Pérez-Rodríguez, R., Borja, V., Wright, P.K., Molina, A.: Sensing, smart and sustainable product development (S3 product) reference framework. Int. J. Prod. Res. **57**, 1–22 (2017). https://doi.org/10.1080/00207543.2017.1401237
35. Nielsen, J.: 10 heuristics for user interface design: article by Jakob Nielsen. https://www.nngroup.com/articles/ten-usability-heuristics/
36. Peham, M., Breitfuss, G., Michalczuk, R.: The "ecoGator" app: gamification for enhanced energy efficiency in Europe. In: Proceedings of the second international conference on technological ecosystems for enhancing multiculturality – TEEM '14, pp. 179–183. ACM Press, Salamanca (2014)
37. Ponce Cruz, P., Ramírez-Figueroa, F.D.: Intelligent control systems with LabVIEW. Springer, London; New York (2010)
38. Ponce, P., Peffer, T., Molina, A.: Framework for communicating with consumers using an expectation interface in smart thermostats. Energ. Buildings. **145**, 44–56 (2017). https://doi.org/10.1016/j.enbuild.2017.03.065
39. Ponce, P., Meier, A., Mendez, J., Peffer, T., Molina, A., Mata, O.: Tailored gamification and serious game framework based on fuzzy logic for saving energy in smart thermostats. J. Clean. Prod., 121167 (2020). https://doi.org/10.1016/j.jclepro.2020.121167
40. Ponce, P., Meier, A., Miranda, J., Molina, A., Peffer, T.: The next generation of social products based on sensing, smart and sustainable (S3) features: a smart thermostat as case study. In: 9th IFAC conference on manufacturing modelling, management and control, p. 6 (2019)
41. Ritchie, H., Roser, M.: Causes of death. Our World in Data (2018) https://ourworldindata.org/causes-of-death, last accessed 2020/07/07
42. Sayago, S. (ed.): Perspectives on human-computer interaction research with older people. Springer, Cham (2019)
43. Schiele, K.: Utilizing gamification to promote sustainable practices. In: Marques, J. (ed.) Handbook of engaged sustainability, pp. 427–444. Springer, Cham (2018)
44. Skouby, K.E., Lynggaard, P.: Smart home and smart city solutions enabled by 5G, IoT, AAI and CoT services. In: 2014 international conference on contemporary computing and informatics (IC3I), pp. 874–878. IEEE, Mysore (2014)

45. Tondello, G.F., Wehbe, R.R., Diamond, L., Busch, M., Marczewski, A., Nacke, L.E.: The gamification user types Hexad scale. In: Proceedings of the 2016 annual symposium on computer-human interaction in play – CHI PLAY '16, pp. 229–243. ACM Press, Austin (2016)
46. Victor, C.R., Scambler, S., Bond, J.: The social world of older people: understanding loneliness and social isolation in later life. Open University Press, Maidenhead (2009)
47. Waltz, E.: Data fusion for C3I: a tutorial. In: Command, control, communications intelligence (C3I) handbook. EW Communications, Palo Alto (1986)
48. Wang, X.: The optimization of smart community model based on advanced network information technology. In: 2020 IEEE 4th information technology, networking, electronic and automation control conference (ITNEC), pp. 2579–2583. IEEE, Chongqing (2020)
49. London smart city: tackling challenges with 20 initiatives. HERE Mobility. https://mobility.here.com/learn/smart-city-initiatives/london-smart-city-tackling-challenges-20-initiatives
50. My coverage of lobby of the social gaming summit. http://www.bretterrill.com/2008/06/my-coverage-of-lobby-of-social-gaming.html
51. Older people are more likely to live alone in the U.S. than elsewhere in the world. Pew Research Center. https://www.pewresearch.org/fact-tank/2020/03/10/older-people-are-more-likely-to-live-alone-in-the-u-s-than-elsewhere-in-the-world/
52. Oslo brings the future home with its multifaceted "smart city" programs. https://www.digitaltrends.com/home/oslo-norway-smart-city-technology/

Chapter 7

Tailored gamification and serious game framework based on fuzzy logic for saving energy in connected thermostats

7.1 Summary of the Chapter

The very foundation of this thesis relies on this journal paper. This journal paper shares authorship with the first two authors. This chapter establishes the first steps for deploying tailored platforms by studying the case of connected thermostats.

Connected thermostats (CTs) often save less energy than predicted because consumers may not know how to use them and may not be engaged in saving energy. Additionally, several models perform contrary to consumers' expectations and are thus not used the way they are intended. As a result, CTs save less energy and are underused in households. This paper reviews aspects of gamification and serious games focused on engaging consumers.

A gamification and serious games framework is proposed for saving energy that is tailored by a fuzzy logic system to motivate connected thermostat consumers. This intelligent gamification framework can be used to customize the gamification and serious game strategy for each consumer so that fuzzy logic systems can be adapted according to the requirements of each consumer. The framework is designed to teach, engage, and motivate consumers while helping them save electrical energy when using their thermostats. It is described the proposed framework as well as a mockup that can be run on a cellphone. Although this framework is designed to be implemented in CTs, it can be translated to their energy devices in smart homes.

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Tailored gamification and serious game framework based on fuzzy logic for saving energy in connected thermostats

Pedro Ponce [a, *], Alan Meier [b], Juana Isabel Méndez [a], Therese Peffer [c], Arturo Molina [a], Omar Mata [a]

[a] Tecnológico de Monterrey, Mexico
[b] UC DAVIS, United States
[c] UC BERKELEY, United States

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ABSTRACT

Connected thermostats (CTs) often save less energy than predicted because consumers may not know how to use them and may not be engaged in saving energy. Additionally, several models perform contrary to consumers' expectations and are thus not used the way they are intended to. As a result, CTs save less energy and are underused in households. This paper reviews aspects of gamification and serious games focused on engaging consumers. A gamification and serious games framework is proposed for saving energy that is tailored by a fuzzy logic system to motivate connected thermostat consumers. This intelligent gamification framework can be used to customize the gamification and serious game strategy to each consumer so that fuzzy logic systems can be adapted according to the requirements of each consumer. The framework is designed to teach, engage, and motivate consumers while helping them save electrical energy when using their thermostats. It is described the proposed framework as well as a mockup that can be run on a cellphone. Although this framework is designed to be implemented in CTs, it can be translated to their energy devices in smart homes.

1. Introduction

In 2018, as part of its revised Energy Performance of Buildings Directive, The European Commission introduced a "smart readiness indicator" as a means to make building energy smartness more understandable and useful for building users, owners, and tenants. This indicator functions by raising awareness of the benefits of smart technologies and information and communication technologies (ICT) in buildings (IEA, 2018). Technological innovation serves to create new opportunities for progress inefficiency, such as the deployment of connected devices. By the end of 2016, four thousand million connected devices were in use by households worldwide. Five hunded million smart meters were contracted to be installed, as they can complement connected devices, allowing consumers to adjust energy use in response to changes in energy prices (IEA, 2017). In addition to smart meters and energy devices that have emerged on the market for saving energy in households and buildings, connected thermostats (CTs) have a significant impact on saving energy in HVAC systems. The fundamental goal of an HVAC control system is to keep temperature and air quality within a comfortable range while minimizing energy usage (Soltanaghaei and Whitehouse, 2018). In (Ponce et al., 2018a), a connected thermostat (CT) is defined as an electrical device that links smart homes with smart grids. CTs are thus designed to automatically learn occupants' schedules and turn heating and cooling on or off on the users' behalf (Soltanaghaei and Whitehouse, 2018). The CTs' design makes it possible to consume low energy, increase consumer comfort, and inform users about the energy conditions of the thermostats through mobile device interfaces. Besides, CTs can improve energy efficiency without affecting consumer satisfaction by making automated decisions regarding temperature conditions once they learn consumer's behavior patterns. The interface of the CTs can assist end-users when dealing with complex tasks. However, CTs have not been entirely accepted because their interfaces do not match consumers' expectations (Ponce et al., 2017). The failed expectations on the part of the users are due to several factors: (1) CTs are usually sold as energy-saving devices that control heating and cooling systems.

* Corresponding author.
E-mail address: pedro.ponce@tec.mx (P. Ponce).

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However, because end-users operate them differently than intended by the manufacturers and designers, they produce major energy waste (Pritoni et al., 2015); (2) Although CTs can automatically adjust the patterns of electrical consumption to save energy, end users do not use these functions. As a result, the users expect features that decrease the complexity of operating the product and do not feel confident in using the functions; (3) End users are unable to accurately understand the features and advantages of the CTs because they do not know what to expect of these devices; (4) Customers should receive accurate and complete information regarding the relationship between kWh and CO_2 so that they can understand the environmental impact of incorrect operation of a CT (Ponce et al., 2018a); (5) The device is designed only for meeting certain types of expectations, it means that those devices are generally designed for the typical user rather than non-typical user; thus it cannot be entirely or quickly adopted because some end users do not consider saving energy to be their main expectation. Their primary expectation is what they look for when buying an air conditioning system: cost, energy efficiency, performance, durability, reliability, brand, greenness, and aesthetics; (6) If customers do not use an HVAC correctly, then the human-machine interface (HMI) will be unable to support the CT in improving the customers' understanding of energy efficiency (Ponce et al., 2018b, 2017). Table 1 describes the main problems when CTs are deployed and their relationship between the behavior and usability problems. These problems are divided according to a consumer's point of view (problems with consumer behavior or problems in the thermostat). For example, the problem of programming and CT can be considered a usability problem that can be solved by improving the thermostat's design. However, this can also be considered a problem that arises because consumers do not read the thermostat manual. In contrast, saving energy can be classified as a behavior problem; this requires changes in the consumers' habits and thus cannot be solved directly by changing the thermostat's interface.

However, according to (Kashani and Ozturk, 2017), 2/3 of typical home energy usage is based on human habits; thus, efforts to target behavior changes have led to an emerging area of interest called gamification and serious games (SGs), which is a way to engage and educate individuals and support environmental awareness through the use of game design elements (AlSkaif et al., 2018; Johnson et al., 2017). SGs and gamification share a common goal: to shape human actions to improve the user experience, offer motivation, and encourage behavior changes (Beck et al., 2019). To this end, the CT designer must implement changes to motivate customers to use the product and change consumer habits. The use of sensing, smart, and sustainable products (S^3 products) has also been proposed for the design process or for developing social products in smart homes (Méndez et al., 2020b). There are two classes of communication between products and processes. There are two classes of communication between products and consumers: (1) natural society behavior, in which consumer data is obtained from the installed product when it is in operation; and (2) non-natural

Table 1
Primary problems with deployed CTs according to a consumer's point of view.

	Behavior problems (Ponce et al., 2018b, 2017)					
	Users operate the CT different than how the design engineers intended.	Users do not understand the functions. They feel using the CT is complicated.	Users do not know and/or care about the advantages of the CT.	Users are not aware of the environmental impacts.	User is not primarily focused on energy saving.	Users do not know how to use the HVAC system.
Usability problems (Ponce et al., 2018b)						
1. Visibility of the status: The interface neither informs the status nor gives appropriate feedback.	x	x	x	x	x	x
2. Match between system and the real world: It uses system-oriented terms rather than following real-world convention language.	x	x				
3. User control and freedom: User feels controlled by the interface and without freedom.	x	x				
4. Consistency and standards: It does not follow platform conventions.	x	x				
5. Recognize, diagnose, and recover from errors: Messages are displayed in code; users cannot recognize, diagnose, and recover from them.	x	x				
6. Error prevention: it is not carefully designed and develop error problems.	x	x				
7. Recognition rather than recall: the objects, actions, and options are not visible.	x	x				
8. Flexibility and minimalism design: Lack of custom actions. Access and operation are limited to average users.	x	x	x	x	x	x
9. Aesthetics: Dialogues contain irrelevant information.	x	x	x	x	x	x
10. Help and documentation: information is complicated to search and is not focused on the user's task and is extensive.	x	x		x	x	
11. Skills: The interface tries to replace the user's capabilities, background, knowledge, and expertise.	x	x				
12. Pleasurable and respectful interaction with the user: The design is unpleasing and nonfunctional.	x	x				
13. Privacy: The system does not protect personal or private information.	x	x				

behavior, in which, depending on the positive or negative performance of the product, the communication reinforces consumer attitude or considers a habit change. Therefore, by taking advantage of the consumer data on natural society behavior and by using gamification and SG strategies to send stimuli for changing consumer attitude in non-natural behavior communication. In addition (Méndez et al., 2019a; Ponce et al., 2019) propose the use of gamification to save energy by improving user habits for better performance of the CT, whereas SGs make it possible to shape user habits through an educational platform (Coursera, 2017; Giessen, 2015; Moloney et al., 2017).

It is therefore necessary to understand how the user behaves or thinks to propose tailored products for those non-typical users that are not considered when the products are designed and deployed. In this regard, fuzzy logic has been used to model human reasoning through a set of If-Then rules to provide a better user experience (Mata et al., 2019). classified five types of energy end-users based on their personality traits using fuzzy logic (Albadán et al., 2018). implemented a fuzzy logic model with gamification elements in a platform to profile five types of aspirants for personnel selection (Méndez et al., 2020a, 2019b). proposed to use tailored gamified HMI to promote physical activity and social interaction in elderly people by classifying them with personality traits or by tracking their mood via voice and image detection (Méndez et al., 2020a, 2019b).

However, the (Mata et al., 2019; Méndez et al., 2020a, 2020b, 2019a, 2019b) proposals have been developed based on this paper premise, propose a tailored gamified HMI based on fuzzy logic system decision for non-typical and typical user to save energy by shaping user behavior. Before the authors' proposal of using fuzzy logic system decision to display gamification elements in HMI to personalize devices based on each user's characteristics and profile, to the best of the authors' knowledge, it has never been proposed.

Therefore, the relevance of this work is the novel proposal of developing personalized interfaces using gamification elements in a fuzzy logic system decision to promote energy-saving habits in all types of users (typical and non-typical users) considering the personality traits of the user, the kind of role player in gamification and SGs contexts, and the relation with the energy end-user segment and target group. Besides, the framework is designed to detect if the user is getting bored to change the gamification strategy and display other gamification elements.

The remainder of this paper is structured as follows. Section 2 describes the personality and type of energy end-users, as well as ecological behavior models, regarding personality traits with pro-environmental behavior based on the energy end-user segment to find users' engagement in ecological behavior. Section 3 describes gamification and SGs in energy-saving and review state of the art in gamification, SGs, and CTs. The proposed methodology is described in Section 4. As a result of the analysis in Sections 1 to 4, Section 5 proposes a framework to fill the gap between consumer expectations and energy consumption to make the CT a suitable S^3 product. Section 6 presents a mockup of the framework that can be used on a mobile phone. In Section 7, it is described the scope of the framework, its advantages and disadvantages, and the benefits for the user and thermostat designer regarding energy terms. Conclusions and future work are presented in Section 8.

2. Type of users

For the proposed strategy, five types of users are described: (1) personality traits that cannot be changed but help understand users' behavior; (2) energy end-users divided into five customer segments; (3) energy target groups divided into three groups; (4) four types of player in SG; (5) six types of gamification players and their associated personality traits.

2.1. Personality traits

Table 2 depicts a descriptive theory in the field of psychology of five broad and replicable personality traits (McCrae and Costa, 1997) that have been vastly supported and are often referred to as the "Big Five" (Oliver and Srivastava, 1999). These personality traits have demonstrated a close relationship between the personalities of individuals and their behavior in different domains (Paunonen, 2003). Research linking personality and environmental behaviors have produced somewhat mixed results; however, the ability to predict environmental concerns through personality traits appears feasible.

Recent studies have explored different methodologies to predict or link engagement in pro-environmental behavior with the Big Five traits. The results are consistent, demonstrating that with higher levels of agreeableness and openness, there is greater environmental engagement. In contrast, conscientiousness displays little positive influence on environmental engagement; however, it is more likely to be related to environmental concern. Extraversion does not appear to have a significant impact on conduct, while neuroticism shows an unexpected finding. Because individuals with high neuroticism levels tend to be more worried about adverse outcomes, they experience more significant environmental concerns (Brick and Lewis, 2016; Hirsh, 2010; Milfont and Sibley, 2012).

2.2. Energy end-users

Table 3 presents the five customer segments proposed in (Ponce et al., 2017) that are related to energy use based on traditional sector divisions, the economic activity of the customer, and the qualitative evaluation of energy end-users: (1) green advocate energy savers, (2) traditionalist cost-focused energy savers, (3) home-focused selective energy savers, (4) non-green selective energy savers, and (5) disengaged energy wasters.

2.3. Energy target groups

Table 4 illustrates the three groups proposed in (Peham et al., 2014) according to their characteristics, household appliances, user availability, and energy awareness as the main aspects to focus on an energy application.

2.4. Four types of role players in SG environment

(Bartle, 1996) profiled four types of role players in a game that works for the SG environment. Table 5 shows these players and their characteristics.

2.5. Six types of users and their relationship with the Big Five personalities

Table 6 presents the (Marczewski, 2015) Hexad framework based on the (Bartle, 1996) role player. Based on (Bartle, 1996) role player, he proposed six types of player need in a gamification system. Then (Tondello et al., 2016), associated those players with the five personality traits.

2.6. Ecological behavior

To tailor a CT requires knowledge of the type of personality, end-user, market segments, and how they are structured in the energy sector. To design a gamified CT is important to define the most

Table 2
Personality traits and characteristics (Oliver and Srivastava, 1999).

Personality trait	Characteristics	Attitude
Openness (Rothmann and Coetzer, 2003)	appreciation of divergent thinking; new social, ethical, and political ideas, behaviors, and values	curious, imaginative and unconventional
Conscientiousness (Barrick and Mount, 1991)	self-discipline, competence, dutifulness, and responsibility	rational, purposeful, strong-willed, like to follow the rules and have a clear objective
Extraversion (Barrick and Mount, 1991)	energized by social interactions, excitement, and diverse activities	talkative, assertive and optimistic
Agreeableness (Judge et al., 1999)	altruism, modesty, straightforwardness and a cooperative nature	sympathetic to others and tolerant
Neuroticism (Judge et al., 1999)	the tendency to experience negative emotions such as fear and sadness	impulsive, stressful and bad-tempered

Table 3
Energy end-user segments and characteristics (Ponce et al., 2017).

Energy end-users			
End-user segment	Characteristics	Technology	Energy awareness
Green advocate	Most positive	Interested in new technologies	Most positive
Traditionalist cost-focused	Motivated by cost savings	Limited interest	Extensive overall energy-saving behavior
Home focused	Interested in home improvement efforts	Interested in new technologies	Concerned about saving energy
Non-green selective	Selective energy saving	Focus on set-and-forget inventions	Not concerned
Disengaged	Less motivated by cost savings	Not interested	Not concerned

Table 4
Energy target groups and characteristics (Peham et al., 2014).

Energy target groups				
Group	Characteristics	Household appliances	User availability	Energy awareness
Early adopter	New technology buffs who buy all the latest gadgets	They prefer to buy them on the cutting edge of technology	Anywhere and anytime via smartphone, they use social media communities	They do not care
Cost-oriented individual	Take care of the household and focus on a cost-oriented way of life	Limited interest	They are mostly connected through their smartphone and are social media users	Energy saving is essential, and they try to be sustainable within their abilities
Energy-conscious individual	They try to lead a sustainable way of life	They buy them with a long lifetime and low energy consumption	They use smartphones and are not necessarily active in social media	They care very much

Table 5
Four types of player (Bartle, 1996).

Role player	Characteristics
Achiever	their main goal is to earn points and levels
Explorer	their main objective is to find out as much information as they can gather for the game and the players
Socializer	they love to interact with other players.
Killer	their main target is to impose themselves on others; therefore, to have control over others.

Table 6
Six types of gamification players and their associated personality traits (Marczewski, 2015; Tondello et al., 2016).

User type	Characteristics	Associated personality traits
Philanthropist	They are motivated by a sense of purpose; the associated design elements are collection, trading, gifting, knowledge sharing, and administrative roles.	Extraversion (E), Agreeableness (A), Conscientiousness (C), and Openness (O).
Socializers	Their motivation is the interaction with others to create social connections, similar to (Bartle, 1996) player type. They prefer game elements that include teams, social networks, social comparison, social competition, and social discovery.	Extraversion (E) and Agreeableness (A).
Free spirits	They prefer autonomy as a manner to express liberty and act without external control, similar to the explorer player type (Bartle, 1996). The design elements include exploratory tasks, nonlinear gameplay, easter eggs, unlockable content, creativity tools, and customization	Extraversion (E), Agreeableness (A), and Openness (O).
Achievers	Competence is their primary motivation (Bartle, 1996). They prefer the challenges, certificates, learning new skills, quests, levels or progression, and epic challenges design elements.	Conscientiousness (C)
Players	Competence is their primary motivation (Bartle, 1996). They prefer the challenges, certificates, learning new skills, quests, levels or progression, and epic challenges design elements.	Conscientiousness (C)
Disrupters	They are motivated by forcing positive or negative changes in the system, and it may also be known as the killer player (Bartle, 1996). Thus, the suggested design elements are innovation platforms, voting mechanisms, development tools, anonymity, and anarchic gameplay.	Neuroticism (N)

significant characteristics. For this reason, it is necessary to engage residential customers by leading them to take an active role in energy applications, which can give them the willingness to control their energy behavior and make decisions that can lead to energy savings (Ponce et al., 2019). claim that social factors are fundamental elements that lead to changes in customer habits. In this sense, a smart system manages the HMI adaptation, such as gamification in the interface, to change practices.

(Mata et al., 2019) classified and assigned a level of Ecological Behavior (EB) through an Artificial Neural Network model using fuzzy logic. This model categorizes the personality traits with pro-environmental behavior based on the energy end-user segment (Ponce et al., 2017) to find users' engagement in ecological behavior. The data used to train the system came from 19719 answered surveys of the Big Five Personality Test from the International Personality Item Pool of a public database available in (Psychometrics Project, 2019). The backpropagation algorithm uses Bayesian regularization with an adaptive weight minimization as the top condition. Then, based on the energy end-user segment (Table 3), a radar map is generated regarding the correlation of personality traits to create the rules for the fuzzy system. Fig. 1 shows a radar map of personality correlation with the type of user.

The theory of planned behavior (TPB) is frequently applied to understand energy-related behavior, pro-environmental behavior, and sustainable choices. This model identifies there antecedents of intentions to perform a behavior: (a) attitudes toward the behavior formed form behavioral beliefs, those beliefs outcomes of behavior and the evaluations of those outcomes: (2) subjective norms formed from the normative expectations of others and motivation to comply with such expectation; and (3) perceived behavior control based on beliefs regarding factors that may enable or hinder the behavior (Rai and Beck, 2017). Therefore, Table 7 presents the

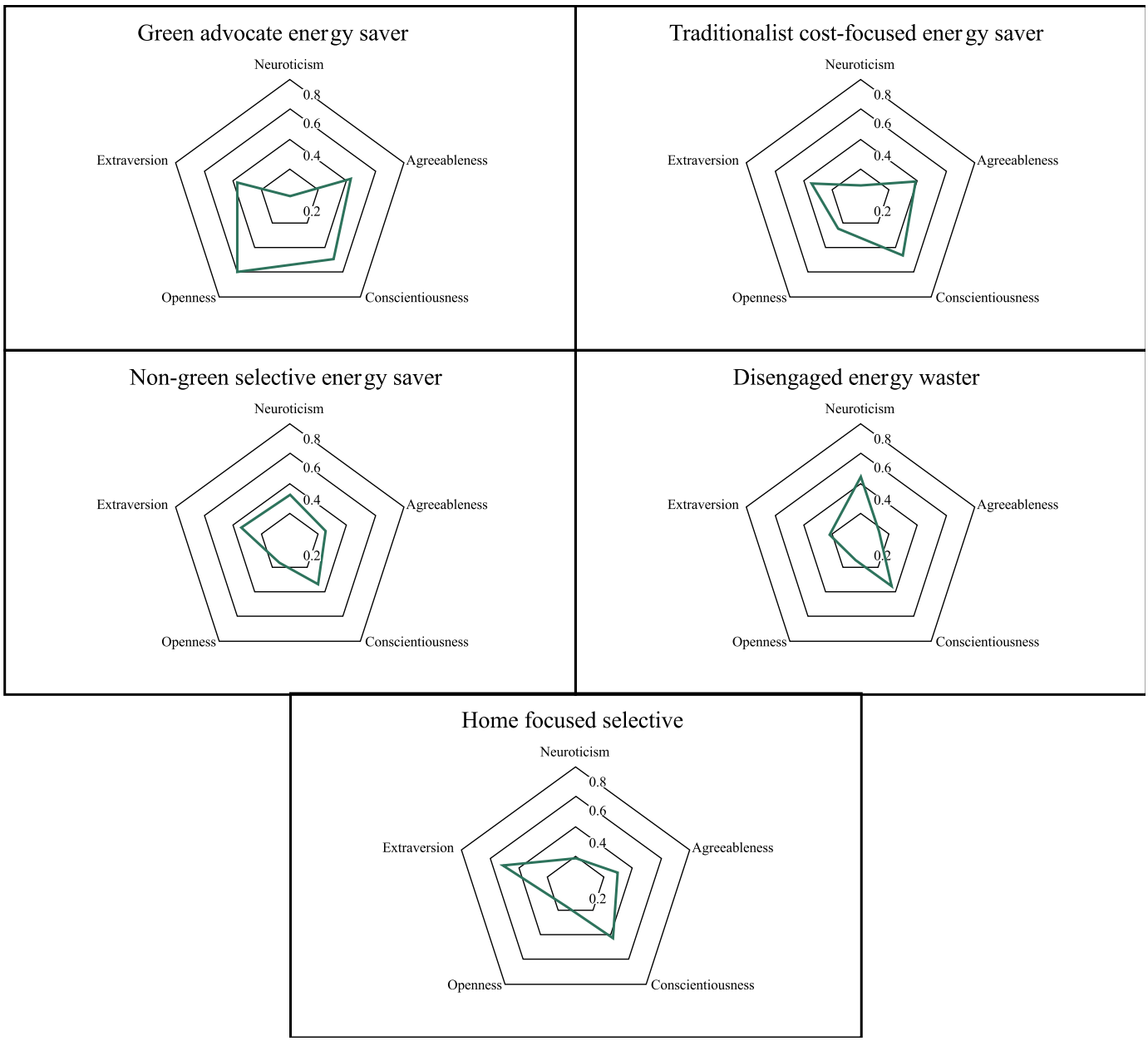


Fig. 1. Radar map of personality correlation with the type of energy end-user segment.

Table 7
Relationship between ecological behavior and the energy target groups.

Ecological behavior relationship (Fig. 1)		Energy end-user segments				
		Green advocate	Traditionalist cost-focused	Home focused	Non-green selective	Disengaged
		Personality traits correlation with the type of energy end-user segment				
Personality trait	**Openness**	0.6	0.25	0.14	0.14	0.1
	Conscientiousness	0.5	0.45	0.41	0.33	0.35
	Extraversion	0.36	0.34	0.5	0.35	0.22
	Agreeableness	0.43	0.38	0.3	0.26	0.15
	Neuroticism	0.03	0.1	0.2	0.33	0.45
		Energy target group and energy user segments relationship				
Energy target groups	**Early adopter**				x	x
	Cost-oriented		x	x		
	Energy-conscious	x				

Table 8
State of the art in gamification and serious games.

Year	Reference	Energy application	Gamification	Serious games
2007	PowerTap (2007)	Power Agent		x
2009	Gustafsson et al. (2009)	Power Explorer		x
2010	(AlSkaif et al., 2018; MIRABEL, 2010)	MIRABEL Project	x	
2012	Geelen et al. (2012)	Energy Battle		x
2013	Peham et al. (2014)	ecoGator	x	
2014	Dorji et al. (2015)	Residence Energy Saving Battle		x
2014	Orland et al. (2014)	Energy Chickens		x
2016	Fijnheer and Van Oostendorp (2016)	PowerSaver Game	x	x
2017	(Barbosa et al., 2017; Casals et al., 2017)	EnergyCat		x
2018	(Game | 2020 Energy, 2018; Ouariachi et al., 2019)	Energy2020		x

Table 9
State of the art in thermostats.

Year	Reference	Home Energy Management	Thermostat	Smart devices
2007	Williams and Matthews (2007)	x	x	x
2009	Vojdani (2008)	x	x	x
2010	Qela and Mouftah (2010)		x	
2015	Pritoni et al. (2015)		x	
2016	Korkas et al. (2016)	x	x	x
2017	Ponce et al. (2017)	x	x	
2018	Baldi et al. (2018)	x	x	x
2018	Soltanaghaei and Whitehouse (2018)		x	x
2018	Ponce et al. (2018a)		x	
2018	Ponce et al. (2018b)	x	x	
2019	Ponce et al. (2019)	x	x	x
2019	Jung and Jazizadeh (2019)	x	x	x

relationships between personality traits, energy end-user segments, and energy target groups with ecological behavior.

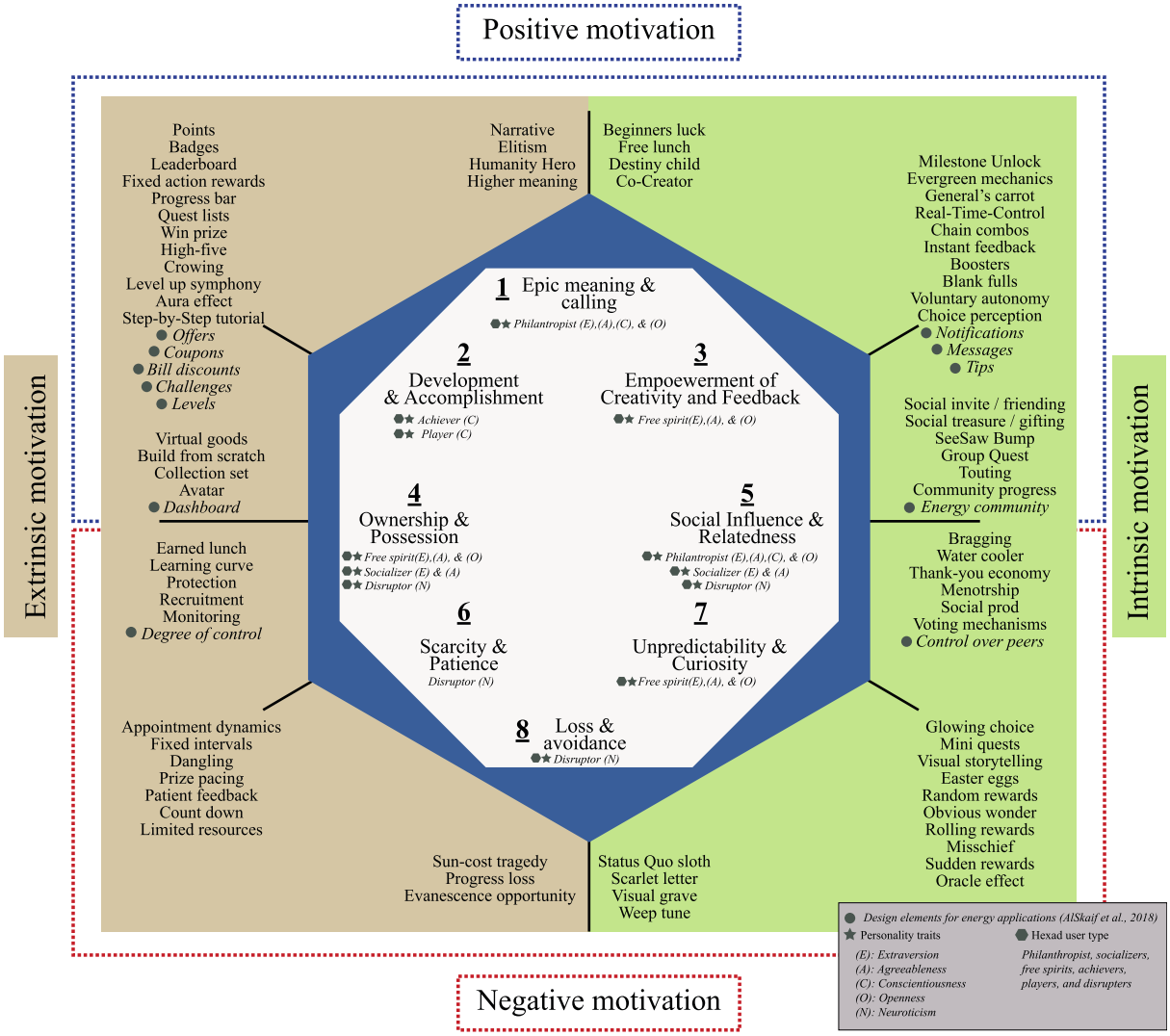
3. Gamification and serious games for energy saving

This section reviews the use of gamification and SGs in the energy field, their main characteristics, and their relationship with the types of users described in the previous section.

3.1. Gamification and energy saving

Gamification is the use of game elements in non-game contexts to improve the user experience and user engagement (Johnson et al., 2017; Lucassen and Jansen, 2014; Peham et al., 2014). In addition, it is "a process of enhancing a service with affordances for gameful experiences in order to support a user's overall value creation" (Huotari and Hamari, 2012) "based on the current consensus game design elements" (Matallaoui et al., 2015). Furthermore, it is the human-focused design process of using game-thinking and game mechanics to engage users and solve problems so that they can be applied to real-world or productive activities. Human-focused design is the process in which instead of optimizing function efficiency within the system, human motivation is optimized (Chou, 2015; Zichermann and Cunningham, 2011). Thus, gamification in energy systems has emerged as a tool for enhancing energy applications by driving customer engagement and energy-related behavior change through targeting a wide set of motives that a customer may have, including economic, environmental, and social incentives (AlSkaif et al., 2018). In (Ponce et al., 2019), the authors propose rewards for consumers by sending stimuli to change consumer behavior.

To design a gamified strategy is essential to understand the components and game elements involved in the development of any application. Several studies have suggested mechanisms for a gamification system (Lucassen and Jansen, 2014). propose five mechanisms (1) progress mechanisms such as popularity/status, competition, scores, badges, leaderboards, achievements, and levels; (2) rewards such as prizes, effort rewards, fixed rewards,



Octalysis core drive (Chou, 2015)	Motivation (Chou, 2015)	Hexad user type (Marczewski, 2015; Tondello et al., 2016)	Role player (Bartle, 1996)	Energy end user segment & target group (Ponce et al., 2017; Peham et al., 2014)
1. Epic meaning and calling	Extrinsic, intrinsic, positive	Philanthropist (E, A, C, & O)*	Socializer	Green advocate & energy-conscious Traditionalist cost-focused & cost-oriented Home focused & cost-oriented Non-green selective & early adopter Disengaged energy waster & early adopter
2. Development and accomplishment	Extrinsic, positive	Achiever & Player (C)*	Achiever	
3. Empowerment of creativity and feedback	Intrinsic, positive	Free spirit (E, A, & O)*	Explorer	
4. Ownership and possession	Extrinsic, positive, negative	Socializer (E & A)* Free spirit (E, A, & O)*	Socializer & Explorer	
5. Social influence and relatedness	Intrinsic, positive, negative	Socializer (E & A)* Philanthropist (E, A, C, & O)*	Socializer	
7. Unpredictability and curiosity	Intrinsic, negative	Free spirit (E, A, & O)*	Explorer	
6. Scarcity and impatience	Extrinsic, positive	Disruptor (N)*	Killer	Traditionalist cost-focused & cost-oriented Home focused & cost-oriented Non-green selective & early adopter Disengaged energy waster & early adopter
8. Loss and avoidance	Extrinsic, intrinsic, negative			

*Personality traits: (E): Extraversion; (A): Agreeableness; (C): Conscientiousness; (O): Openness; (N): Neuroticism

Fig. 2. Octalysis framework and its relation with the Hexad framework, role player, and energy end-user segment and target group (Bartle, 1996; Chou, 2015; Marczewski, 2015; Peham et al., 2014; Ponce et al., 2017; Tondello et al., 2016).

monetary rewards, non-monetary rewards, variable rewards, free goods, and virtual rewards; (3) social mechanisms of gifts, altruism, cooperation with friends, rating community submissions, helping a friend, feeling part of a group, differentiation, and controlling over peers due to the increase in users' engagement status; (4) restriction techniques such as punishment for not participating, expiration, scarcity, time constraints, limited resources, and access restrictions; and (5) challenges, collections, promotions, and goals, which can increase brand awareness.

In addition (Chou, 2015; Gonczarowski and Tondello, 2017; Tondello et al., 2016) created a complete framework that analyzed and built strategies around various systems that made games

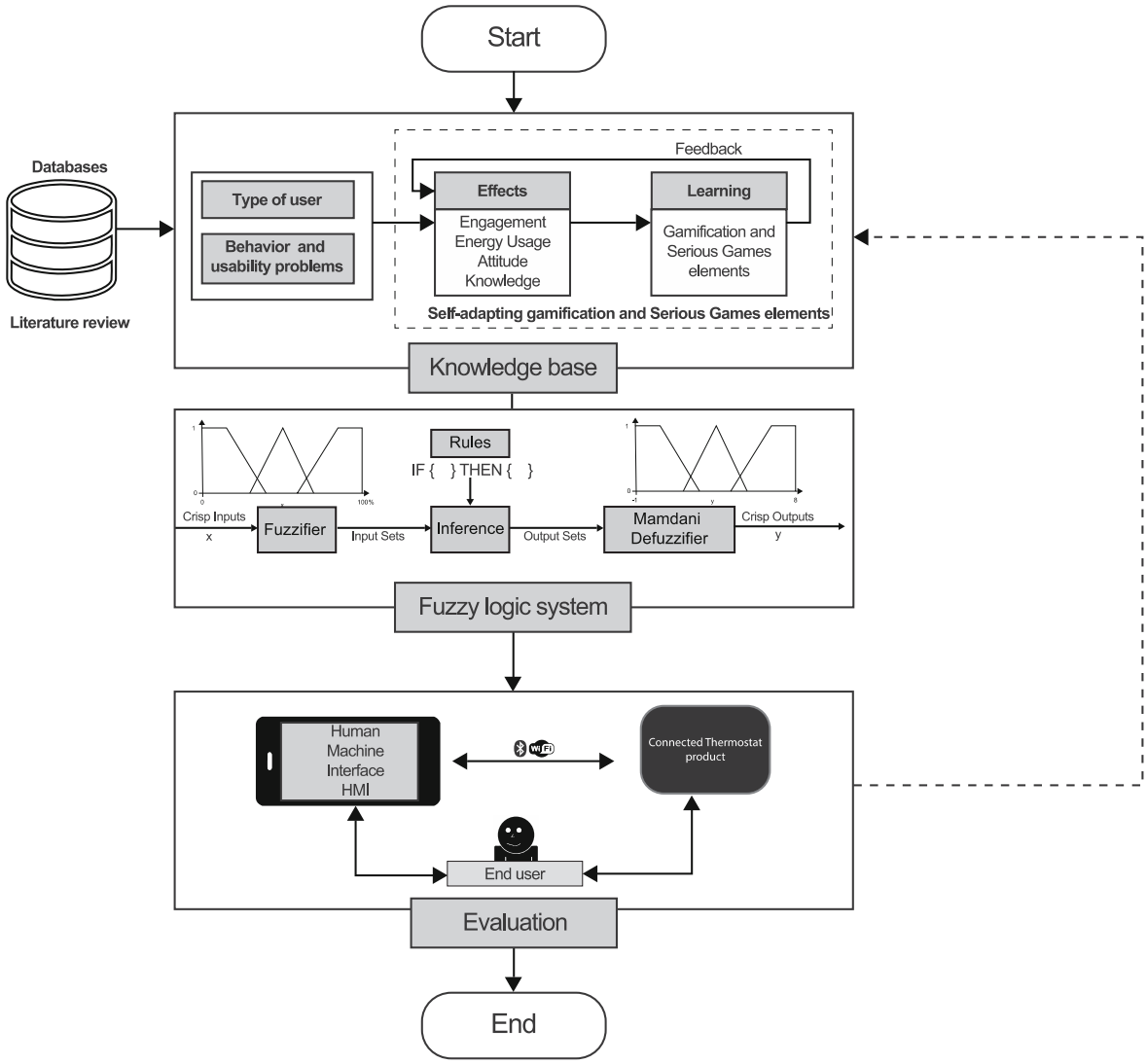


Fig. 3. Diagram of the proposed framework.

engaging. Therefore, this study focuses on the Octalysis (Chou, 2015) and Hexad frameworks (Marczewski, 2015; Tondello et al., 2016).

The Octalysis framework has eight core drives and extrinsic, intrinsic, positive, and negative motivation, which motivate and engage users to continue using a game. Each core has the following significance:

- Core 1. Epic meaning and calling: Users believe that they are doing something greater than themselves and are chosen to take action.
- Core 2. Development and accomplishment: Intern drive for succeeding progressing, developing skills, achieving mastery, and so on.
- Core 3. Empowerment of creativity and feedback: Users become engaged in a creative process when they try different combinations to achieve goals. They also need to see the results of their creativity, receive feedback, and adjust their creativity.
- Core 4. Ownership and possession: the desired core, in which users are motivated because they believe and feel that they own or are in control of something.
- Core 5. Social influence and relatedness: This core has social elements that motivate people, including mentorship, social acceptance, social feedback, companionship, competition, and even envy.
- Core 6. Scarcity and impatience: Users want something just because it is extremely rare, exclusive, or immediately unattainable.
- Core 7. Unpredictability and curiosity: People constantly become engaged because they do not know what is going to happen later; this is the core behind gambling addictions.
- Core 8. Loss and avoidance: Users try to prevent something negative from happening. They feel the urgency to act immediately; otherwise, they may lose the chance to act.

In contrast, the four types of motivations are as follows:

- Extrinsic motivation: People are motivated because they want something they cannot obtain, and obtaining it implies external recognition or even economic rewards.
- Intrinsic motivation: The activity is rewarding on its own without a specific target to achieve.

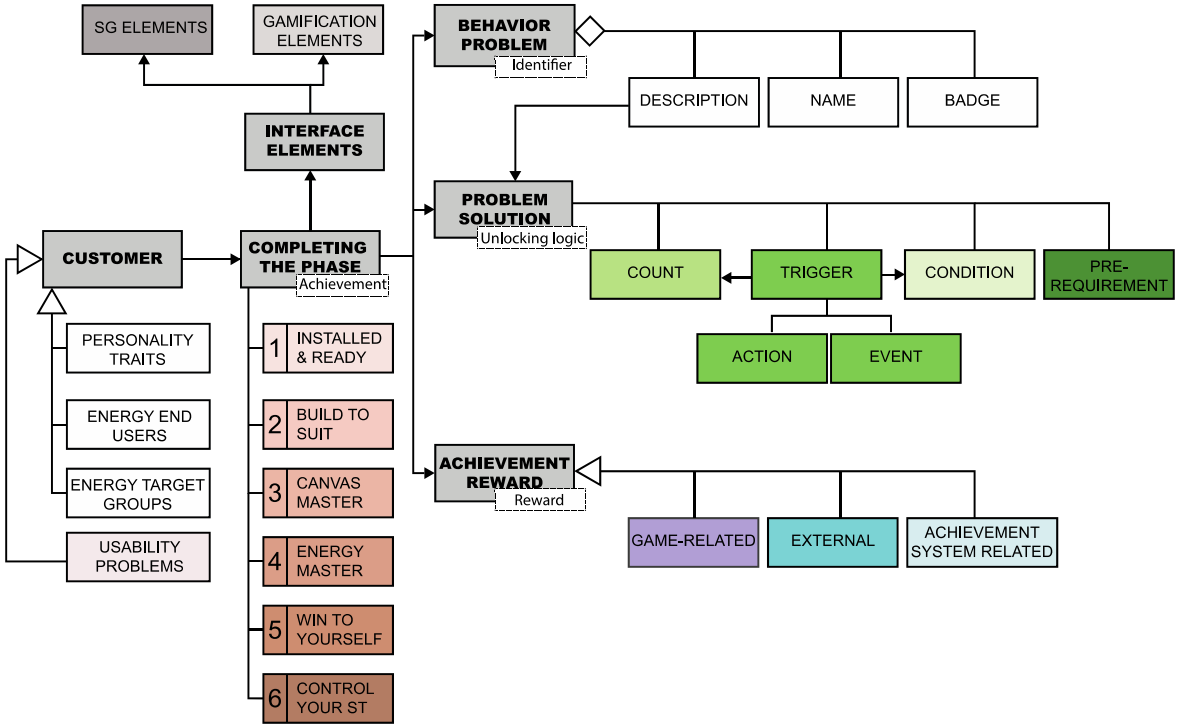


Fig. 4. Gamification and serious game achievement diagram.

- Positive motivation: The activity is engaging because it lets the user feel successful, happy, and powerful.
- Negative motivation: The activity is engaging because the user is constantly in fear of losing something.

Moreover, researchers of energy applications researchers suggest that a gamified application should consider the following: (1) information provision, such as statistics, data-driven messages, and tips, which can give residential customers a clear view of their energy-related behavior and allow them to understand how their actions impact the amount of electricity they use; (2) a reward system based on the customers' energy consumption comportment, effort, and impact, which can incentivize users to take specific actions and increase satisfaction; (3) social connections that can make energy applications more fun and appealing to residential customers, for example, in the form of social competition, collaboration, or energy community, (4) an interactive interface that users can perceive as useful, easy to use, enjoyable, and exciting; (5) a performance status that makes it possible to follow the progress of customers through points, badges, and levels to change the way in which they behave and interact with a specific application; and (6) feedback according to the users' psychological and behavioral outcomes (AlSkaif et al., 2018; Beck et al., 2019).

The (Fijnheer and Van Oostendorp, 2016) steps were proposed for the PowerSaver energy game, and it works as a guideline for designing a household energy game by measuring the practical effects (knowledge, attitude, energy usage, and engagement) to develop a game and dashboard prototype. However, these steps can be improved with a methodology that considers its implementation in physical products, for instance, by saving energy through smart devices and continuously measuring a user's activity. In addition, instead of only using fictional scenarios to test user improvement, the improvements can be examined with real situations, such as comparing users' performance by displaying their amount of energy and money saved in real-time.

3.2. Serious games and energy saving

SGs refer to games designed for primarily non-entertainment purposes with an explicit and carefully thought-out educational purpose. A correct balance between entertainment and education to allow games not to be intrusive or cease being intrinsically motivating is required. Therefore, regardless of whether SGs are analog or digital, they exhibit characteristics such as a goal-oriented nature with specific rules or a feedback system, competitive comparative elements, and element challenging activities, choices, and fantasy elements. They have been found to be effective for the following reasons: (1) the player is immersed in the gaming experience and receives feedback from the other participants; (2) the games provide information in a ludic way so that the players feel active; (3) on a large scale, they permit further investigation into the intervention's effectiveness strategy in influencing behavior (Coursera, 2017; Giessen, 2015; Moloney et al., 2017).

According to (Madani et al., 2017), energy SGs have the following characteristics:

- Theme: The main focus of the game, which is an energy game theme.
- Player's role: The identity of the character that a player assumes in the game (Achiever, explorer, socializer, and/or killer (Bartle, 1996)).
- Game objective: The specific result that a player must achieve to complete the game.
- Number of players: The number of players that can join the game.
- Participants: The group of players, such as students, professionals, and stakeholders.
- Type of game: The classification of each game (board game, card game, digital game, online game, hybrid simulation including the previous types).
- Graphics: 2D or 3D game.

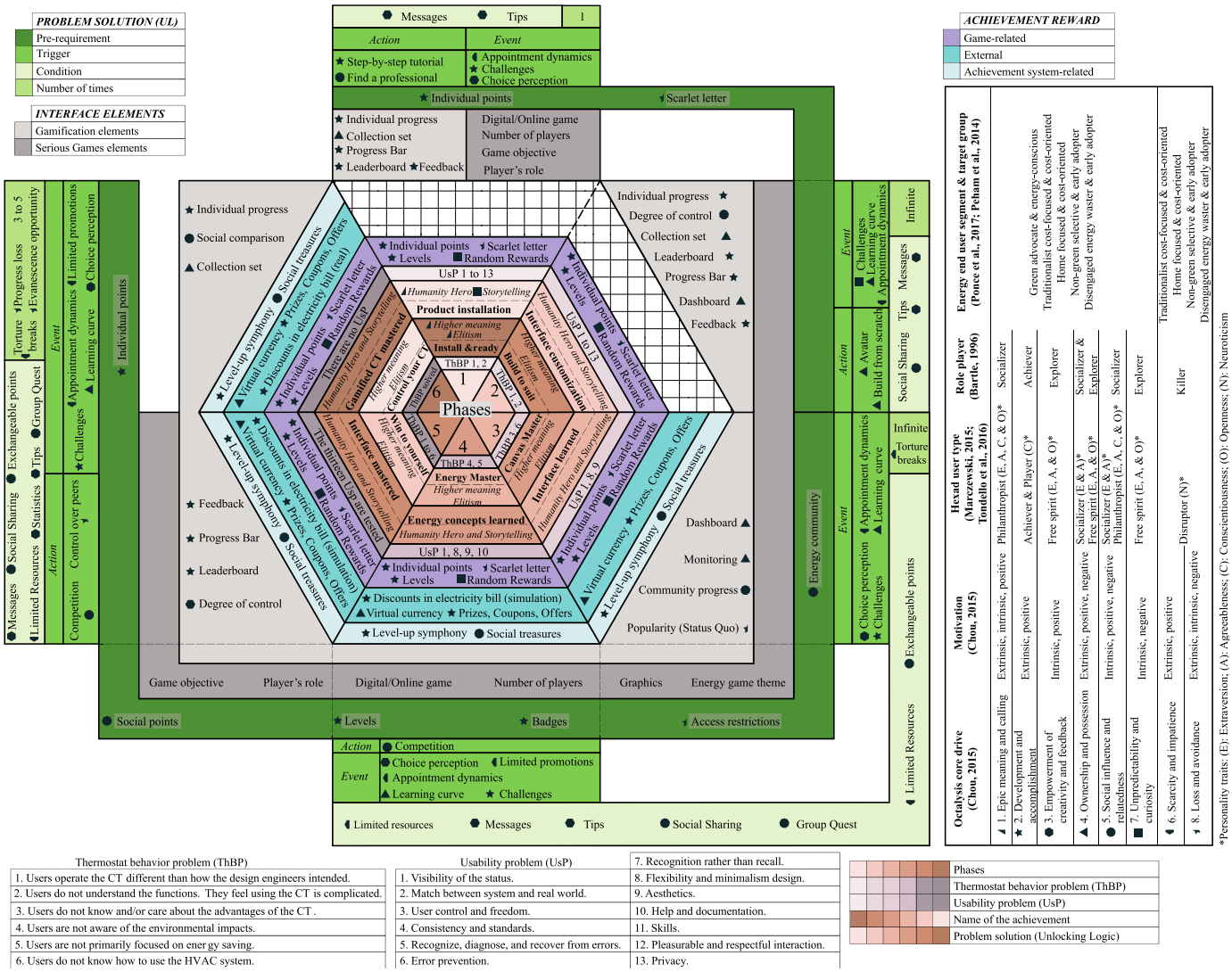


Fig. 5. Elements involved in the smart thermostat interface.

- Availability: How the game is obtained or purchased.

3.3. State of the art in gamification, serious games, and connected thermostats

Table 8 presents state of the art in gamification and SGs related to energy, in particular, efficiency, consumption, and sustainability. In addition, Table 9 shows state of the art in CTs since 2007 when CTs were proposed as a controllable vent for zone heating/cooling. As the literature review demonstrates and to the best of the authors' knowledge, there is no evidence of an application that fits with gamification and SG concepts for the behavior and usability problems observed in CTs, besides for the one proposed by the authors in (Méndez et al., 2019a), in which suggestions were based on using gamification elements excluding the SG elements. The proposal was made based on this work. Many energy applications involving SGs teach users how to be aware of energy consumption. The closest gamification game that pertains to energy awareness in households is ecoGator. However, this application only helps users achieve energy efficiency, not control, or become immersed in the functions of a smart device.

Subsections 3.1. and 3.2. show gamification and SG categories from the literature. As this paper is not focused on developing a new gamification framework, Fig. 2 shows the collected information from Section 2 and Subsections 3.1 and 3.2. This figure, due to its completeness, takes a basis for the Octalysis framework (Chou, 2015). The eight-core drives, the game mechanics, and their motivations are related with the six gamified users types and their personality traits (Bartle, 1996), the four SG role players (Bartle, 1996), and the most common gamification elements in energy applications (AlSkaif et al., 2018) to propose any gamified application.

4. Methodology

Step 1: Knowledge base phase: this step collects information provided by questionnaires, longitudinal, or transversal studies obtained from literature review and databases. This information is related to the energy end-users, their behavior, and usability problems, as well as the associated effects with the most common gamification and serious game elements in energy applications. Therefore, for this work, it is considered the type of user described in Section 2, in addition to the behavior and usability

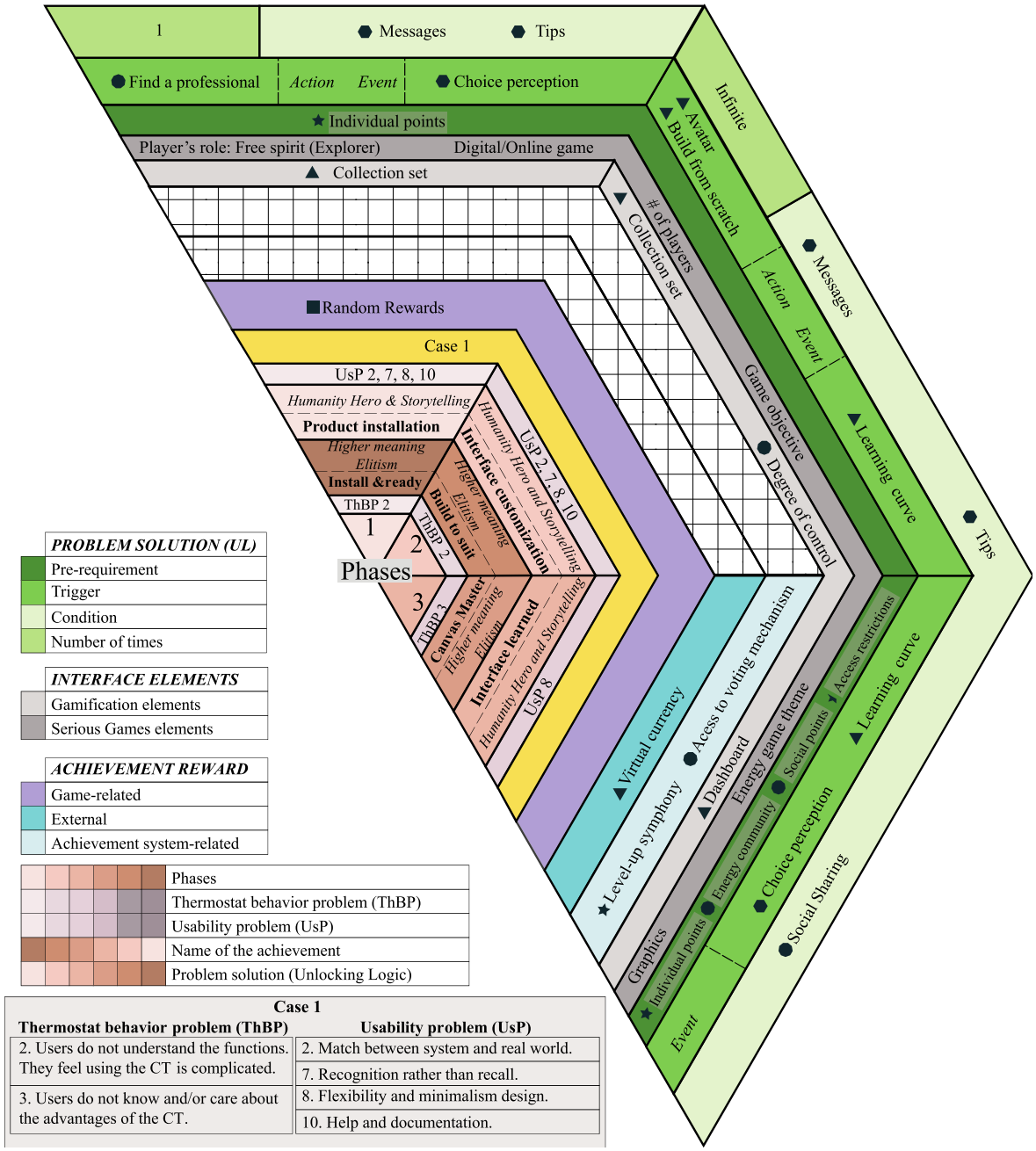


Fig. 6. Case 1 diagram.

problems explained in Table 1, the gamification elements in Fig. 2, and the four effects attributed to a successful energy game (knowledge, attitude, energy usage, and engagement (Fijnheer and Van Oostendorp, 2016)). As a result, these elements can self-adapt to keep the user continuously learning, engaged, and motivated while saving electrical energy when using the CTs.

In this phase, the Octalysis and Hexad frameworks (described in Fig. 2) plays the leading role because of the game mechanics considered in every core drive associated with the type of gamification user help to test the elements that keep the user interested (Chou, 2015; Tondello et al., 2016). Thus, it is proposed to use the extrinsic factors that are suggested in energy applications as they are tangible and measurable, and they seek to achieve external recognition and economic rewards as well as positive motivation to make users feel successful, happy, and powerful (AlSkaif et al., 2018; Beck et al., 2019).

Step 2: Fuzzy logic phase: In this phase, the fuzzy logic type 1 system decision is used to determine which gamification and SG elements must be displayed in the HMI that best fit each type of consumer. This step proposes the tailored interface for the typical and non-typical user.

Step 3: Evaluation phase: The natural society behavior and non-natural behavior in (Ponce et al., 2019) evaluate the interactions between the consumer data that stem from CT and

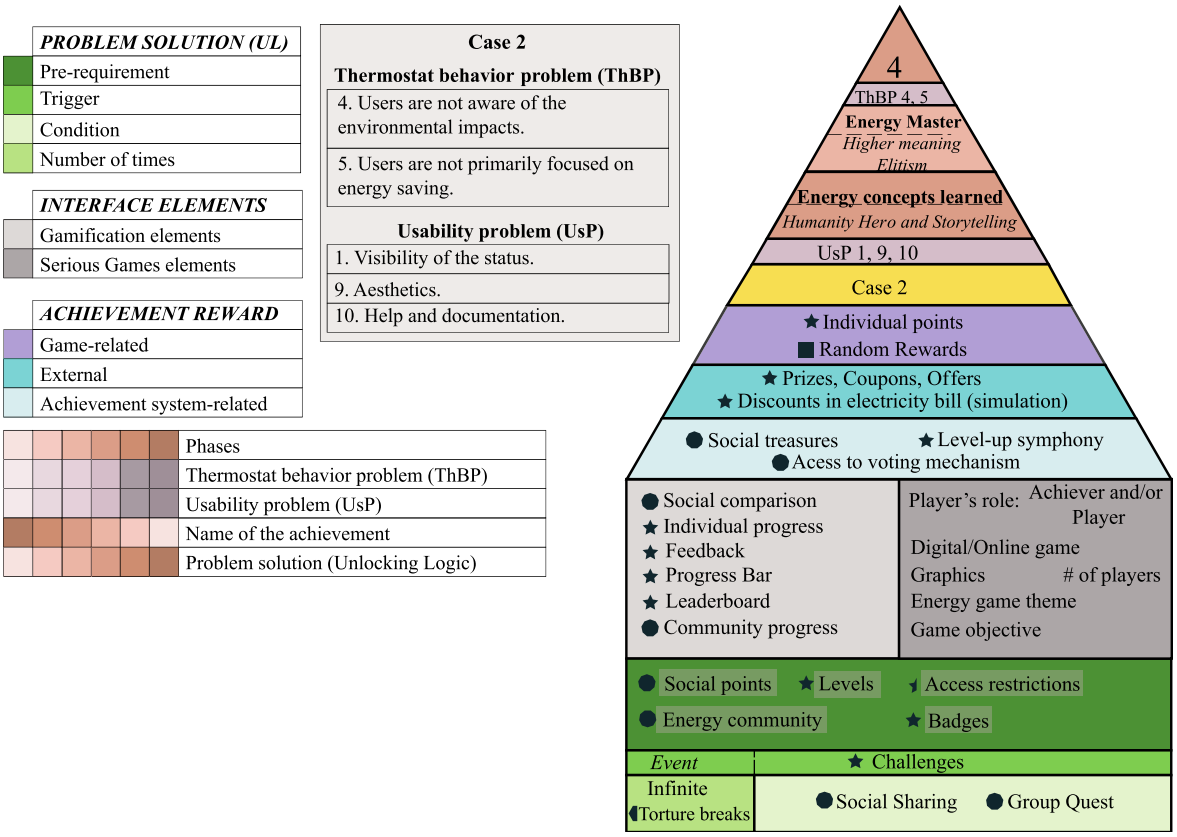


Fig. 7. Case 2 diagram.

the users' conducts changes. If the users continue to behave with no changes, then it is necessary to change the output values of the fuzzy logic; thus, the application provides feedback to the knowledge base to rerun the process.

5. Proposed framework

Fig. 3 illustrates the three-step framework proposed for the development of an S^3 product that aims to bridge the gap between the information provided by the CT, the user's expectations, and the environmental impact through an HMI.

5.1. Knowledge base phase

To become engaged in the energy application, the consumers (users) must complete several stages. This leads them to increase their energy awareness and knowledge (AlSkaif et al., 2018) by mastering the application through gamification and SG elements and produces a solution to the behavior and usability problems.

Fig. 4 presents a diagram derived from the achievement structure (Hamari and Eranti, n.d.; Matallaoui et al., 2015; Stieglitz et al., 2016), which, in addition to the identifier, unlocking-logic, and reward components, has an interface elements component and a customer component. The customer component pertains to the different types of users according to their personality traits, energy end-users, and energy target groups. Each achievement phase is proposed to solve the usability problems detected in the use of CTs. The interface of an interactive system influences the users' decisions, expectations, and motivations; thus, the interface should be useful, easy to use, and designed to be enjoyable and exciting (AlSkaif et al., 2018). The problem solution unlocking logic (UL) aims to solve the behavior problems displayed in Table 1 and, depending on the phase, immerse the users in real and fictional scenarios so that they can understand energy concepts and how the CT operates. The users can interact with elements that commonly appear in a CT interface, such as the system mode, humidity, indoor temperature, weather, quick changes, voice control, manual temperature adjustment, and menu options (ecobee, 2016).

Fig. 5 demonstrates that every element presented in the achievement diagram is followed by gamification and/or SG elements that provide the user with game-like techniques to allow them to feel real ownership and purpose when they become engaged with tasks (Peham et al., 2014). The Customer element contains three large groups categorized according to personality, energy end-users, and energy target; however, this group is not static and can self-adapt. Thereafter, to perform each Completing the Phase achievement, the user must solve the Thermostat Behavior Problem Identifier by completing the problem solution UL to finally be awarded with an Achievement Reward. The application thus requires Interface Elements that have a positive effect on and increase customer engagement (AlSkaif et al., 2018; Peham et al., 2014).

a) Thermostat behavior problem identifier: This is the visible part that transmits the information presented to the player about the achievement that makes the identifier unique, playing an essential role in creating the experience of an achievement meta-game (Hamari and Eranti, n.d.; Matallaoui et al., 2015; Stieglitz et al., 2016). For example, the

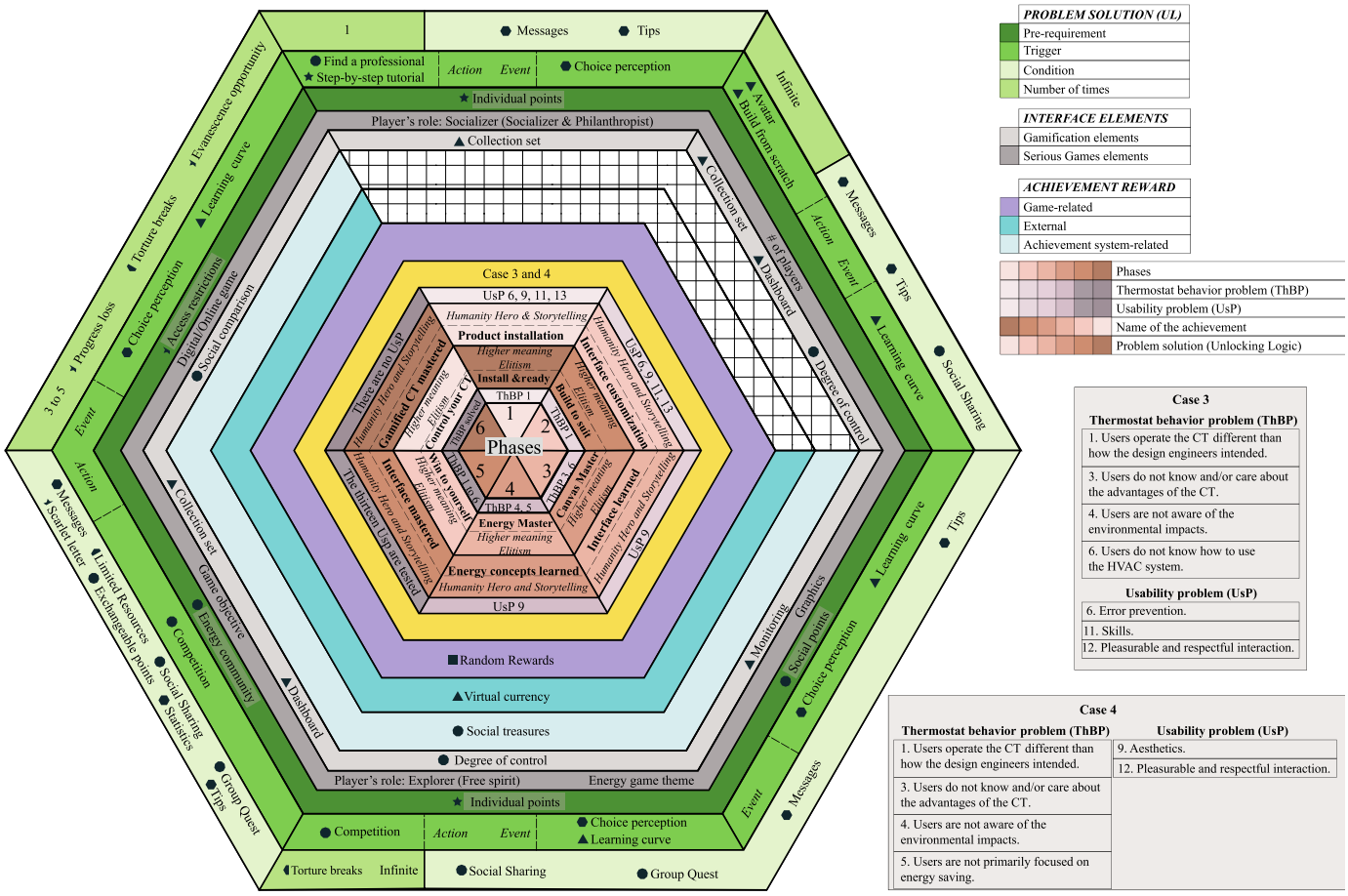


Fig. 8. Case 3 and 4 diagrams.

2020 Energy game has three identifier scenarios: energy saving, energy efficiency, and renewable energy. Every situation has several tasks to complete; thus, the user must play all scenarios to win (Game | 2020 Energy, 2018).

- **Description of the game objective:** this has operational rules that describe what the player must do. According to (Chou, 2015), including gamification elements such as Humanity, Hero, or Storytelling makes users feel that they are part of a community in which their skills are helpful for achieving tasks.
- **Name of the achievement:** This sets a theme for Completing Phase achievement. A narrative element inside the achievements name is useful for engaging users so that they can understand why their help is essential for the success of the task. In addition, the elitism element encourages users to feel that being part of the game is something that makes them unique and that only a few individuals have access to the game (Chou, 2015).
- **Badge:** This usually has two forms: unlocked or locked achievement (Hamari and Eranti, n.d.).

b) Problem solution UL: This defines what is required from the user and from the game state for the achievement to be completed (Hamari and Eranti, n.d.; Stieglitz et al., 2016).

- **Trigger:** This element defines an action done by a user or an event.
  - o **Action:** This is what the user must do. The players explore the game to ensure that the conditions match and then trigger the action themselves (Bartle, 1996).
- **Event:** A system-invoked event takes place by playing in a way in which the conditions match the conditions described in the Completing the Phase achievement task (Hamari and Eranti, n.d.; Matallaoui et al., 2015; Stieglitz et al., 2016).
  - o **Condition:** This includes the requirements for the prevailing game state of existing, as well as the historical events within the game session that must occur before the trigger takes place. Questions are answered, including when, where, in what time frame, and with whom the trigger should take place; that is, what the trigger is based on.
  - o **Pre-requirement:** Global requirements for the game setting that do not affect the game session. These can be the selection of the game mode, difficulty, character class, or playing during a determined season.

c) Achievement reward: Users are rewarded with a cue for unlocking the achievement. Usually, these achievements are visible to players (AlSkaif et al., 2018; Barbosa et al., 2017; Bartle, 1996; Casals et al., 2017; Chou, 2015; Dorji et al., 2015; ecoGator, 2016; Fijnheer and Van Oostendorp, 2016; Game | 2020 Energy, 2018; Geelen et al., 2012; Hamari and Eranti, n.d.; Matallaoui et al., 2015; Ouariachi et al., 2019; Stieglitz et al., 2016).

- **Game-related:** Players earn points toward the maximum achievement points possible as a manner to dispose and accumulate high-value rewards (Bartle, 1996).

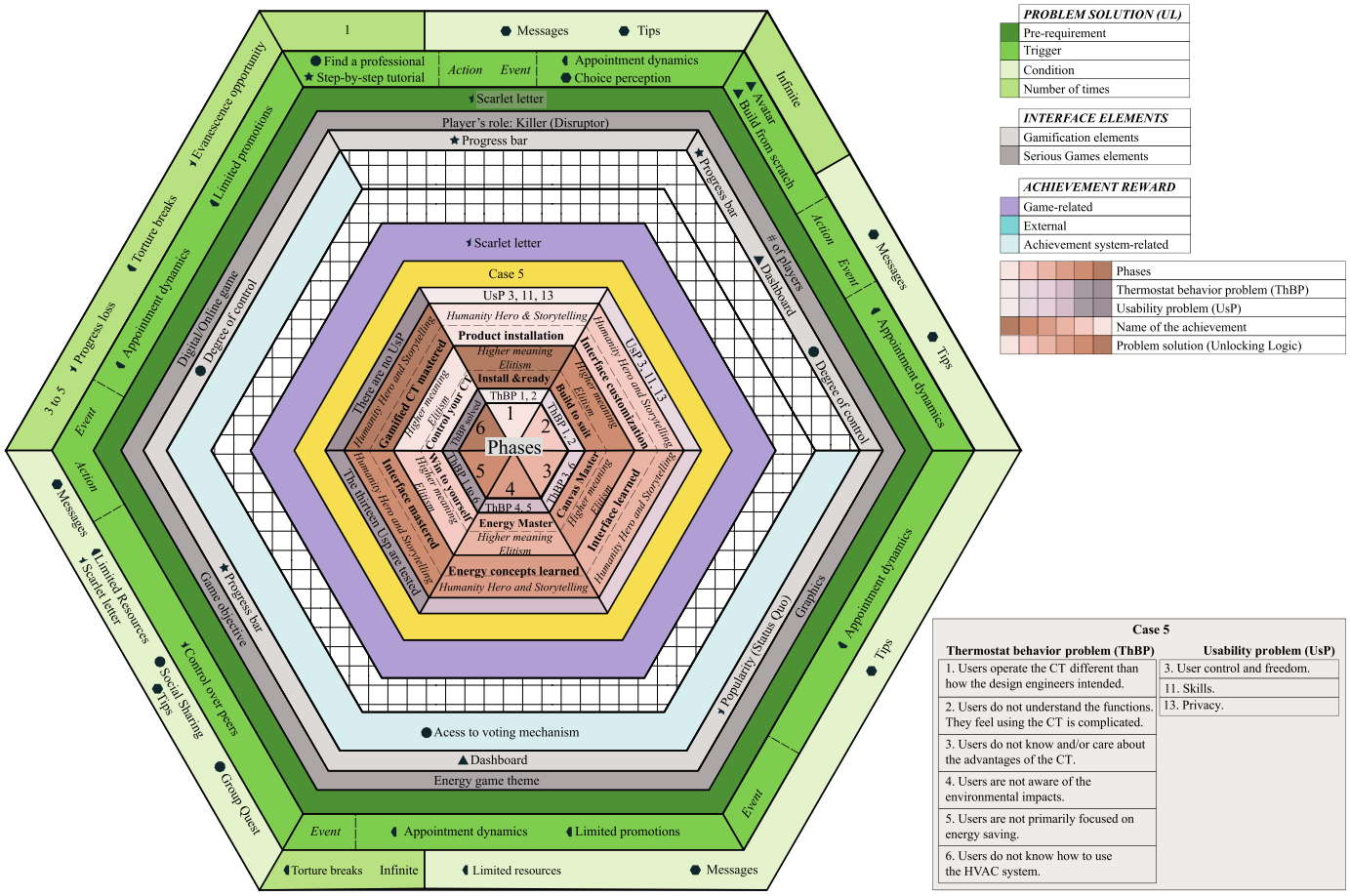


Fig. 9. Case 5 diagram.

- **External:** Rewards are external to the achievement system and the game itself (e.g., users are rewarded with a shopping coupon).
- **Achievement system based:** Rewards related to the achievement system, (e.g., by unlocking a given achievement, the user fulfills the conditions for unlocking another type of achievement).

d) Interface elements: The interface influences the users' motivation. An attractive user interface is required with stimulation visuals and exciting interaction concepts (AlSkaif et al., 2018; Barbosa et al., 2017; Casals et al., 2017; Chou, 2015; Dorji et al., 2015; ecoGator, 2016; Fijnheer and Van Oostendorp, 2016; Game | 2020 Energy, 2018; Geelen et al., 2012; Hamari and Eranti, n.d.; Matallaoui et al., 2015; Moloney et al., 2017; Ouariachi et al., 2019; Stieglitz et al., 2016).

- SG: This option is available from step 1 to step 5, the Install and ready, Build to Suit, Canvas Master, the Energy Master, and the Win to yourself achievements. The users learn six thermostat behavior problems. Any serious energy game requires objective, energy game theme, an identity of the player's role based on the Hexad Framework, and its association with the personality trait (Marczewski, 2015; Tondello et al., 2016), and the (Bartle, 1996) role player. This type of game displays the option of on-line or off-line mode, and the group or single-mode to promote socialization or imposition with the others (Bartle, 1996; Dorji et al., 2015; Geelen et al., 2012; Huotari and Hamari, 2012).

Gamification: The gamification elements display to the users the options to monitor the thermostat status to have a degree of control, to receive feedback, to show popularity. The interface displays a leaderboard to track his/her progress and community progress and collection set to display all the badges and rewards achieved. The Dashboard is displayed from step 2 to six and is mandatory for all the typical and non-typical user. The progress bar element appears in all the phases and for all the types of costumers.

5.1.1. Proposed cases for knowledge base

To better explain the goals in this study, it is examined five types of users and how tailored gamification and SG mobile application can help customers become engaged, change their behavior, and save energy. To use the application is not required to pass all the phases. This means that a user can be in My Real Interface mastered without achieving Phases 3, 4, or 5. However, the main principle of this structure is that customers understand the functionalities and capabilities of the CT and how improving energy consumption can lead to economic, social, and environmental benefits. The concept of having several phases is that the users master each and can, at the final stage, deeply understand how to manage their CTs to save energy.

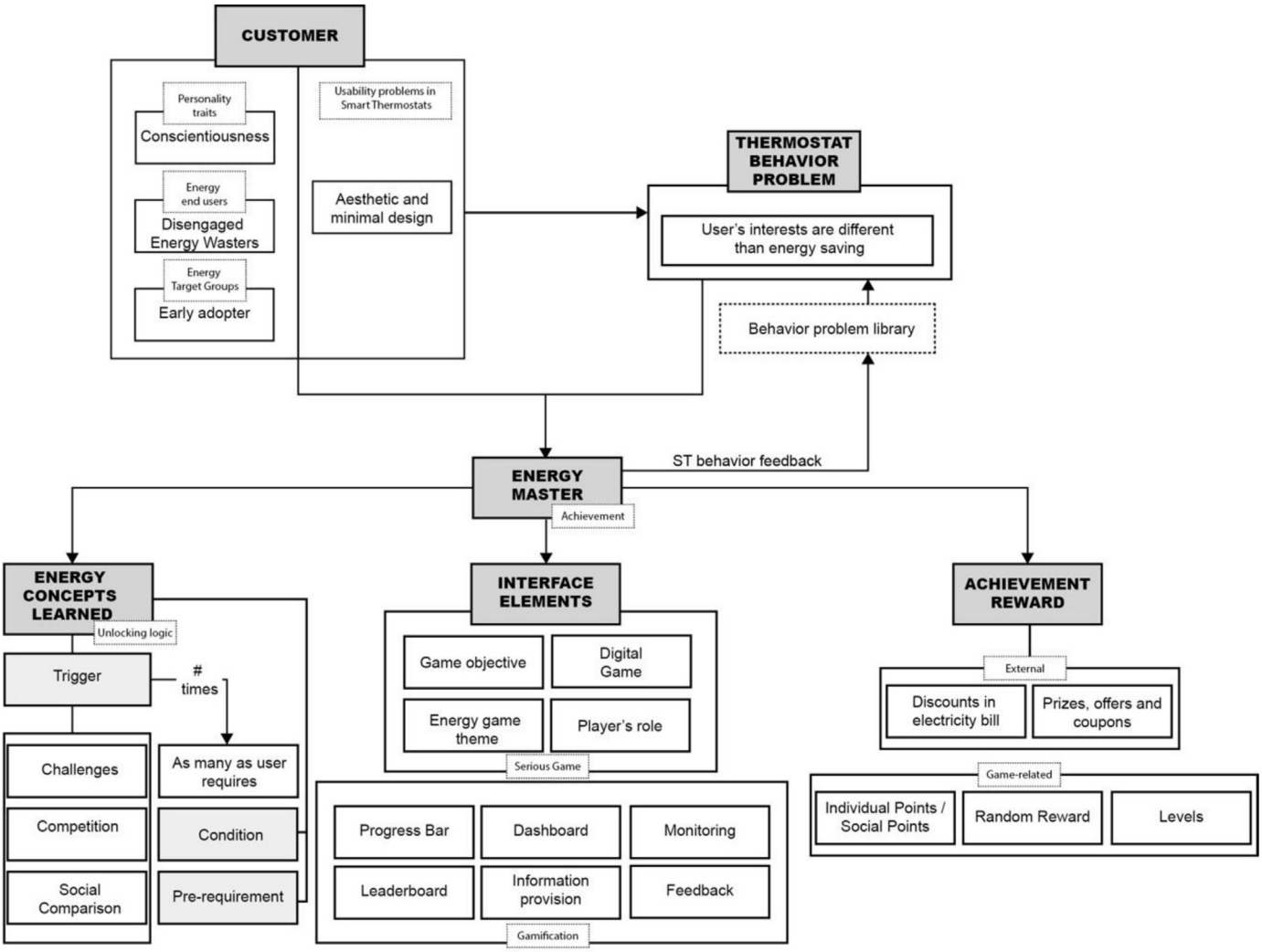


Fig. 10. Energy saving strategy diagram.

5.1.2. Case 1 (Fig. 6)

a) Type of user: The user is pro-environmental but does not know how to use an ST. The user has the following features:
   - Openness, green advocate, and energy-conscious.

b) Usability problem: Help and documentation, flexibility and minimalism design, match between system and real-world, and recognition rather than recall.

c) Behavior problem in the CT: The user does not understand the functions of the CT; the user believes that CT is complex. The user does not know about the advantages of using a CT.

d) Problem solution suggested: product installation, interface customization, and interface learned.
   - These steps are designed to help users better understand how to use their thermostats. First, the users must customize their CT interface according to the method in (Ponce et al., 2017). Then, by applying SG techniques in the Interface Learned, the application displays users' CT customized canvases as a game so that they can learn how to use every button and understand the implications of taking actions regarding energy consumption. Once the users understand the CT display, they can comprehend how to use the Real Interface to interact with their thermostats and observe the consequences of every action they take.

e) Achievement Reward: Game-related.
   - Rewarding users based on their conduct, effort, and impact, can incentivize them to take specific actions and increase their satisfaction (AlSkaif et al., 2018). This can take place through points, achieving levels, or even by providing, for example, smiley faces to users who improve their average or are at the top (Gonczarowski and Tondello, 2017).
   - Interface elements:
   - As discussed in (Ponce et al., 2018b), end-users often do not understand programmable thermostats and are not motivated to overcome difficulties in programming them; thus, they have low expectations for the performance of the CTs. To motivate users to learn how to use the thermostats is necessary to have an interface in which the primary system has contact with the end-users through tailored, interactive tips, information, and data-driven messages that can give users a clear view of how their actions impact the amount of energy they waste and how they can have improved engagement and active participation (AlSkaif et al., 2018).

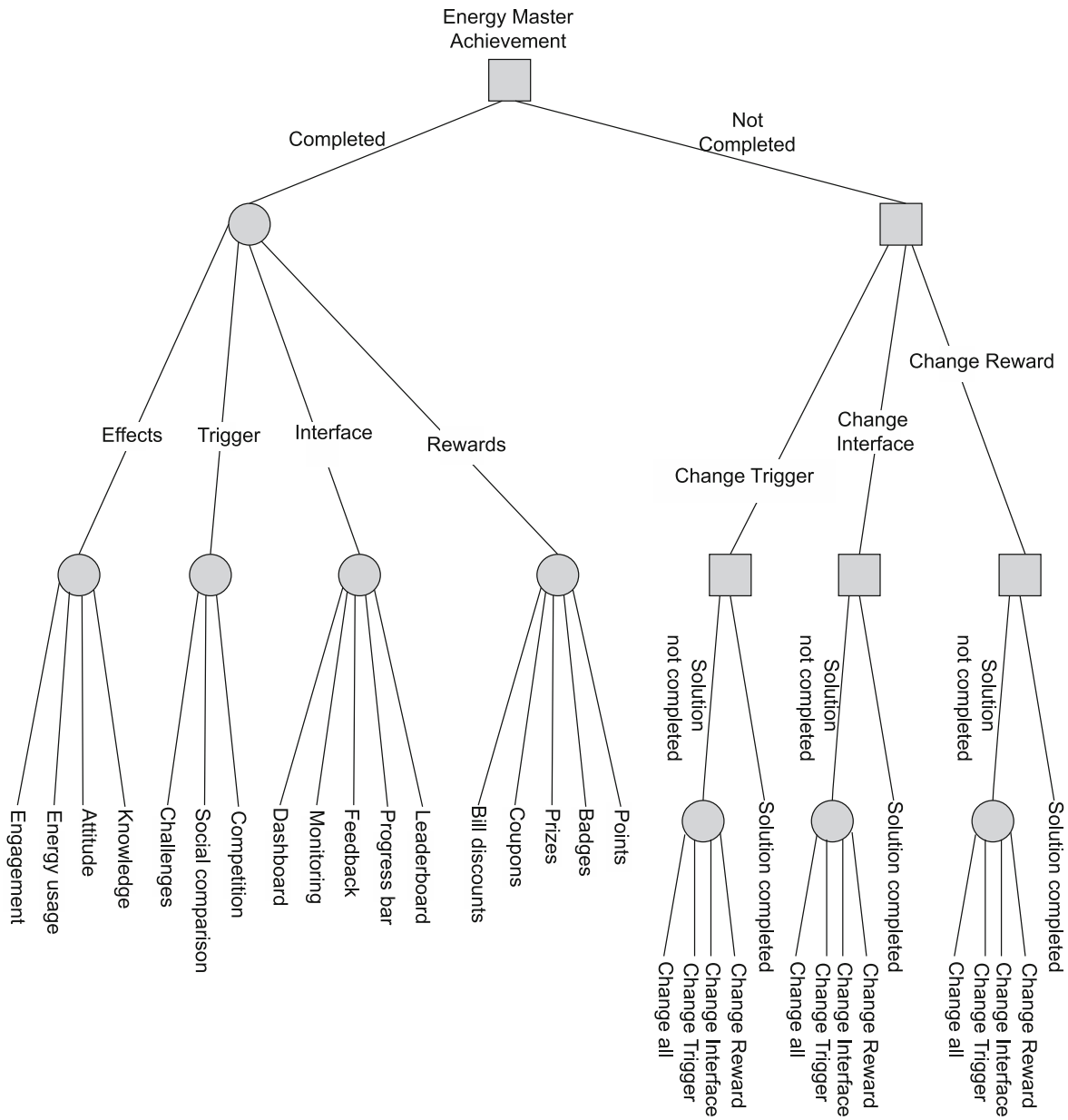


Fig. 11. Decision tree.

Table 10
Energy Master achievement completed Case 2a.

Energy Master achievement completed							
Effects		Trigger		Interface elements		Rewards	
Engagement	H	Challenges	H	Dashboard	H	Points	H
Energy usage	L	Social Comparison	M	Monitoring	H	Badges	H
Attitude	M	Competition	H	Feedback	H	Prizes	H
Knowledge	H			Progress bar	H	Coupons	L
				Leader-board	H	Bill dis-counts	L

- Users can follow their progress through the dashboard, leaderboard, progress bar, message box, and notifications about their performance. These elements are used to motivate individuals to be at the top and achieve the Win-State of completeness, as (Chou, 2015) proposes. In addition, using a dashboard can prompt users to constantly

Table 11
Energy Master achievement completed Case 2b.

Energy Master achievement completed							
Effects		Trigger		Interface elements		Rewards	
Engagement	L	Challenges	M	Dashboard	M	Points	M
Energy usage	M	Social Comparison	M	Monitoring	M	Badges	M
Attitude	M	Competition	M	Feedback	M	Prizes	H
Knowledge	H			Progress Bar	L	Coupons	M
				Leader-board	M	Bill Dis-counts	M

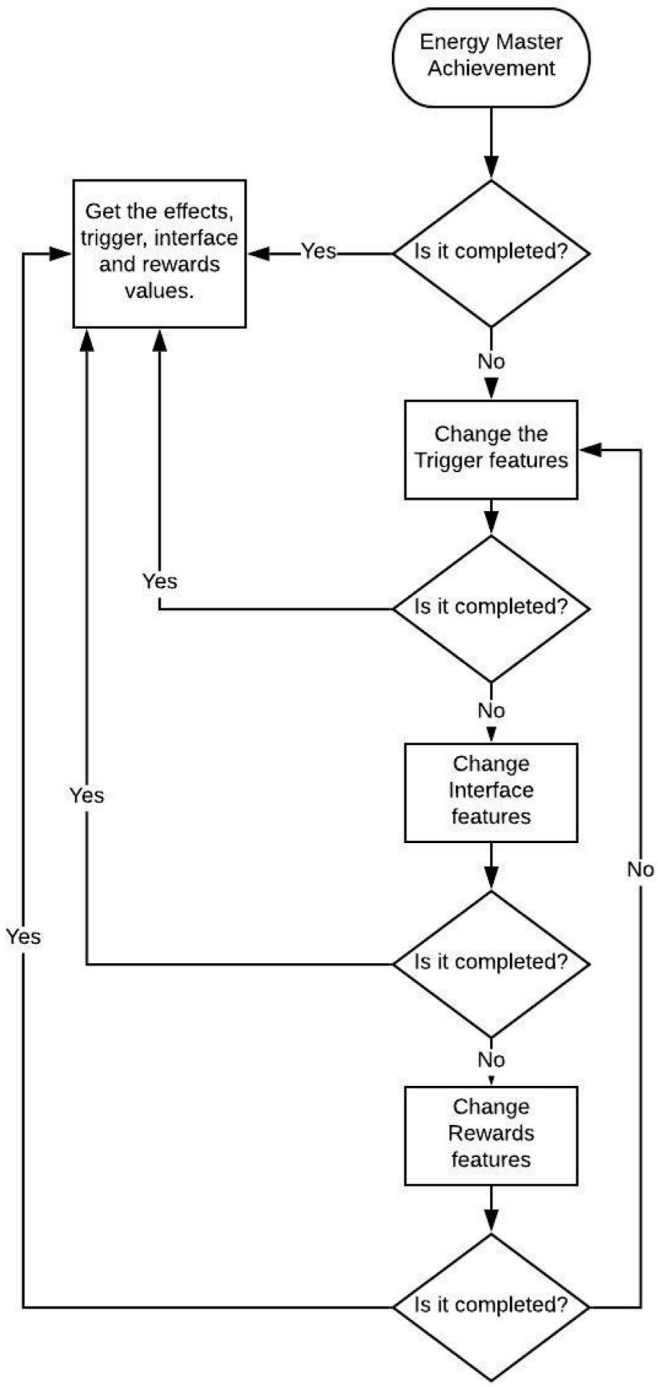


Fig. 12. Energy Master achievement not completed diagram.

monitor the progressive output of the CT development. The use of a leaderboard serves to make users feel optimistic about accomplishing the task and act with urgency so they can increase their status.

- Using a digital game of the user's CT interface can help users understand how the CT operates.

5.1.3. *Case 2 (Fig. 7)*

a) Type of user: The user is at the cutting edge of technology, understands the CT functions, but is not familiar with saving energy. The user has the following features:
   - Conscientiousness, disengaged energy waster, and early adopter.

b) Usability problem: Aesthetics, visibility of the status, and help and documentation.

c) Behavior problem in the CT: Users' interests are different from energy saving, and they are not aware of their environmental impact.

d) Problem solution suggested: Energy concepts learned.
   - Educational information for a deeper understanding of saving energy that leads to a sustainable lifestyle helps users identify basic concepts of energy consumption and provide useful forms for reducing daily consumption. This information can be presented as tips and hints, and in the end, the user can be quizzed on the content.
   - Social competition, collaboration, and energy community are key components for success (AlSkaif et al., 2018). The best way to motivate households to consume less energy is through a chart that compares their consumption with that of their neighbors (Chou, 2015).
   - Applying the gamification mechanisms collected in Table 7 can provide incentives that are in the customer's interest by demonstrating, for instance, the social and environmental outcomes resulting from a new energy consumption habits, or by compensating them with rewards in proportion to the effort they provide in a certain application (Prochaska and Velicer, 1997).
   - In (Geelen et al., 2012), feedback about energy consumption is an effective way to enable individuals to modify their conduct. The feedback must be provided frequently and over a long period of time and should allow users to see the consequences of their actions.

e) Achievement Reward: Game-related, external.
   - In (AlSkaif et al., 2018; Ponce et al., 2019), the authors propose an electricity discount as an incentive for improved consumption behavior.
   - Individual and Social Points or by giving a number of credits proportional to a customer's effort that can be redeemed within the game economy for valuables or points that can be traded with other users in the

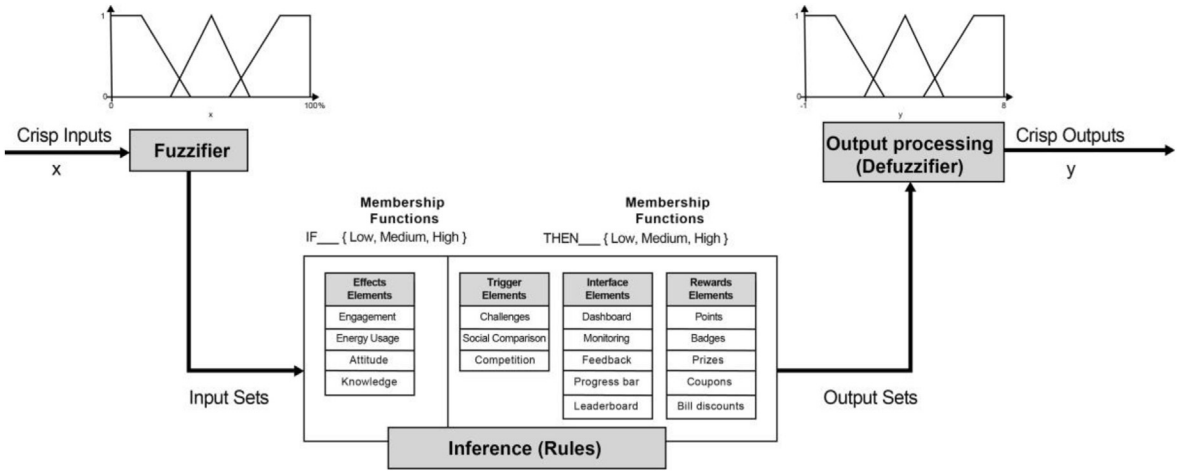


Fig. 13. Algorithm structure.

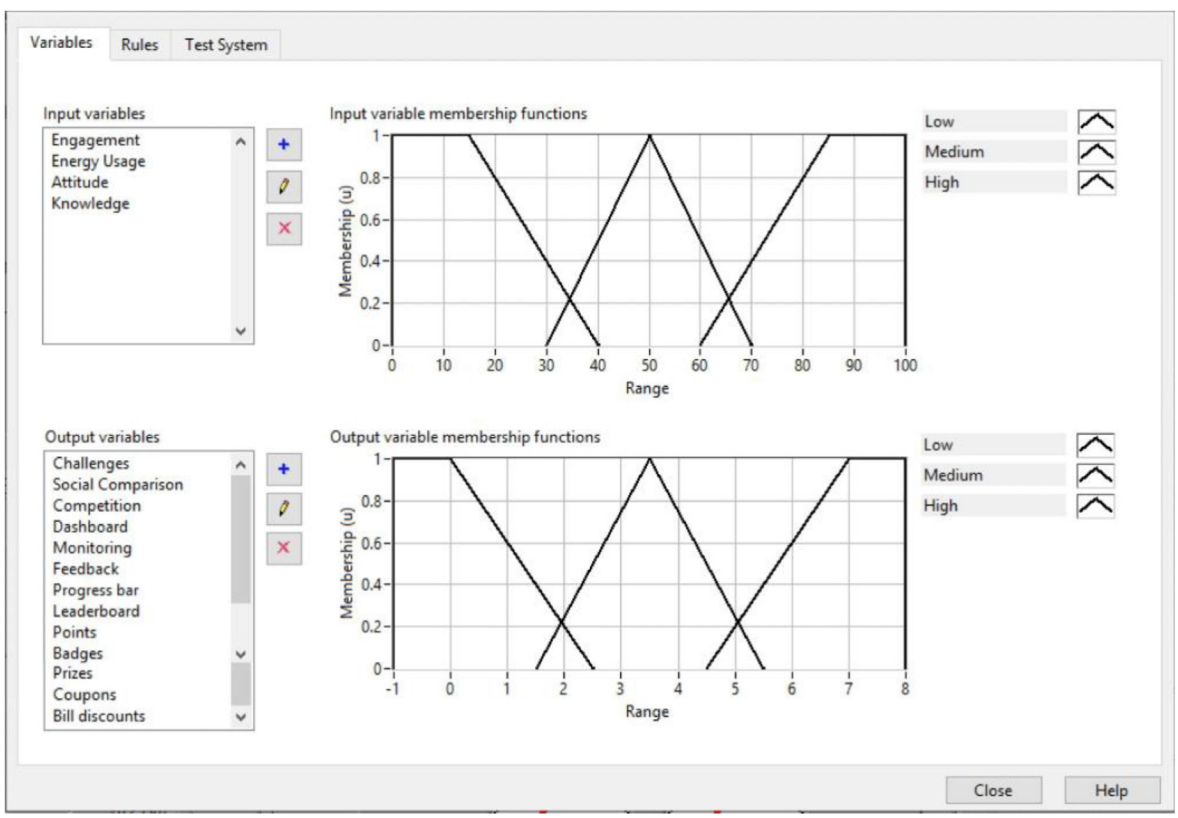


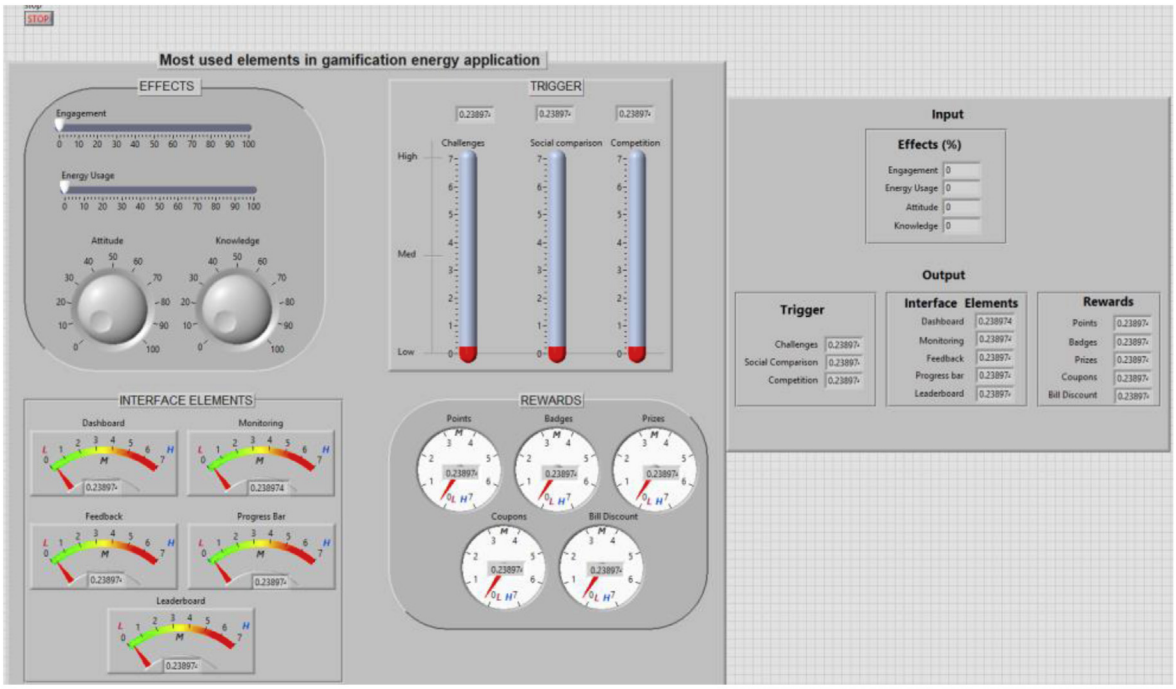
Fig. 14. Membership functions for the Energy Master achievement.

application. Exchangeable points can allow users to trade individuals outside of the gamified system (AlSkaif et al., 2018; Chou, 2015).

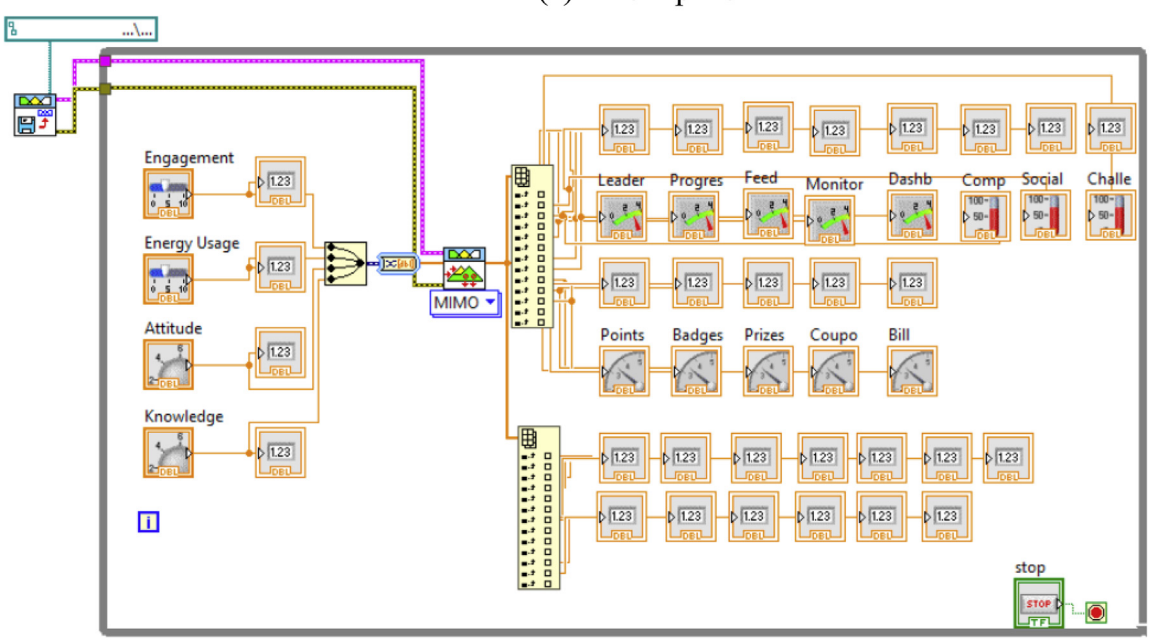
- Prizes, offers, and coupons are occasionally the main reasons to continue (AlSkaif et al., 2018; Geelen et al., 2012).

f) Interface elements:

- The dashboard, leaderboard, progress bar, message box, and notifications about the customers' performance (AlSkaif et al., 2018; Peham et al., 2014).
- Statistics that allow customers to compare their performance with that of other customers (AlSkaif et al., 2018; Peham et al., 2014).



(a) Front panel



(b) Block diagram

Fig. 15. Proposed fuzzy logic system to test the application (front panel (a) and block diagram (b)).

- Providing users with items, characters, and badges of a Collection Set can prompt them to want to collect them all and complete the set (Moloney et al., 2017).

5.1.4. Case 3 (Fig. 8)

a) Type of user: The user wishes to learn how to use a thermostat and become a pro-environmental user. The user has the following features:
   - Agreeable, home-focused, and cost-oriented.

b) Usability problem: Skills, error prevention, and pleasurable and respectful interaction with the user.

c) Behavior problem in the CT: The users' operation is different from the operation intended by the CT engineers. Users do not understand the functions or know and/or care about the advantages of a CT. Users are also unaware of the environmental impact and do not use the HVAC correctly.

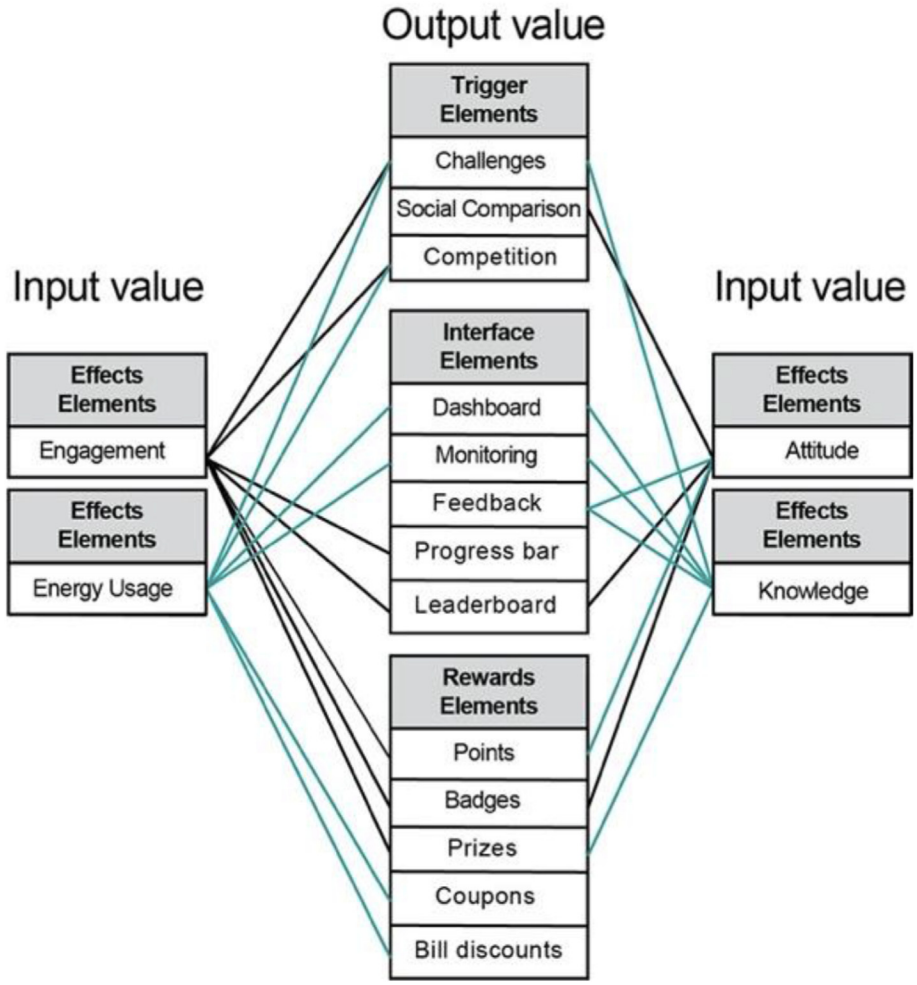


Fig. 16. Proposed input-output relationships.

d) Problem solution suggested: Product installation, Interface customization, Interface learned, Energy concepts learned, Interface mastered, and Gamified CT mastered.
   - Since the problems require a deep understanding of every step of the game, the proposal is to teach users the skills needed to understand the application.
e) Achievement Reward: All are related to the six phases.
f) Interface elements: All are related to the six phases.

5.1.5. *Case 4 (Figs. 6 and 9)*

a) Type of user: These users are motivated by cost savings, know about HVAC systems, but do not wish to be green users. They bought their CT for social motives and want the product to save energy for themselves. The user has the following features:
   - Extraversion, non-green selective, and early adopter.
b) Usability problem: Aesthetics and pleasurable and respectful interaction with the user.
c) Behavior problem in the CT: The users' operation is different than the operation intended by engineers. Users do not care about the advantages of CT, and their interests are not to save energy. Users are not aware of their environmental impact.
d) Problem solution suggested: Product installation, Interface customization, Interface learned, Energy concepts learned, Interface mastered, and Gamified CT mastered.
   - Users must complete the Product Installation phase before becoming engaged. In this step, the CT manual provides the users with step-by-step guidance to install the product through the mobile application. Once in the application, the game instructs the users to create a personalized profile and thermostat interface. The users can then learn the options that are displayed even if they are not interested and just wish to gain cultural knowledge. In addition, the game provides the users with rewards and demonstrates that by understanding how the CT operates, the more economic benefits they can achieve. Although the CT can help improve energy usage, it is important for the users to learn which options can help them save more energy and to not become upset if their expectations are not fulfilled.
e) Achievement Reward: All are related to the six phases tailored to the customer.

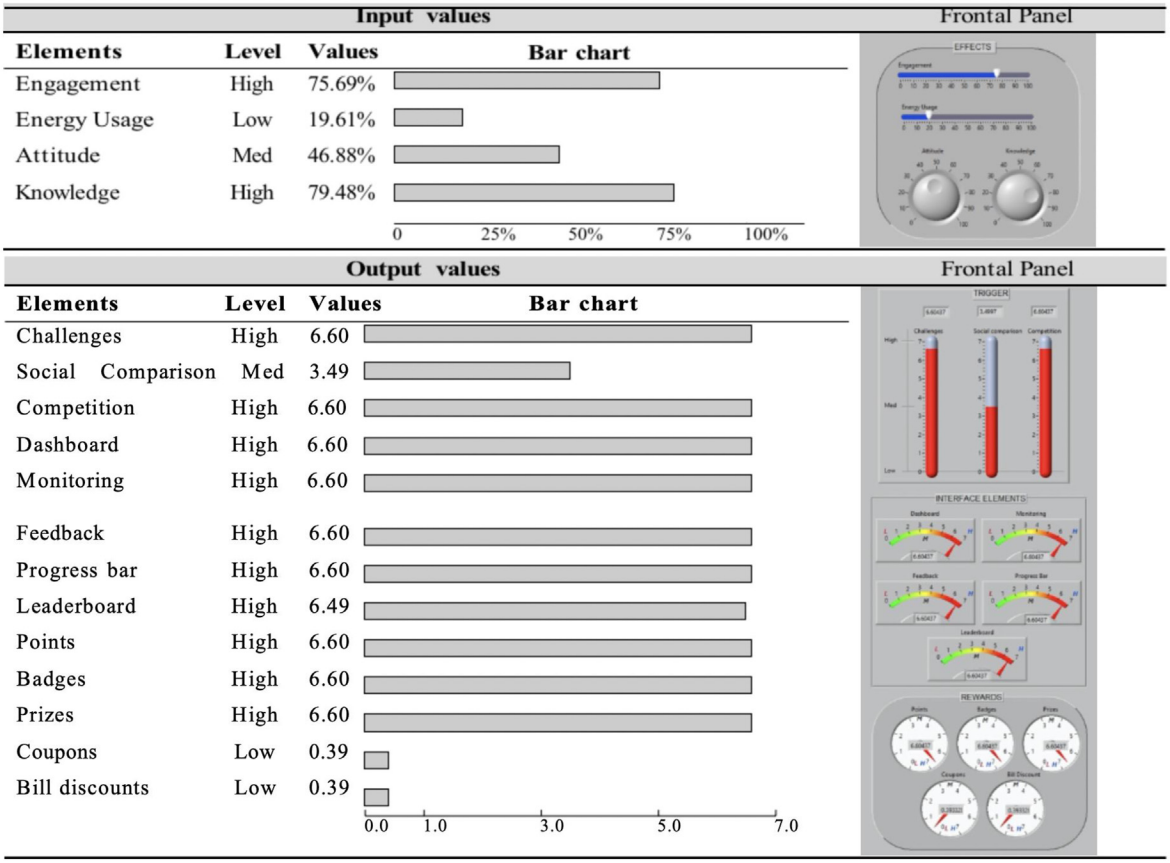


Fig. 17. Case 2a example results.

f) Interface elements: All are related to the six phases tailored for the customer.

5.1.6. Case 5 (Fig. 9)

a) Type of user: These users are motivated to save money through energy savings, believe that using new technologies does not fulfill their expectations, and are insecure because the device is internet-based. They do not know how to use a CT. The user has the following features:
b) Neuroticism, traditionalist cost-focused, and cost-oriented.
c) Usability problem: User control and freedom, skills, and privacy.
d) Behavior problem in the CT: The user's operation is different than the operation intended by the engineers. The user does not understand the functions and does not care about the advantages of the CT. The user is not aware of environmental impact, and his/her interests are not to save energy. The user also does not use the HVAC correctly.
e) Problem solution suggested: Product installation, Interface customization, Interface learned, Energy concepts learned, Interface mastered, and Gamified CT mastered.
   - This type of user is the most reluctant to undergo a conduct change. As a result, the gamification and SG for this user should be focused on economic rewards, messages, videos, and tips about the benefits of the CT, primarily emphasizing the security of the CT through several secure and encrypted elements that lead to a secure network.
   - The gamified and SG elements are primarily focused on the benefits of managing the CT with specific features without losing the comfortable temperature.
   - Because this user hardly wishes to engage in online activities or competitions with other users, the application should encourage the user to understand the interface through an SG interface in which the user is taught the characteristics and uses of every feature in the application. The control over peers element is displayed as a manner to push the user to interact with the others. However, this user is a Disruptor or Killer player that may try to impose themselves on others; therefore, for a limited time, the user can interact with the others.
f) Achievement Reward: All are related to the six phases.
g) Interface elements: All are related to the six phases.

5.1.7. Proposed energy-saving strategy

Using the six levels of the achievement structure with the gamification and SG elements proposed in Figs. 6–9 is possible to get five cases; these five cases have the purpose of providing solutions for each user regarding his/her usability and behavior problems. These cases are proposed considering the different types of users, behavior, and usability problems to exemplify the phases required to succeed in operating the CT and saving energy. This signifies that users are not required to complete the six stages of the Achievement to solve the problem they experience with the CT. However, the elements of gamification considered in each phase can be changed by other elements that meet the expectations of the users to lay the foundations of knowledge. Then, in Phase 2 of the

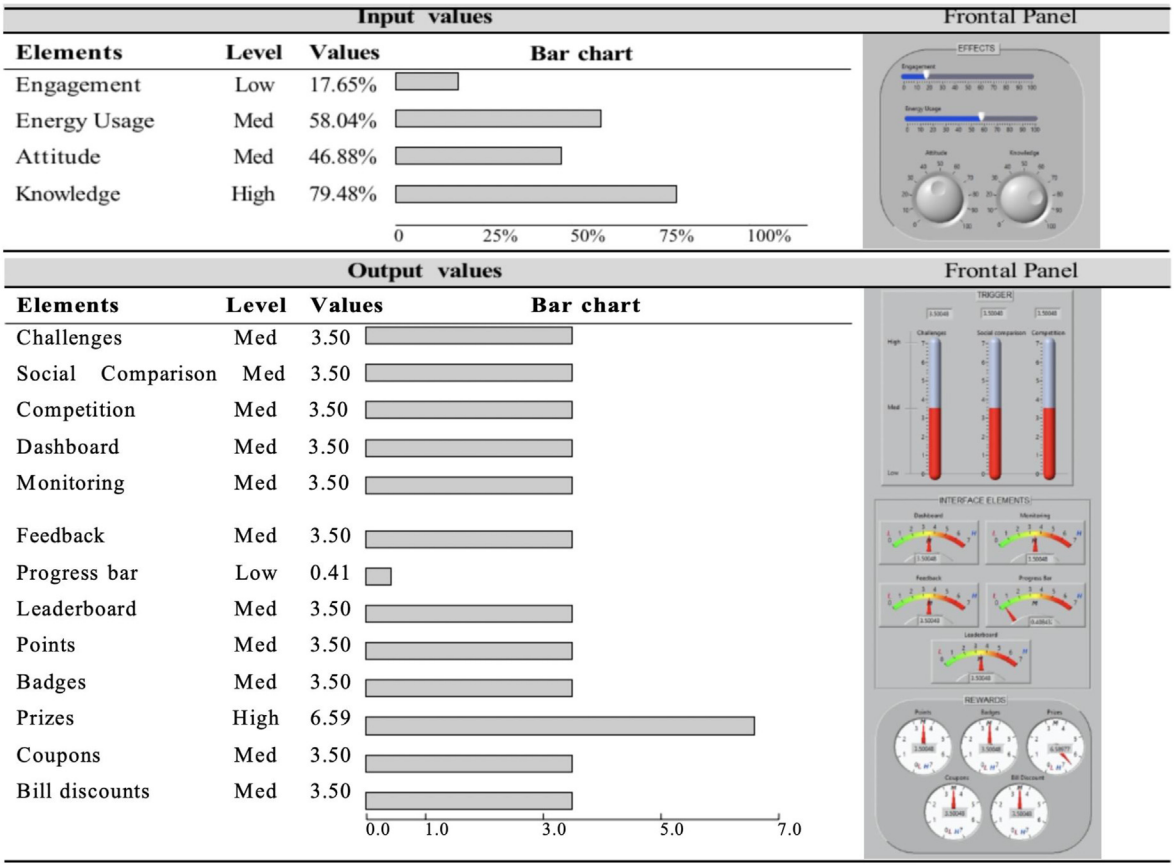


Fig. 18. Case 2b example results.

framework, fuzzy logic is used. For developing a deeper strategy, the energy-saving strategy is focused on Case 3: Energy Master Achievement. Every step related to the achievement serves to develop a Behavior problem library, in which each detected problem becomes part of the Thermostat Behavior Problem. Then, the strategy is based on attempting to solve the habits problem (Fig. 10).

Fig. 11 presents a decision tree for the energy problem solution. The elements are divided according to the method proposed in (AlSkaif et al., 2018; Beck et al., 2019; Fijnheer and Van Oostendorp, 2016) for the development of energy gamified applications. Inside the Effects element, the four reported effects of energy games (knowledge, attitude, energy usage, and engagement) are considered. The Trigger elements considered are social connection, which pertains to the comparison with peers. The Interface elements considered consist of information provision, an interactive interface, and performance status, which customers perceive as useful, easy to use, and which allow them to follow their progress. Finally, the Reward elements are proposed based on the users' energy consumption behaviors and effort.

To complete the Energy Master achievement; the decision tree considers the following two options:

1. **Completed Achievement:** The impact of each gamification element is measured to determine which elements are used the most. Based on the results, the application shows more of these elements to continue engaging the users. The principle is to not allow users to get bored and stop using the application.
2. **Not Completed Achievement:** If the users are unmotivated, then the Trigger, Interface, and/or Rewards elements must be changed, and the Achievement must be tested again until the user becomes engaged. Because the reported Effects of the energy games allow the authors to determine the success of the application, they do not change.

For example, Table 10 illustrates the type of user in Case 2 (conscientiousness, disengaged energy waster, and early adopter) with the following respective usability and behavior problems: the information is complicated to search because it is not focused on the user's task, and the user's interest is not to save energy. After testing the game, if the user displays these levels of commitment (i.e., has a low energy usage effect but high engagement and knowledge levels), the gamification strategy bust is changed without compromising the engagement and knowledge levels. To move the user from low to medium or high energy usage is necessary to focus on the higher elements by changing the elements appearing on the interface, potentially by sending additional recommendations or tips on how to save energy, but with a minimum number of functions so that the user feels comfortable (Ponce et al., 2017). Because bill discounts are considered medium, by providing the benefits of bill discounts, the user is likely to be more engaged. However, a test must be first be performed. In Table 11, the same case is proposed as above, including the usability and behavior problems mentioned in Table 7. However, the difference is that the user scores high on neuroticism, and is non-green selective, and cost-oriented. The strategy is such that after using the application, the user becomes more engaged through the elements of social comparison and economic rewards (AlSkaif et al., 2018; Peham et al., 2014; Ponce et al., 2019).

If the achievement is not completed, then it is necessary to

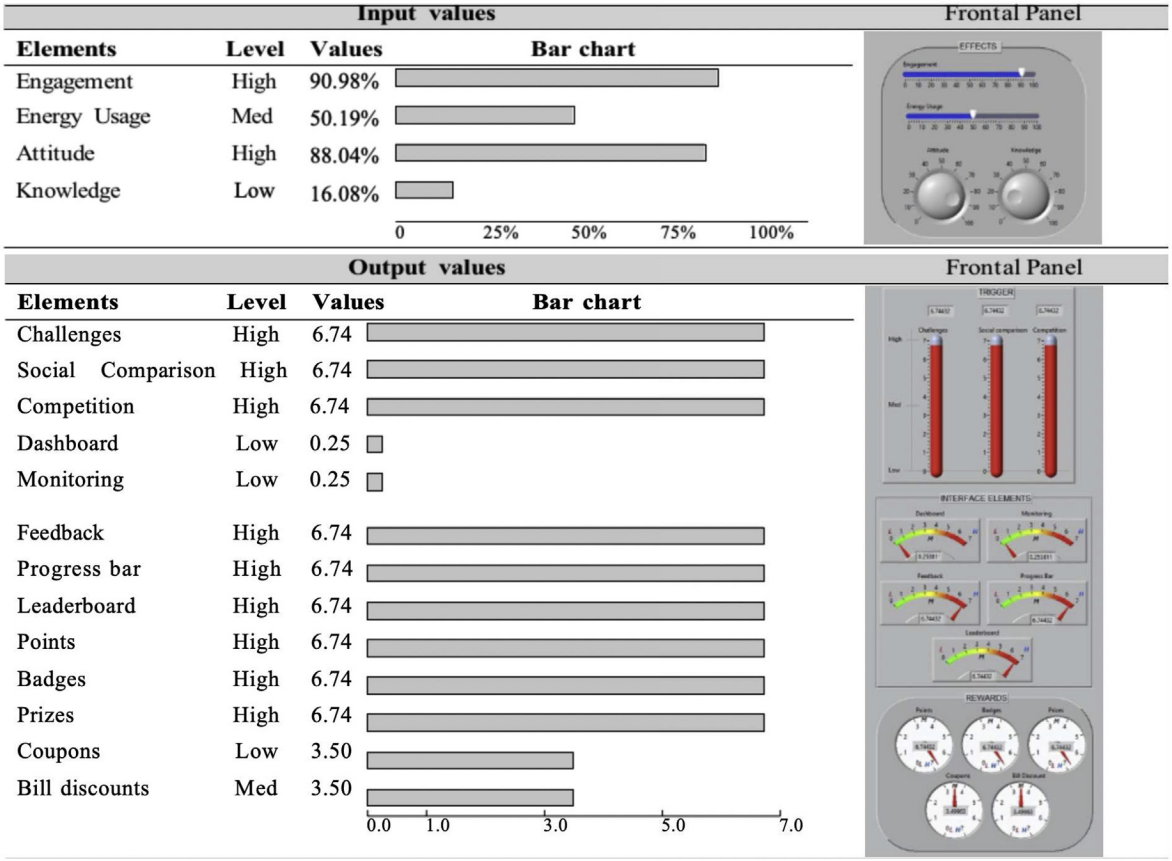


Fig. 19. First example of fuzzy logic phase.

change the features involved in the Trigger, Interface, and Reward elements according to the gamification elements, as presented in Fig. 12. Once completed, the Energy Master achievements, Effects, trigger, Interface, and Rewards values are collected and analyzed to obtain a positive value for the effects, as proposed in (Fijnheer and Van Oostendorp, 2016).

5.2. Fuzzy logic phase

To test the most used elements in a gamification energy application once they are defined, it is proposed to implement Type 1 fuzzy logic using LabVIEW 2018. The Effects elements are defined as Inputs in the system, while the Trigger, Interface, and Rewards elements are defined as Outputs. In addition, the Membership functions of the inputs are measured as percentages. It is proposed in (Fijnheer and Van Oostendorp, 2016) to measure the Knowledge, Attitude, and Engagement elements through questionnaires before and after the consumer uses the. Application. Furthermore, knowledge is measured with in-game tests, while engagement is determined through monitoring a player's behavior when the application is used. Energy usage is measured by tracking the energy meter of the CT; this measure must thus be observed before the user begins using the application. In contrast, the Membership functions of the output elements are measured before and after using the application through questionnaires by applying the semantic differential scale, which detects any behavior changes. This measure mainly involves using a pair of antonyms of a given concept; in this case, the concepts are the 13 elements included in the Trigger, and Interface elements, and Rewards groups using a scale ranging from 1 to 7 (where 4 is considered a neutral pole or not applicable for the specific element) (Evans, 1970).

In 1965, computer scientist Lotfi Zadeh from the University of California Berkeley, proposed fuzzy set theory as a class of sets based on membership grades from 0 to 1 and inference rules that do not require a mathematical model of the real system, but rather, rules generated by experts, polls, or consensus-building (Ponce, 2011; Ponce-Cruz et al., 2016; Zadeh, 1965). Fuzzy logic was created to model uncertainty based on linguistic words and sentences (linguistic variables) associated with human logic rather than the use of numerical values (e.g., Engagement variable = High, Low, Medium). This type of fuzzy set is known as Type-1.

Fig. 13 illustrates the algorithm structure using the Mamdani fuzzy method proposed by Ebrahim Mamdani, while Fig. 14 displays its Membership Functions proposed for the Energy Master achievement. To elicit the desired result; fuzzy logic required the following three stages: (1) The variables have a certain degree of metalinguistic uncertainty that pass through a fuzzifier process, which consists of determining which value degree belongs to a fuzz se3t between 0 and 1; (2) Inference rules are proposed from the membership functions and are defined as a conditional statement in the form of "if x is A, then y is B" (Ponce-Cruz et al., 2016). These rules serve as a guide for the system to behave in a desired way according to a reference model, and they assign a degree of membership to the fuzzy set that characterizes the outputs; (3) It is determined through a defuzzification method, the center of are to be converted into a crisp number (Ponce, 2011; Ponce-Cruz et al., 2016).

As proposed in (Ponce et al., 2018a), signal detection theory

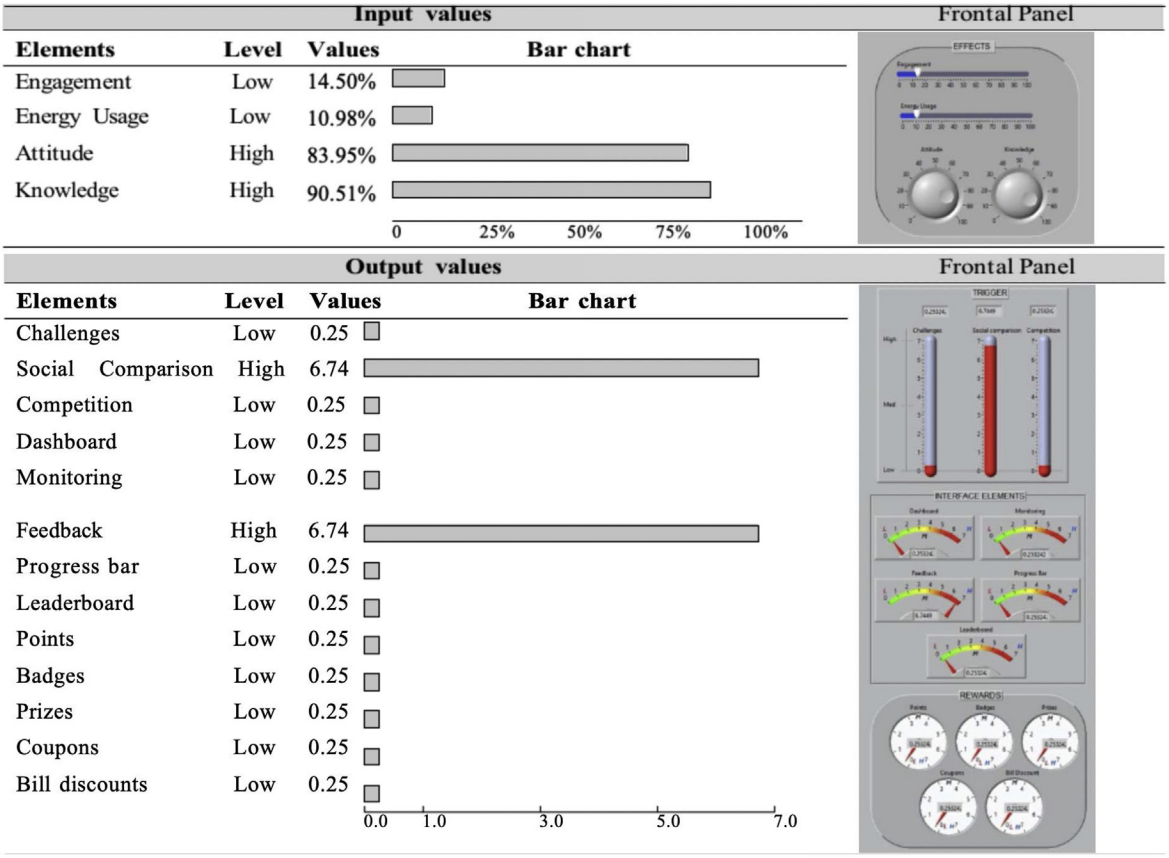


Fig. 20. Second example of the fuzzy logic phase.

(SDT) and fuzzy detection theory (FDT) are used to determine whether the output values are related to the input values introduced to the system. Therefore, it is proposed to develop an experimental study by surveying 50 participants to understand which elements of gamification and SG lead them to get engaged and improve their energy usage, attitude, and knowledge. In addition, the study intends to solve participants' behavior and usability problems to determine the best energy strategy for each user. The study is designed to help users understand how the CT operates.

In Fig. 15, a fuzzy system design is proposed to test whether the proposed rules are in accordance with the users' answers or whether the output values must be changed. Fig. 16 illustrates the relationship between the input values and the output values.

- **Engagement:** Challenges, Competition, Progress bar, Leaderboard, Points, Badges, and Prizes. In (Fijnheer and Van Oostendorp, 2016), it is proposed to monitor users' behavior while they use applications; thus, these elements are used to determine how engaged a user is.
- **Energy Usage:** Challenges, Competition, Dashboard, Monitoring, Coupons, and Bill Discounts. In (Fijnheer and Van Oostendorp, 2016), monitoring an energy meter is suggested for measuring energy usage; thus, in this case, the CT energy usage is monitored using these elements.
- **Attitude:** Social Comparison, Leaderboard, and Badges. This measures whether the user has a change in attitude toward saving energy (Fijnheer and Van Oostendorp, 2016).
- **Knowledge:** Challenges, Dashboard, Monitoring, Feedback, Points, Prizes. Knowledge is measured by in-game quizzes (Fijnheer and Van Oostendorp, 2016). In this case, gamification elements are proposed to determine whether the user is learning how to save energy and how to operate a thermostat.

Similar gamification elements in the input effect values may be repeated because it complements between each other; for instance, Energy Usage and Knowledge have common gamification elements that determine whether the users, through the challenges, dashboard, and monitoring, understand how the CT operates and whether they are saving energy.

5.3. Evaluation phase

As a result of the fuzzy logic phase, during this phase, the system displays the values of the gamification elements. Fig. 17 presents the results for a user who scores high on conscientiousness and is a disengaged energy waster, and early adopter. In this example, the behavior problem is that the user's interests are different from those of saving energy, and the usability problem is that the information is complicated to search because it is not focused on the user's task.

The input value effects for this type of user are as follows.

- Engagement and Knowledge Effects: High.
- Attitude Effect: Medium.
- Energy Usage: Low.

The output values are:

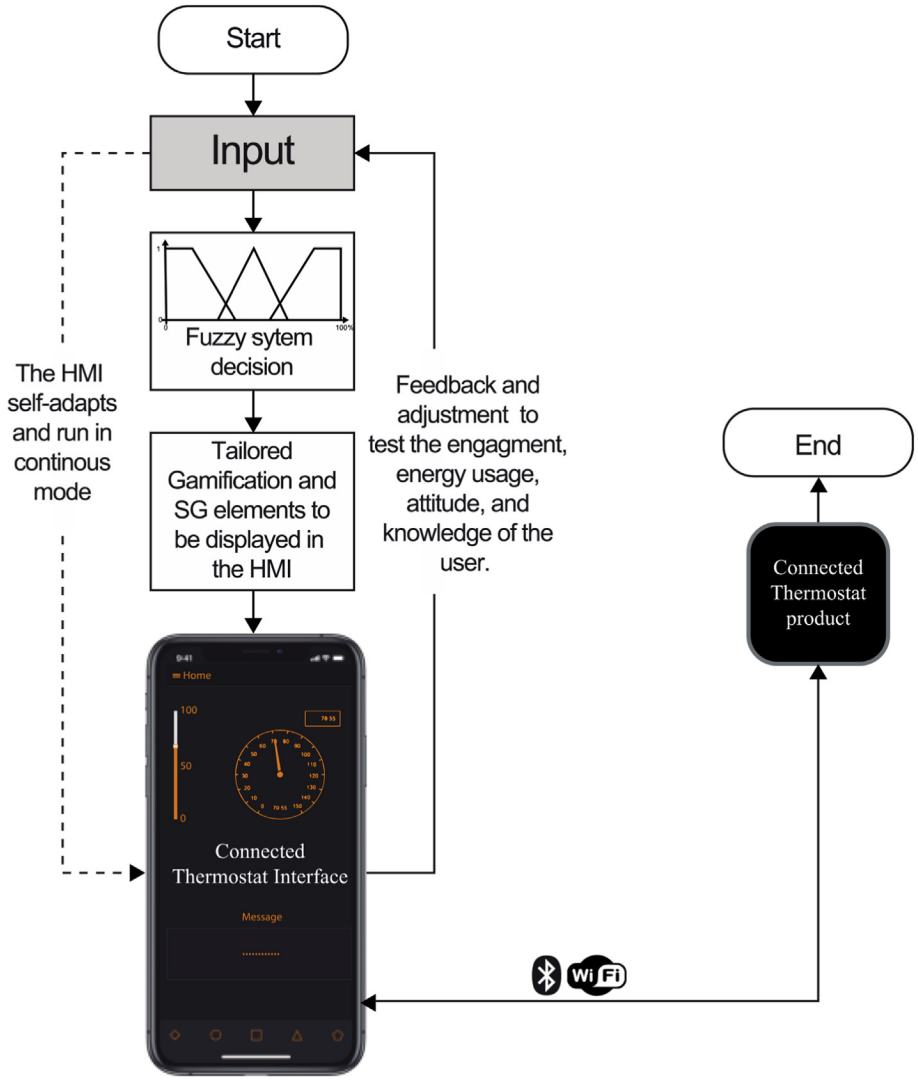


Fig. 21. HMI using the fuzzy system.

- **Trigger:** High in Challenges and Competition; Medium in Social Comparison.
- **Interface Elements:** High in all elements.
- **Rewards:** High in Points, Badges, and Prizes; Low in Coupons and Bill Discounts.

Based on the High and Medium levels, the proposal to motivate these users to become energy-aware involves providing them with more of these gamification elements corresponding to their amount of electricity reduction. Fig. 18 displays the results for a user with high neuroticism, who is non-green selective and cost-oriented with the same behavior and usability problems presented in Fig. 17.

The input values for this user are:

- Knowledge Effect: High.
- Energy Usage and Attitude effects: Medium.
- Engagement: Low.

Giving as a result:

- **Trigger:** Medium in all elements.
- **Interface Elements:** Medium in Dashboard, Monitoring, Feedback, and Leaderboard; Low in Progress Bar.
- **Rewards:** High in Prizes; Medium in Points, Badges, Coupons, and Bill Discounts.

Because this user is cost-oriented and has low Engagement, the application focuses on the high and medium output values; that is, the application aims to provide the user with greater Rewards based on how much the user knows about the CT and its economic benefits.

Two examples are provided to detail how the evaluation phase works.

a) Fig. 19 refers to the type of user with high levels of openness, who is home-focused and cost-oriented. The behavior problem is that these users do not know how to use the HVAC system, and the usability problem is that the interface tries to replace the users' skills, background knowledge, and expertise. The fuzzy system displays the following values:
   - Input values:
     - o Engagement and Attitude: High
     - o Energy Usage: Medium

Table 12
Knowledge base used in gamification and the serious game interface.

Knowledge base	
Type	Characteristics
Personality	Conscientiousness
Energy end-user	Disengaged energy waster
Energy target group	Early Adopter
Usability problem	Aesthetic and minimal design
Thermostat behavior problem	User's interests are different from energy saving

Table 13
Fuzzy logic used in gamification and the serious game interface.

Fuzzy logic elements			
Effects	Trigger	Interface	Rewards
Engagement	Challenges	Dashboard	Points
Energy usage	Social comparison	Monitoring	Badges
Attitude	Competition	Feedback	Prizes
Knowledge		Progress bar	Coupons
		Leaderboard	Bill discounts

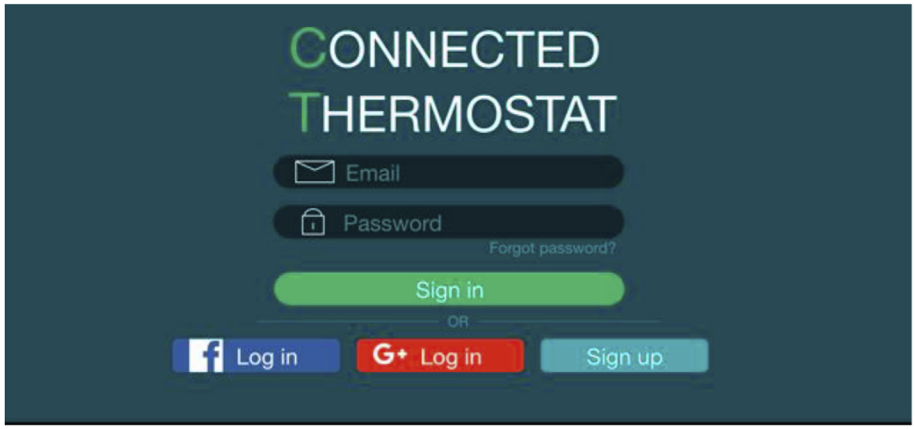


Fig. 22. Achievement 1.

- o Knowledge: Low
- Output values:
  - o **Trigger:** High in all elements.
  - o **Interface Elements:** High in Feedback, Progress bar, and Leaderboard; Low in Dashboard and Monitoring.
  - o **Rewards:** High in Points, Badges, and Prizes; Medium in Coupons and Bill Discounts.
- Solution proposed:
  - o Although this user has high engagement and attitude elements and an average value for energy usage, the knowledge is low. As this user must understand how the HVAC system works and has an open personality, the way to teach the user should be through the trigger elements. Feedback has a high value; thus, the application pays special attention by displaying tips to the user on how to improve knowledge of air conditioning. In terms of design, the thermostat designer should change the interface in such a way that the users do not feel that the application aims to replace them.

b) Fig. 20 refers to a type of user with high extraversion, who is disengaged and an early adopter. The behavior problem is that these users' interests are not to save energy, while the usability problem is that messages are displayed in code, and users cannot recognize, diagnose, or recover from errors. The fuzzy system shows the following values:

- Input values:
  - o Attitude and Knowledge: High
  - o Engagement and Energy usage: Low
- Output values:
  - o **Trigger:** High in Social Comparison; Low in Challenges and Competition.
  - o **Interface Elements:** High in Feedback; Low in Dashboard, Monitoring, Progress bar, and Leaderboard.
  - o **Rewards:** Low in all elements.
- Solution proposed:
  - o Because these users are not interested in saving energy but are interested in being part of social media communities, the application displays a blog where the users can post comments on any doubts or questions they have. This serves to encourage users to compare themselves with other users in terms of energy reduction. The thermostat designer should change the information so that the users can understand the benefits of becoming energy-aware.

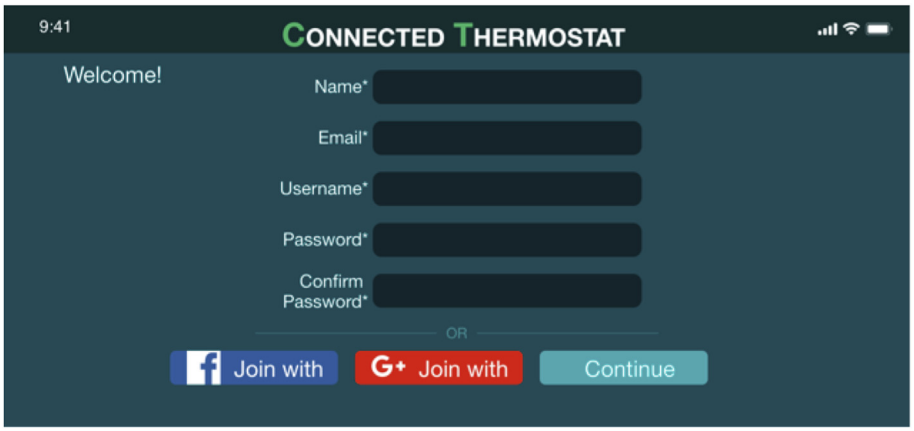


Fig. 23. Achievement 1.

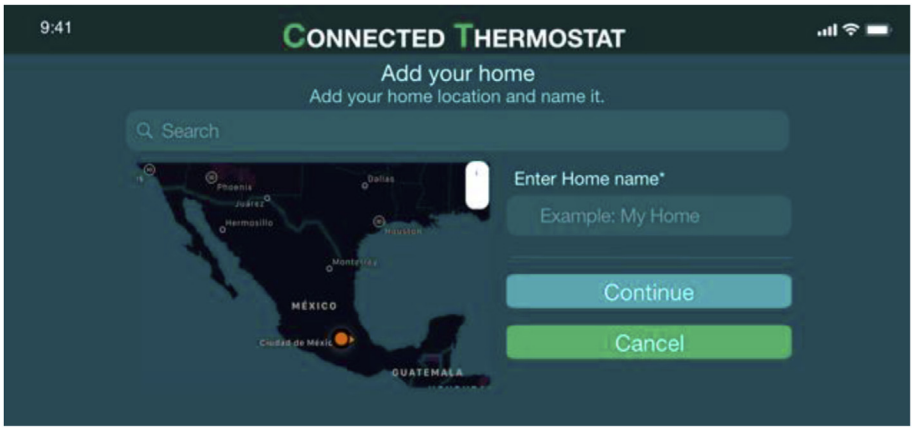


Fig. 24. Achievement 1.

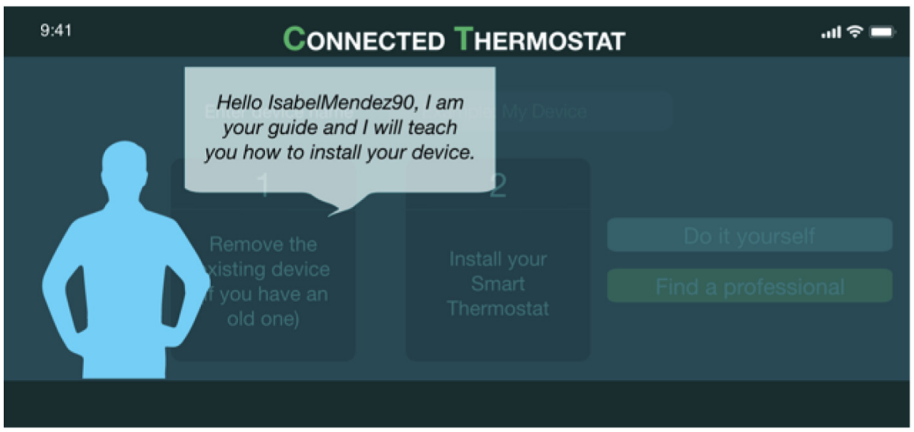


Fig. 25. Achievement 1.

6. Results

Fig. 21 presents a diagram for the operation of the fuzzy system. The fuzzy system displays the most important gamification and SG elements required in the CT interface for a specific user. Then, the application and CT communicate with each other, and the application provides feedback to the input system to continue self-adapting to the interface. The main goal of the application is to change the user's behavior to save energy; thus, the input values are intended as the highest values.

Tables 12 and 13 present a summary of the elements considered in the Energy Master achievement illustrated in Fig. 10, as well as the methodology proposed (Fig. 3) for the knowledge base and fuzzy logic elements. The HMI required for the specific type of user,

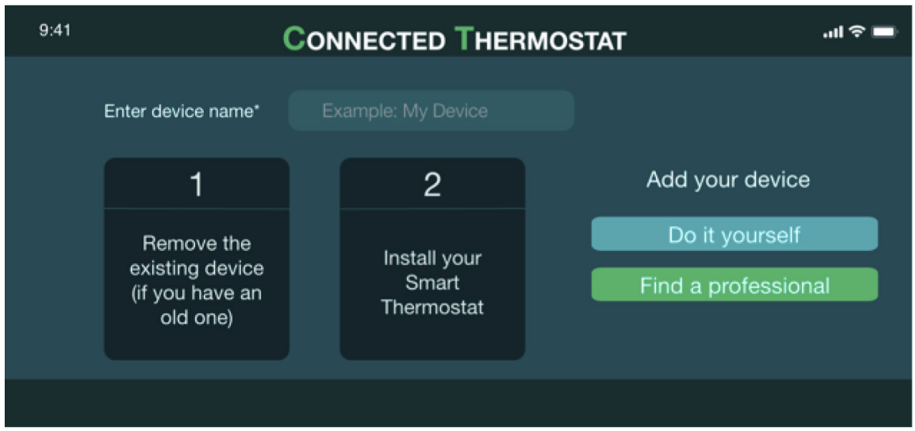


Fig. 26. Achievement 1.

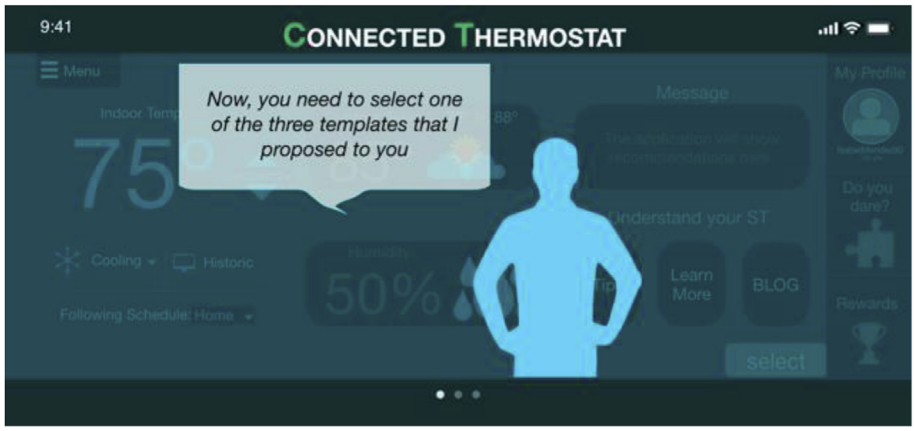


Fig. 27. Achievement 2.

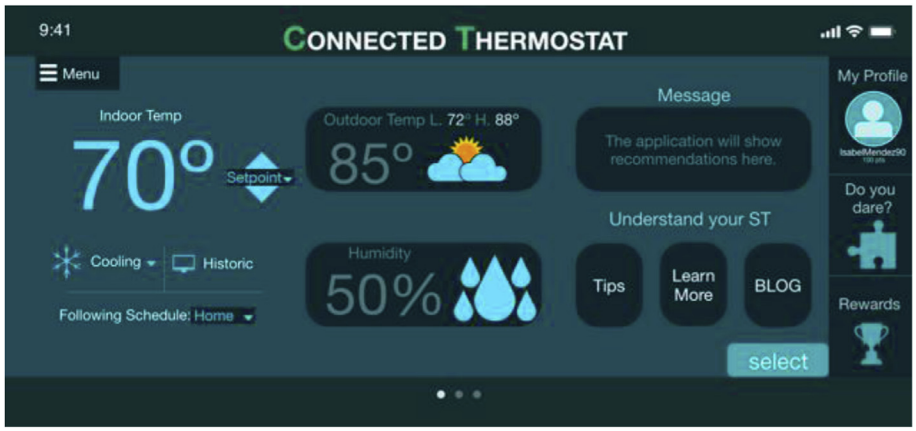


Fig. 28. Achievement 2.

usability, and thermostat behavior problem requires the use of gamification and SG elements to shape the users' conduct and make them energy-aware.

It is important to understand which elements of gamification and the SG improve engagement, energy usage, attitude, and knowledge, and solve users' behavior and usability problems. These results guide us to propose the gamification and SG elements required by the customer and the fuzzy logic and determine the output values needed in the HMI.

For the development of the HMI, every new user must first

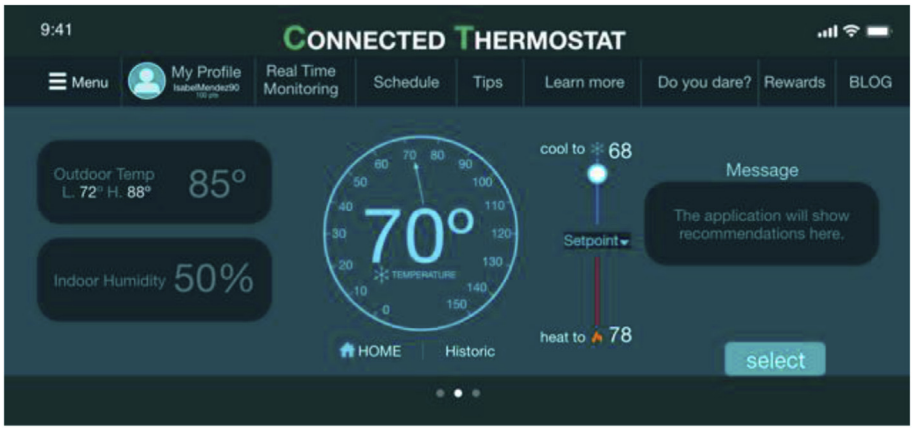


Fig. 29. Achievement 2.

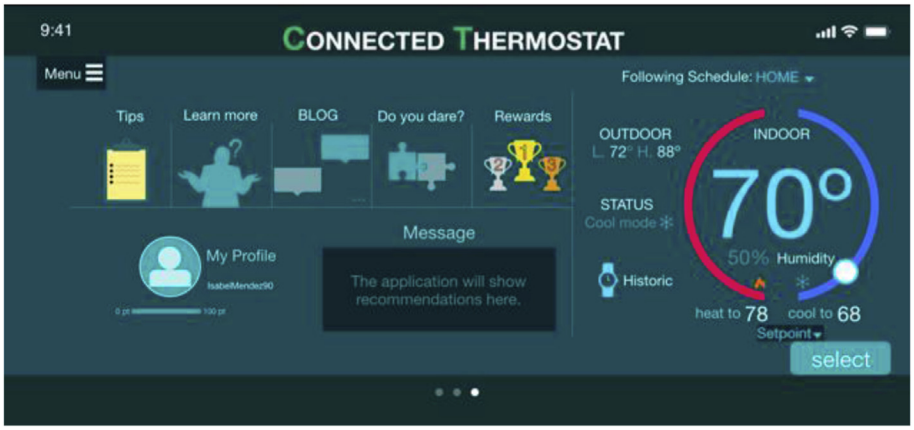


Fig. 30. Achievement 2.

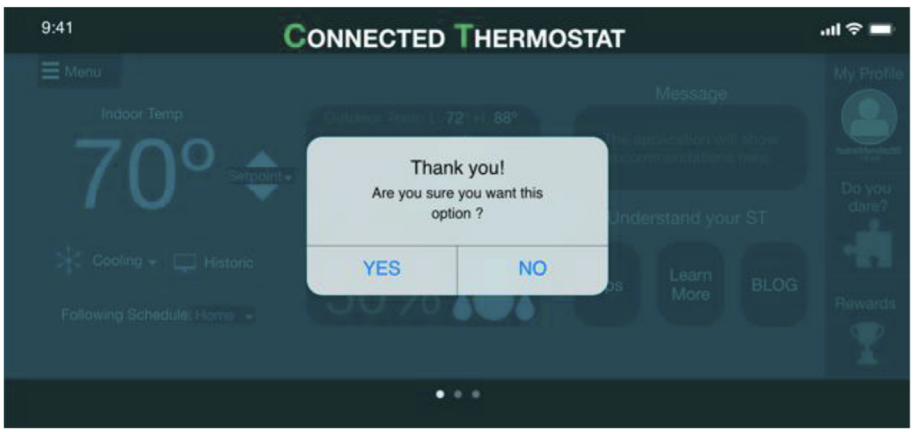


Fig. 31. Achievement 2.

complete Achievement 1: Installed and Read, and Achievement 2: Build to Suit, which is related to product installation and interface customization, respectively. In Figs. 22 and 23, the users must log in to the CT application either by using Google or Facebook or by creating a new account. Once the users have logged in, the application instructs them to locate and assign a name to their home and device so that the interface search for climate data and electricity rates. In addition, users can develop a sense of belonging as suggested by core drive 4 Ownership and Possession (Chou, 2015) (Figs. 24–26). Furthermore, in Fig. 26, the application asks the users if they wish to install the thermostat using a tutorial (i.e., using the core drive 2 Development and Accomplishment (Chou, 2015)) or to call an expert to help them perform the installation. Even if the users request the option of a professional, later, when they gain confidence, if they decide to install another CT, they will have another chance to install it on their own in the menu option of Add/

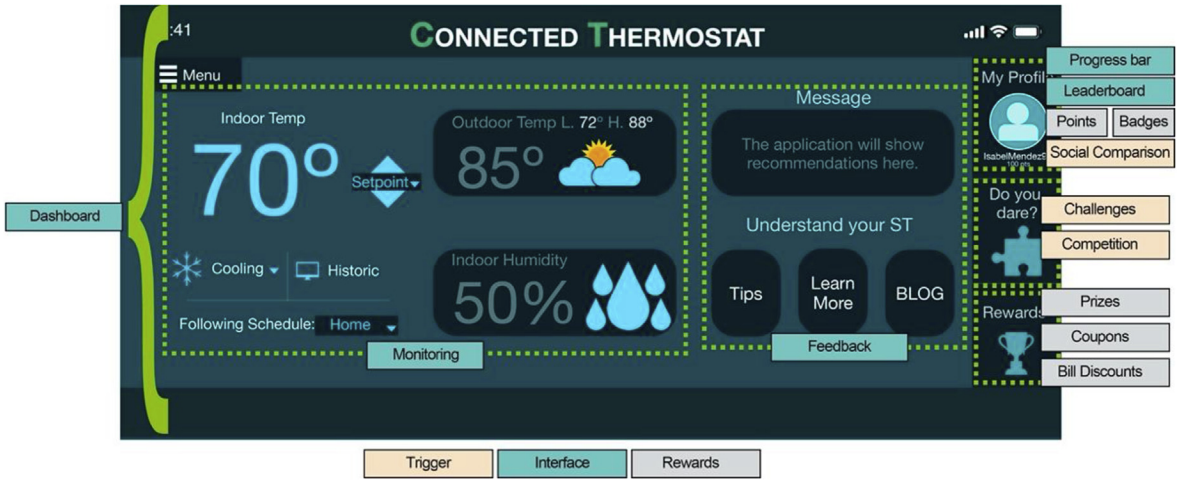


Fig. 32. Dashboard elements.

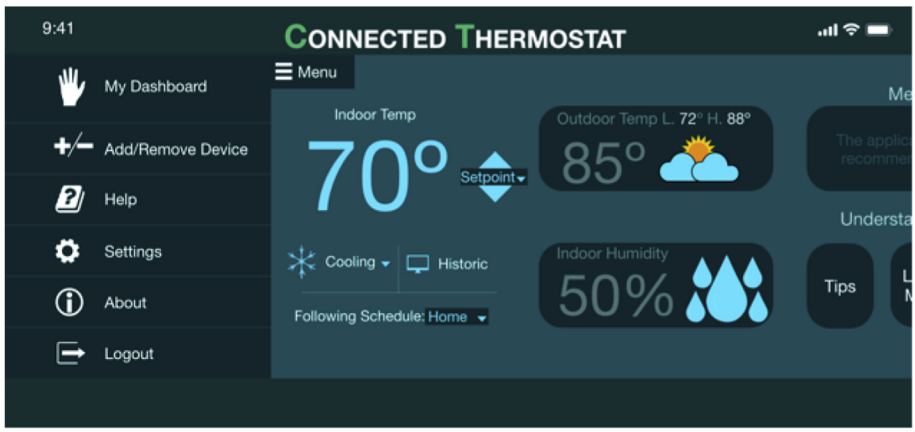


Fig. 33. Menu option.

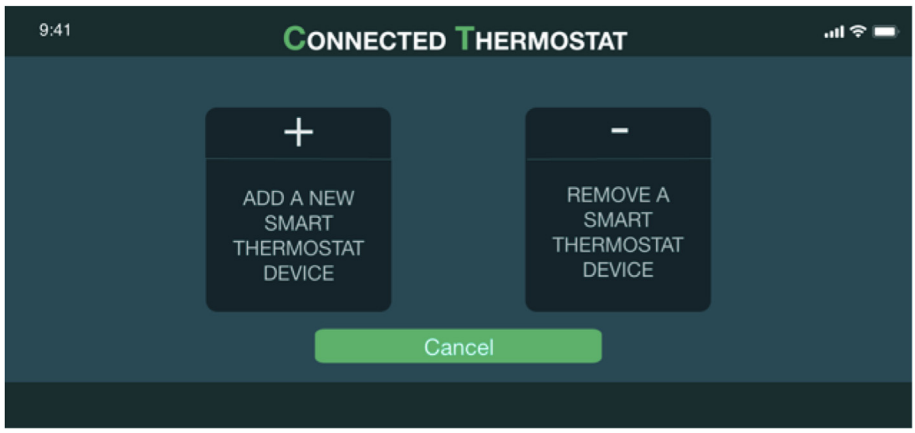


Fig. 34. Add/remove device.

Remove Device (Figs. 34 and 35). From Figs. 27–31, the application uses core drive four by instructing the users to select one of the three available templates in accordance with the type of user previously defined in Table 9. To develop this idea is supposed that the user selects the first template (Figs. 28 and 31); thus, hereinafter, the menus displayed are designed for this type of user.

Appearing next is the description of the options with the core drive, which are related to the descriptions in Fig. 5. The dashboard is the home page of the application; thus, because the main goal is to engage the user, the most representative elements are illustrated in Fig. 32. On the right side of the image, the menu bar considers options related to the system, (Figs. 33–39); meanwhile, on the

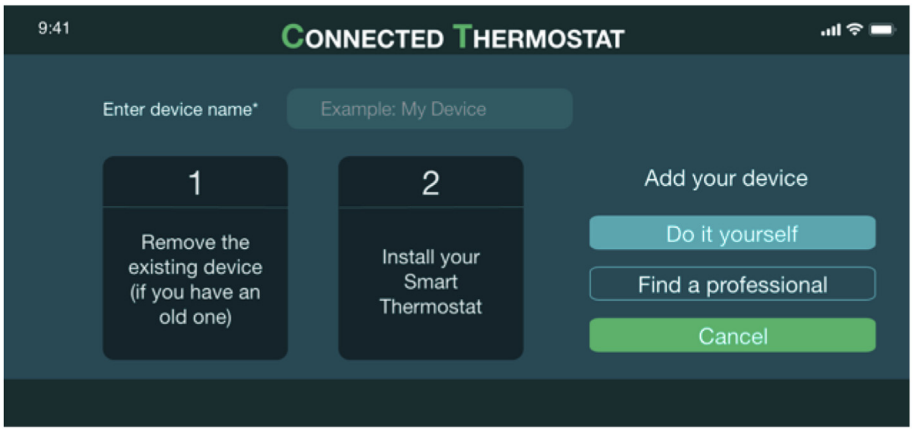


Fig. 35. Add/remove device (2).

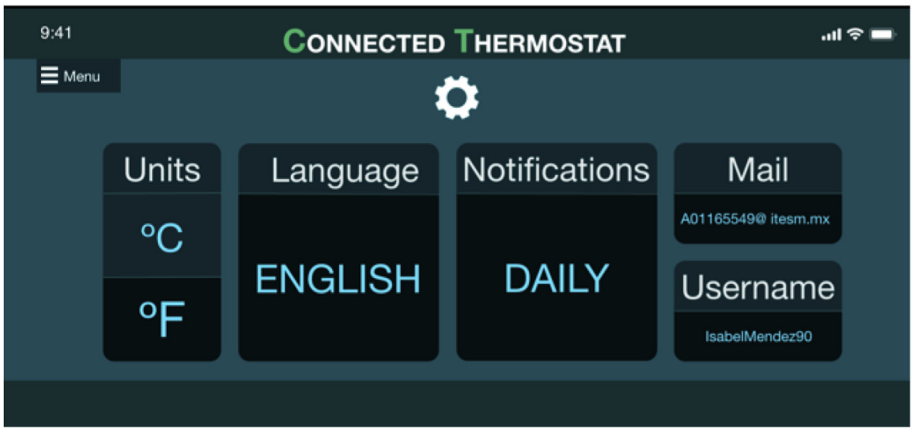


Fig. 36. Settings in °F.

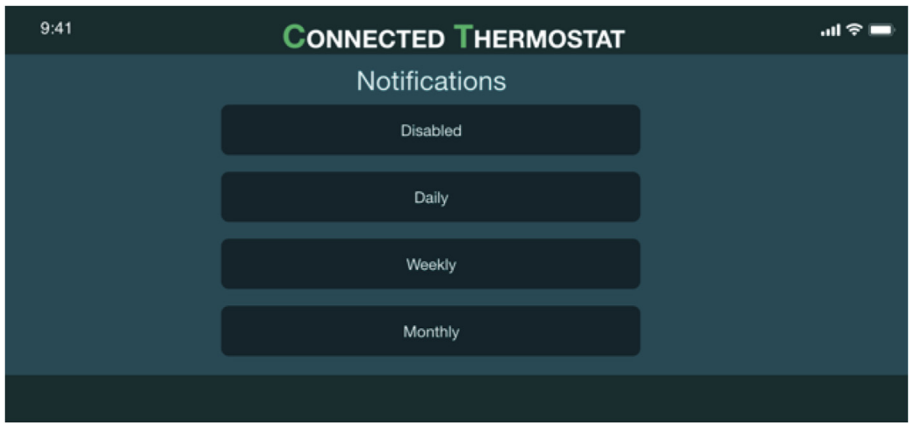


Fig. 37. Notification settings.

right side, three-button bars are displayed: (1) inside the "My Profile" button (Fig. 40), the users are able to change their profile images with a photo or avatar; to monitor their progress bar punctuation, rank in the leaderboards, badges they have won; and, if desired, post on Facebook. These actions belong to core drives 1, 2, 4, 5, and 8 (Chou, 2015); (2) In the button "Do you dare?" (Fig. 41) The challenges assign the users daily, weekly, and monthly goals to push them to save energy; for instance, Table 14 displays an example of those energy challenges. In order to prevent possible monotony due to repeating similar goals, the challenges are designed to change when they are achieved. Thus, if the user performs a month of kWh reduction, the application will ask the user to achieve six periods of monthly kWh reduction to continue the engagement. If the achievement is not completed and/or the user is not interested, the application is designed to receive that feedback and change the type of challenges.

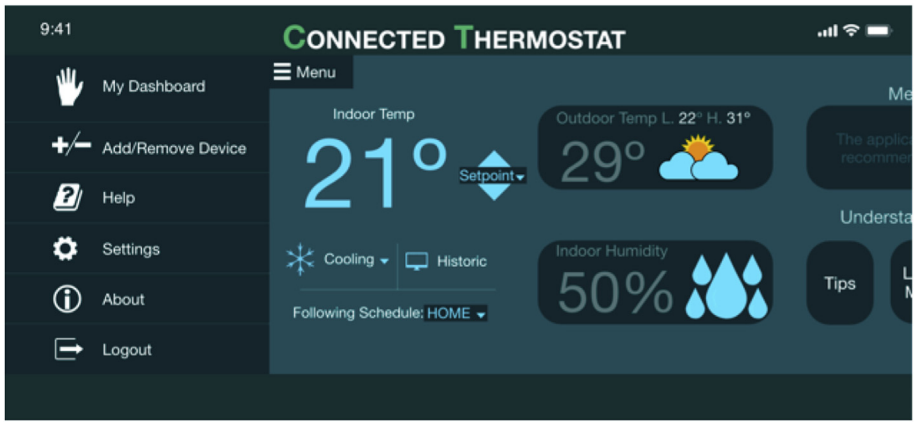


Fig. 38. Dashboard in °C.

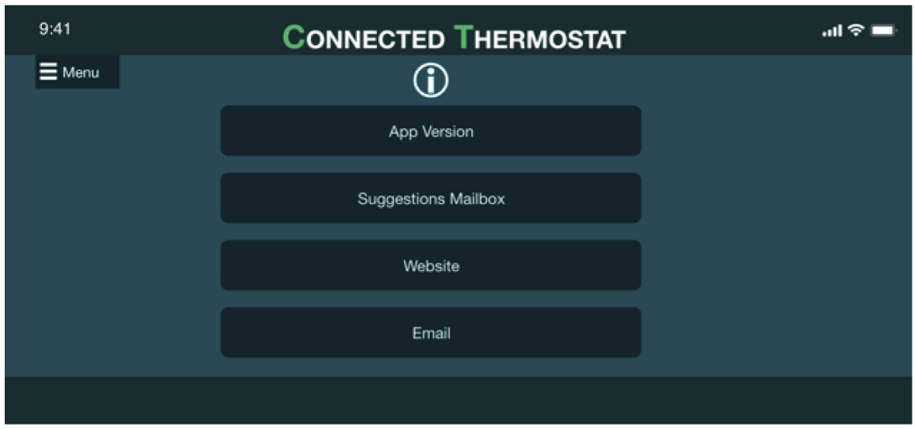


Fig. 39. About Menu option.

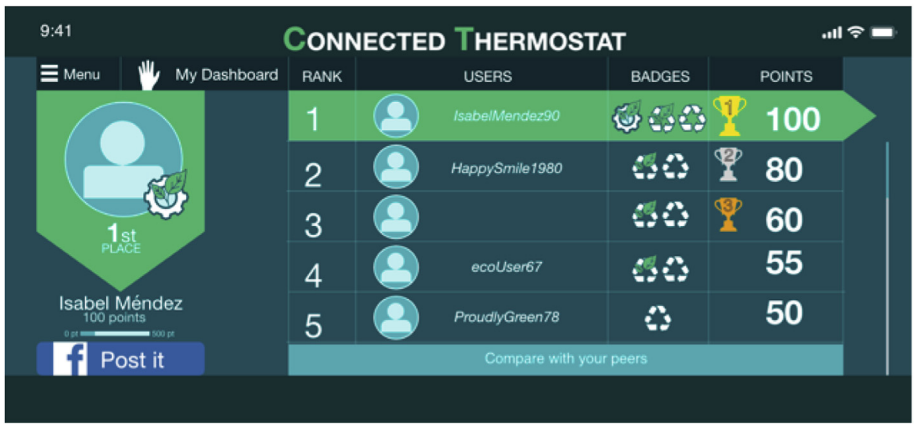


Fig. 40. Profile.

In the competition section, users can compete with other users to determine who is the thriftiest of all. The 6th and 8th core drive (Chou, 2015) belong to this general button; (3) The Rewards button (Fig. 42) contains the prizes, coupons, and bill discounts elements; these elements are related to core drives 4, 5, 6, and 7 (Chou, 2015). On the central layout, the feedback rectangle (right side) is composed of three options: (1) inside the Tips button (Fig. 43), the HVAC and Dwelling sections provide advice on how to improve the use of air conditioning and learn tips to improve energy usage for the housing; core drive 3 and 4 belong here (Chou, 2015); (2) By using SG techniques such as virtual scenarios, the Learn More button (Fig. 44) has the purpose of making users understand how the dashboard works; thus, the use of the CT can be improved; (3) The BLOG button (Fig. 36) redirects users to a webpage where they can post every doubt, complaint, or comment that they have regarding the application; this section is composed of core drives 3

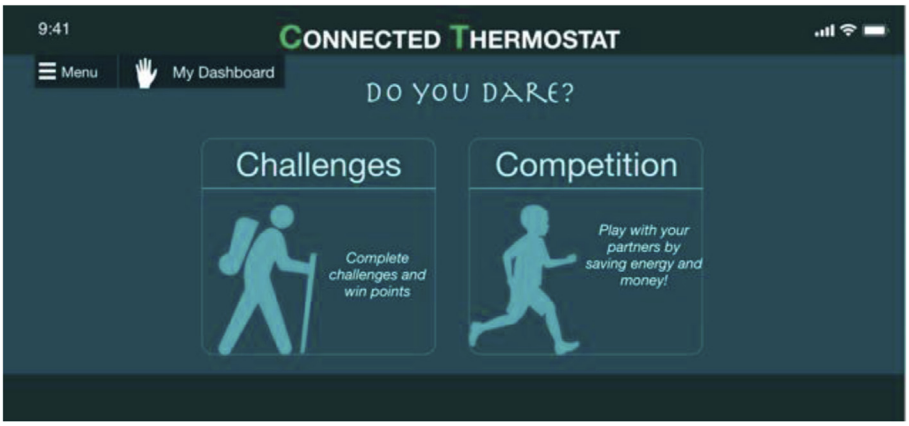


Fig. 41. Do you dare?.

Table 14
Daily, weekly, and monthly challenges examples.

Daily	Weekly	Monthly
Save 100 kWh per day: Turn off the HVAC when you are not at home. Reward: 10 points	Save 700 kWh per week by achieving a daily challenge. Reward: 70 points	Save 2800 kWh to 3100 kWh per month by achieving the weekly challenge. Reward: 350 points
If your HVAC is on, check if the windows are closed. Reward: Access to the energy quiz.	Complete the energy quiz. Reward: two badges.	Compete with your friends in the local tournament. Reward: win the pass to the regional tournament.
		Save 10% of your electric bill. Reward: a coupon to exchange it for real products in the market.
	Play in the Dashboard Serious Game section and master its operation. Reward: Random	Master the monthly Dashboard operation to understand the Connected Thermostat operation. Reward: Rand, simulated discounts in the electric bill, and coupons.
		Achieve six periods of kWh reduction. Reward: 10,000 points and bill discounts

Fig. 42. Rewards.

and 4. Finally, on the Monitoring block (left side), the elements displayed are the Setpoint degree temperature (Fig. 45), HVAC mode (cool, fan, heat, auto; see Fig. 46), schedule (home, vacations, or custom; see Fig. 47), and the Historic button. In the Historic button, on the left side, four blocks are displayed, where the users are able to see how much energy and money they are using and saving. The central part presents a graphic in a day, week, month, and year mode, so that the users can monitor their energy usage (Figs. 48–52). For instance, for the day option, Fig. 49 displays the graph at 10.00 h. To demonstrate to the users how much they use at that specific hour. Fig. 53 shows an example of a reduction in energy usage on a common day. The image is just for illustrative purposes because a real scenario needs to be done.

7. Discussion

In this paper, based on the literature review, it is proposed a framework composed of three phases: the knowledge base phase, the fuzzy logic phase, and the evaluation phase. For the development of this framework, in the first phase, it is used the analysis of the gamification and SG achievement diagram to develop a solution according to a single behavior problem and single usability problem. To this end, it is used the Energy Master achievement to develop a decision tree that leads to the Membership Functions of

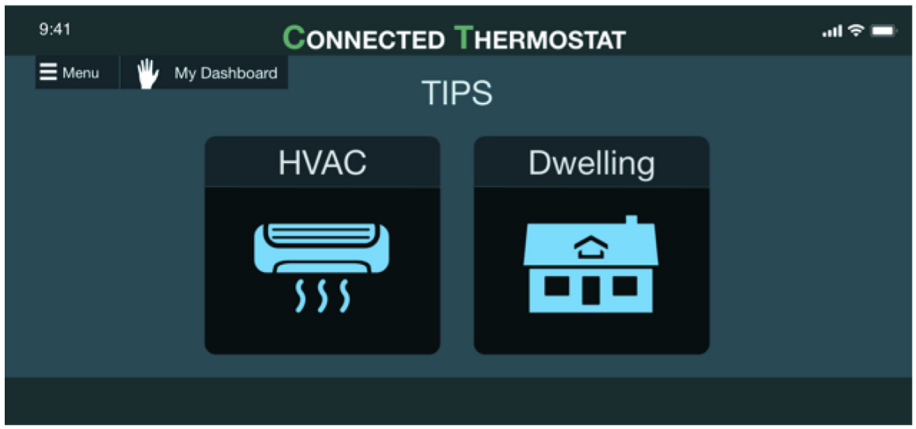


Fig. 43. Tips.

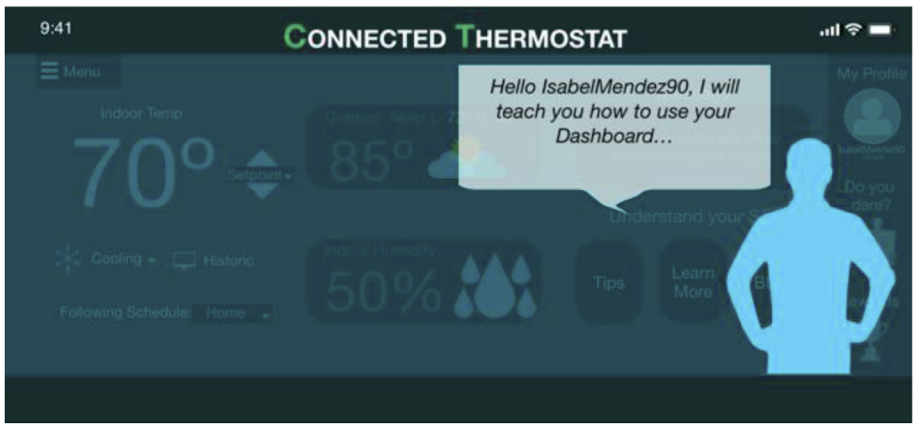


Fig. 44. Learn more.

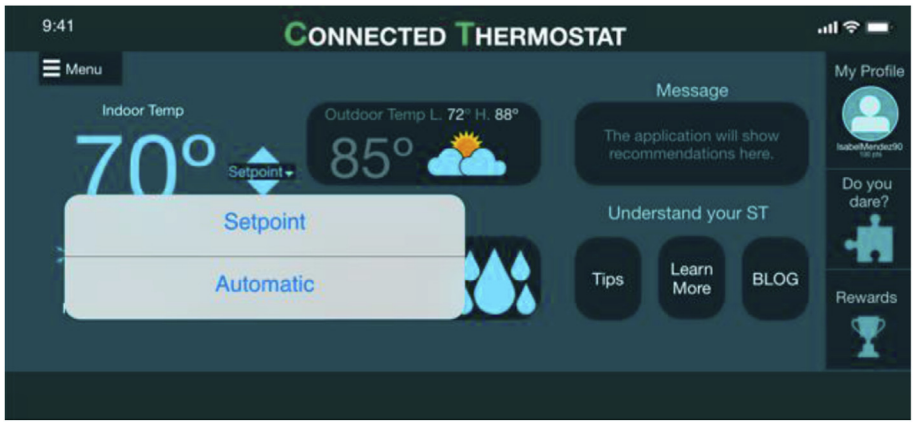


Fig. 45. Setpoint.

the fuzzy logic phase. The fuzzy logic uses the knowledge base to determine how the input and output values are related by proposing a tailored HMI for every customer. Finally, in the evaluation phase, the interaction between the CT and the interface, known as natural and non-natural behavior communication proposed in (Ponce et al., 2019) for S^3 products, tests the levels of engagement, energy usage, change of attitude, and knowledge in terms of how much energy savings the user achieves. Based on the tested values obtained from the system, it is reviewed which gamification and SG elements require reinforcement, to change them.

This framework can be improved by automating the process of the knowledge base with an artificial neural network. This network can gather information to be fed back to the knowledge base to identify which gamification and SG elements are required by the customer. Thereby, the knowledge base can be strengthened to propose more than one solution to usability and behavior

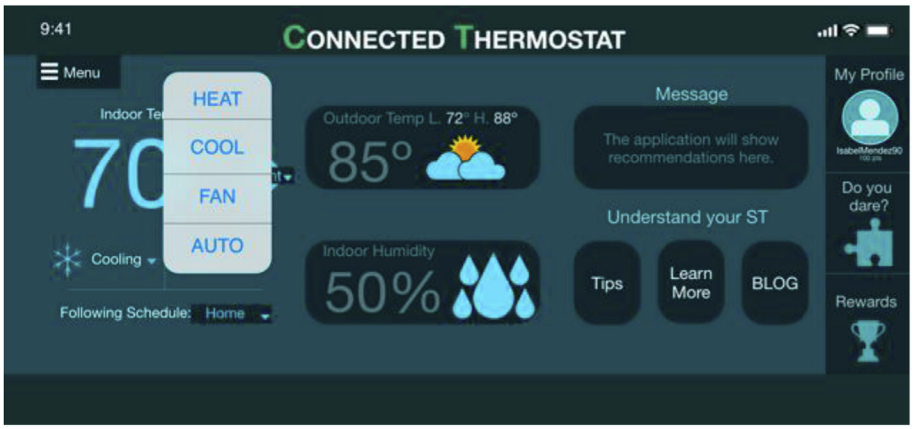


Fig. 46. HVAC mode.

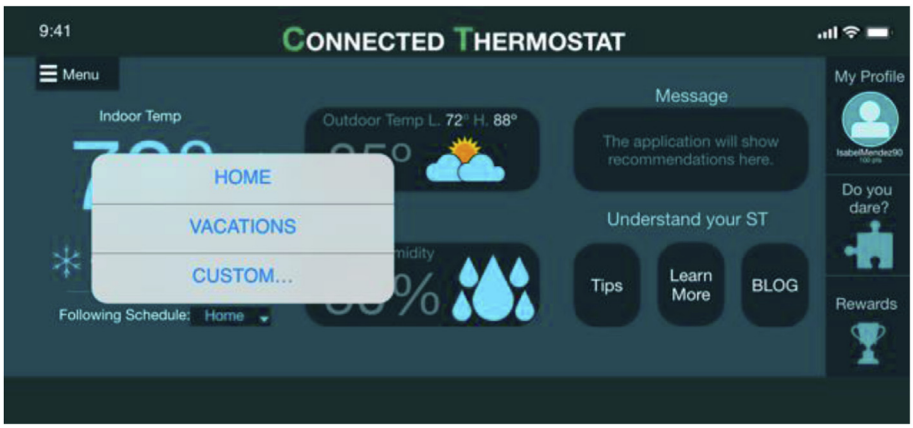


Fig. 47. Schedule options.

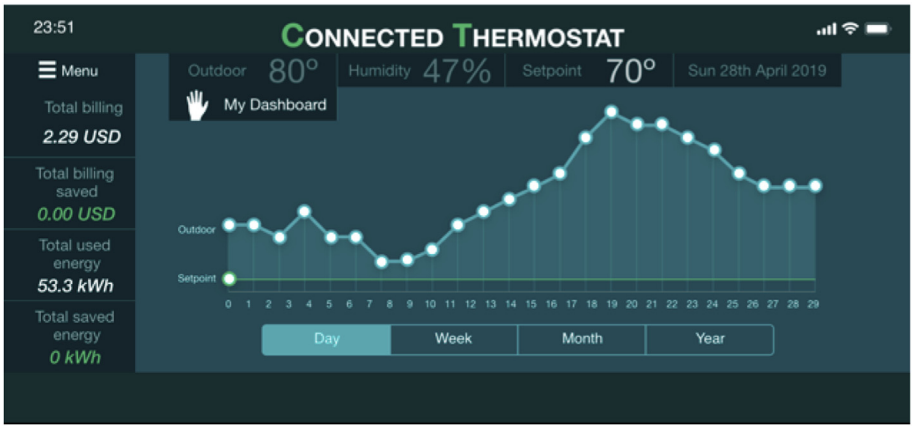


Fig. 48. Historical graph – Day.

problems. This framework does not consider its interaction with other smart devices; however, this will be feasible with further research that allows the knowledge base to know the usability and behavior problems of the smart devices. With the proposed interface, the behavior problems presented in (Ponce et al., 2018b, 2017) can be solved by providing users with gamification and SG elements that are designed to teach them to take advantage of their product. In addition, to solve the physical usability problems, the thermostat designer can propose a design based on the suggestions of the knowledge base. Thus, once the knowledge base and fuzzy logic are completed, the usability problems can be solved as well, and the designer can propose a design for the interface and its variants.

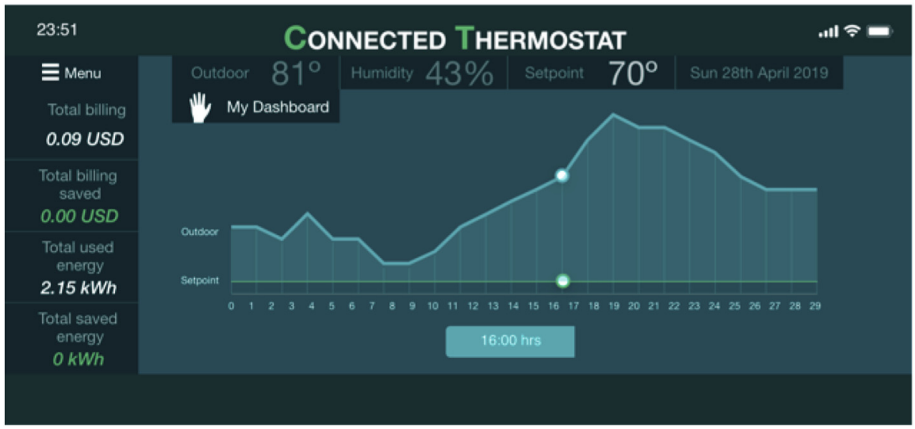


Fig. 49. 10:00 h. Example day.

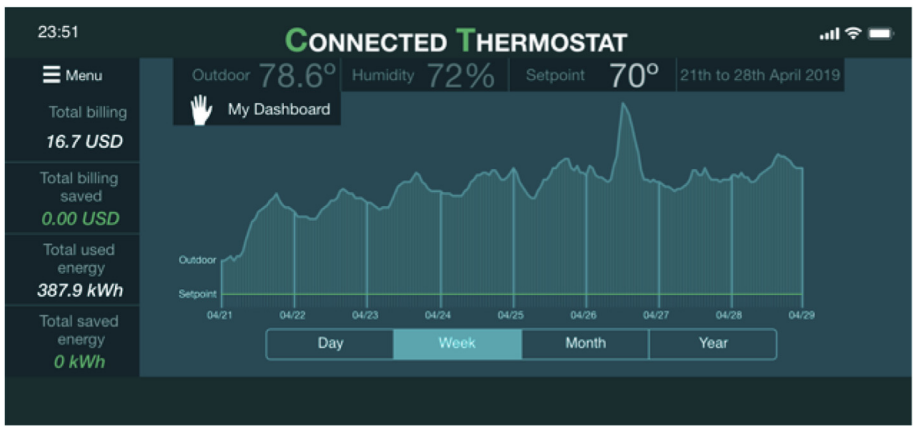


Fig. 50. Historical chart – Week.

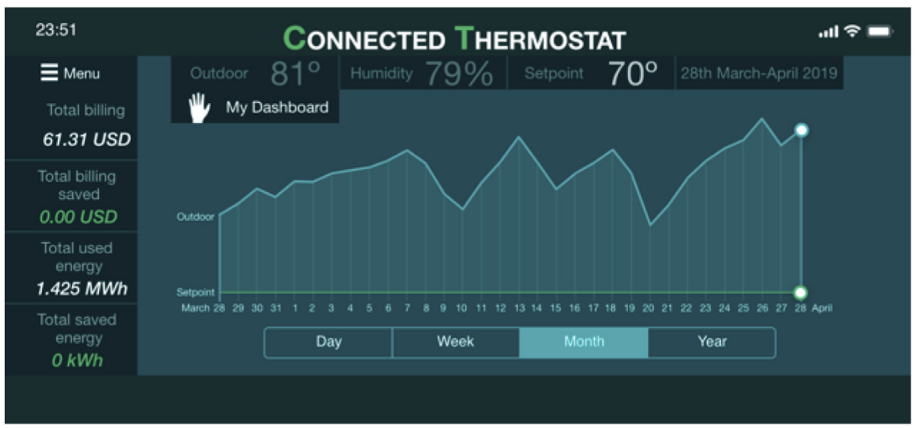


Fig. 51. Historical chart – Month.

8. Conclusion and directions for future work

State of the art shows that there does not yet exist a dynamic interface that uses gamification and SGs using the fuzzy logic analysis to save energy using smart devices by considering behavior and usability problems when a connected product is deployed, such as a CT. However, the combination of those techniques allows designers to achieve a dynamic interface that engages end-users to adopt cleaner production technologies. Moreover, the dynamic interface improves the sustainability of connected devices at smart homes or buildings. Thus, the main goal of this paper is to propose a comprehensive framework that enables the customer to save energy in the CT by teaching, engaging, and motivating end-consumers through this novel dynamic interface. Besides, the proposed framework has only three friendly phases for designing a smart, sensing, and sustainable product, so it contributes to

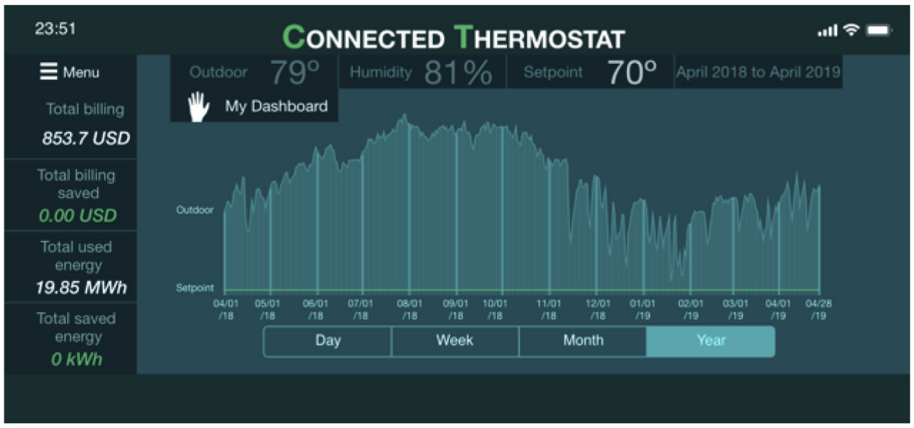


Fig. 52. Historical chart – Year.

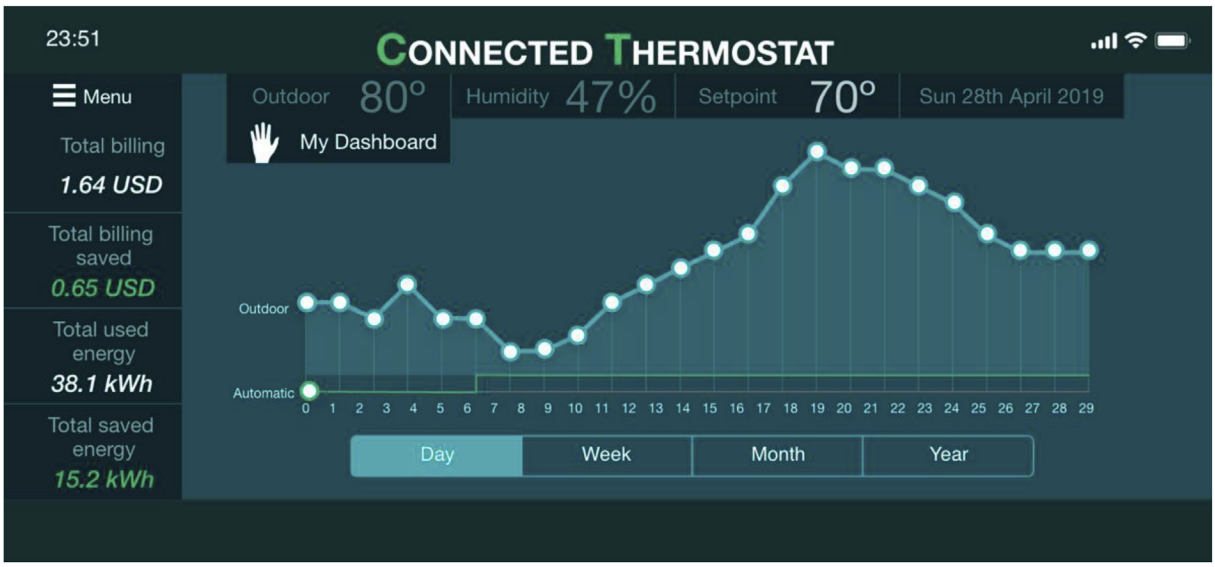


Fig. 53. Example of electrical energy reduction.

improving the performance of connected devices at smart homes when those phases are implemented on a clenear product design. Besides, this framework is created to bridge the gap between users' expectations and their usability and behavior problems about achieving fundamental goals, such as saving energy in the HVAC system through the correct operation of thermostats.

The ultimate goal of this proposal is to shape the users' behavior by proposing a customized interface and therefore achieve energy consumption reduction in the household, so they can become energy aware even if they are not interested in it. This proposal covers all types of users (non-typical and typical users); however, to validate this proposal meticulously in the real end-user market, it is required to (1) develop more questionnaires that confirm the classification of each user by its personality traits for gameful experiences; (2) evaluate and improve the proposed application according to the external evaluation of end-users under different real scenarios. Not only does run the proposed application into controlled environments such as university laboratories but also it has to be evaluated in several countries in which cultural factors could be a factor to consider in the framework; (3) update the application as required according to an acceptable sample of end-users that represents more than a few end-users' behaviors.

Moreover, the implications of this work on the development and adoption of cleaner production technologies are through the promotion of eco-efficient products at the household that helps the customer achieve sustainable attitudes and lifestyle allowing a reduction in pollution and carbon footprint; the framework is also designed to allow an energy auditing through the electric bills reviews and provide a sustainability analysis by the charts and the on-line monitoring system available at the dashboard. Hence, automatic self-evaluation and feedback regarding energy consumption can be provided, so the end-user could change his energy consumption behavior in a short period of time. Thus, it could be possible to construct sustainable energy communities based on this proposal.

Declaration of competing interest

No conflicts of interest.

CRediT authorship contribution statement

Pedro Ponce: Conceptualization, Methodology, Investigation, Writing - original draft, Formal analysis, Validation, Supervision.

Alan Meier: Conceptualization, Methodology, Writing - original draft, Formal analysis, Investigation. **Juana Isabel Méndez:** Conceptualization, Methodology, Writing - original draft, Formal analysis, Data curation, Visualization. **Therese Peffer:** Conceptualization, Methodology, Investigation. **Arturo Molina:** Conceptualization, Methodology, Investigation. **Omar Mata:** Software, Formal analysis, Validation.

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References

Albadán, J., Gaona, P., Montenegro, C., González-Crespo, R., Herrera-Viedma, E., 2018. Fuzzy logic models for non-programmed decision-making in personnel selection processes based on gamification. Informatica 29, 1–20. https://doi.org/10.15388/Informatica.2018.155.

AlSkaif, T., Lampropoulos, I., van den Broek, M., van Sark, W., 2018. Gamification-based framework for engagement of residential customers in energy applications. Energy Res. Soc. Sci. 44, 187–195. https://doi.org/10.1016/j.erss.2018.04.043.

Baldi, S., Korkas, C.D., Lv, M., Kosmatopoulos, E.B., 2018. Automating occupant-building interaction via smart zoning of thermostatic loads: a switched self-tuning approach. Appl. Energy 231, 1246–1258. https://doi.org/10.1016/j.apenergy.2018.09.188.

Barbosa, P., Barros, A., Pinho, L.M., 2017. The EnerGAware middleware platform. In: IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society. Presented at the IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society. IEEE, Beijing, pp. 8662–8667. https://doi.org/10.1109/IECON.2017.8217521.

Barrick, M.R., Mount, M.K., 1991. The big five personality dimensions and job performance: a meta-analysis. Person. Psychol. 44, 1–26. https://doi.org/10.1111/j.1744-6570.1991.tb00688.x.

Bartle, R., 1996. HEARTS, CLUBS, DIAMONDS, SPADES: PLAYERS WHO SUIT MUDS 28.

Beck, A.L., Chitalia, S., Rai, V., 2019. Not so gameful: a critical review of gamification in mobile energy applications. Energy Res. Soc. Sci. 51, 32–39. https://doi.org/10.1016/j.erss.2019.01.006.

Brick, C., Lewis, G.J., 2016. Unearthing the "green" personality: core traits predict environmentally friendly behavior. Environ. Behav. 48, 635–658. https://doi.org/10.1177/0013916514554695.

Casals, M., Gangolells, M., Macarulla, M., Fuertes, A., Vimont, V., Pinho, L.M., 2017. A serious game enhancing social tenants' behavioral change towards energy efficiency. In: 2017 Global Internet of Things Summit (GIoTS). Presented at the 2017 Global Internet of Things Summit (GIoTS). IEEE, Geneva, Switzerland, pp. 1–6. https://doi.org/10.1109/GIOTS.2017.8016257.

Chou, Y., 2015. Actionable Gamification beyond Points, Badges, and Leaderboards. CreateSpace Independent Publishing Platform.

Coursera, 2017. Serious gaming | coursera [WWW Document]. URL. https://www.coursera.org/learn/serious-gaming (accessed 4.11.19).

Dorji, U., Panjaburee, P., Srisawasdi, N., 2015. Gender differences in students' learning achievements and awareness through residence energy saving game-based inquiry playing. J. Comput. Educ. 2, 227–243. https://doi.org/10.1007/s40692-015-0033-2.

ecobee, 2016. How to Install Your Ecobee4 [WWW Document]. ecobee. URL. https://images.homedepot-static.com/catalog/pdfImages/7a/7a6ecf71-32a9-4944-b524-f623e7505643.pdf (accessed 4.11.19).

ecoGator, 2016. ecoGator App –Energy Efficiency in the Palm of Your Hand. Empowering consumers to choose energy efficient products and sustainable lifestyles [WWW Document]. URL. https://www.buildup.eu/sites/default/files/content/ecogator_final_publishable_report.pdf (accessed 4.11.19).

Evans, G.T., 1970. Use of the semantic differential technique to study attitudes during classroom lessons. Interchange 1, 96–106. https://doi.org/10.1007/BF02214884.

Fijnheer, J.D., Van Oostendorp, H., 2016. Steps to design a household energy game. IJSG 3. https://doi.org/10.17083/ijsg.v3i3.131.

Game | 2020 Energy, 2018. Game | 2020 energy [WWW Document]. URL. http://www.2020energy.eu/game (accessed 4.11.19).

Geelen, D., Keyson, D., Boess, S., Brezet, H., 2012. Exploring the use of a game to stimulate energy saving in households. J. Des. Res. 10, 102–120. https://doi.org/10.1504/JDR.2012.046096.

Giessen, H.W., 2015. Serious games effects: an overview. Procedia Soc. Behav. Sci. 174, 2240–2244. https://doi.org/10.1016/j.sbspro.2015.01.881.

Gonczarowski, Y.A., Tondello, G.F., 2017. Incentives and gamification. XRDS 24, 9–11. https://doi.org/10.1145/3123766.

Gustafsson, A., Bång, M., Svahn, M., 2009. Power explorer: a casual game style for encouraging long term behavior change among teenagers. In: Proceedings of the International Conference on Advances in Computer Enterntainment Technology - ACE '09. Presented at the the International Conference. ACM Press, Athens, Greece, p. 182. https://doi.org/10.1145/1690388.1690419.

Hamari, J., Eranti, V., n.d. Framework for Designing and Evaluating Game Achievements 20.

Hirsh, J.B., 2010. Personality and environmental concern. J. Environ. Psychol. 30, 245–248. https://doi.org/10.1016/j.jenvp.2010.01.004.

Huotari, K., Hamari, J., 2012. Defining gamification: a service marketing perspective. In: Proceeding of the 16th International Academic MindTrek Conference on - MindTrek '12. Presented at the Proceeding of the 16th International Academic MindTrek Conference. ACM Press, Tampere, Finland, p. 17. https://doi.org/10.1145/2393132.2393137.

IEA, 2018. Energy Efficiency 2018, Market Report Series. International Energy Agency.

IEA, 2017. Energy Efficiency 2017, Market Report Series. International Energy Agency.

Johnson, D., Horton, E., Mulcahy, R., Foth, M., 2017. Gamification and serious games within the domain of domestic energy consumption: a systematic review. Renew. Sustain. Energy Rev. 73, 249–264. https://doi.org/10.1016/j.rser.2017.01.134.

Judge, T.A., Higgins, C.A., Thoresen, C.J., Barrick, M.R., 1999. The big five personality traits, general mental ability, and career success across the life span. Person. Psychol. 52, 621–652. https://doi.org/10.1111/j.1744-6570.1999.tb00174.x.

Jung, W., Jazizadeh, F., 2019. Human-in-the-loop HVAC operations: a quantitative review on occupancy, comfort, and energy-efficiency dimensions. Appl. Energy 239, 1471–1508. https://doi.org/10.1016/j.apenergy.2019.01.070.

Kashani, A., Ozturk, Y., 2017. Residential energy consumer behavior modification via gamification. In: 2017 IEEE 6th International Conference on Renewable Energy Research and Applications (ICRERA). Presented at the 6th International Conference on Renewable Energy Research and Applications (ICRERA), San Diego, California, USA, pp. 1221–1225. https://doi.org/10.1109/ICRERA.2017.8191247.

Korkas, C.D., Baldi, S., Michailidis, I., Kosmatopoulos, E.B., 2016. Occupancy-based demand response and thermal comfort optimization in microgrids with renewable energy sources and energy storage. Appl. Energy 163, 93–104. https://doi.org/10.1016/j.apenergy.2015.10.140.

Lucassen, G., Jansen, S., 2014. Gamification in consumer marketing - future or fallacy? Procedia Soc. Behav. Sci. 148, 194–202. https://doi.org/10.1016/j.sbspro.2014.07.034.

Madani, K., Pierce, T.W., Mirchi, A., 2017. Serious games on environmental management. Sustain. Cities Soc. 29, 1–11. https://doi.org/10.1016/j.scs.2016.11.007.

Marczewski, A., 2015. Even Ninja Monkeys like to Play: Gamification, Game Thinking and Motivational Design. CreateSpace Independent Publishing Platform.

Mata, O., Ponce, P., Méndez, I., Molina, A., Meier, A., Peffer, T., 2019. A model using artificial neural networks and fuzzy logic for knowing the consumer on smart thermostats as a S3 product. In: Martínez-Villaseñor, L., Batyrshin, I., Marín-Hernández, A. (Eds.), Advances in Soft Computing. Springer International Publishing, Cham, pp. 430–439. https://doi.org/10.1007/978-3-030-33749-0_34.

Matallaoui, A., Herzig, P., Zarnekow, R., 2015. Model-driven serious game development integration of the gamification modeling language GaML with unity. In: 2015 48th Hawaii International Conference on System Sciences. Presented at the 2015 48th Hawaii International Conference on System Sciences (HICSS). IEEE, HI, USA, pp. 643–651. https://doi.org/10.1109/HICSS.2015.84.

McCrae, R.R., Costa, P.T., 1997. Personality trait structure as a human universal. Am. Psychol. 52, 509–516. https://doi.org/10.1037/0003-066X.52.5.509.

Méndez, J.I., Mata, O., Ponce, P., Meier, A., Peffer, T., Molina, A., 2020a. Multi-sensor system, gamification, and artificial intelligence for benefit elderly people. In: Ponce, H., Martínez-Villaseñor, L., Brieva, J., Moya-Albor, E. (Eds.), Challenges and Trends in Multimodal Fall Detection for Healthcare. Springer International Publishing, Cham, pp. 207–235. https://doi.org/10.1007/978-3-030-38748-8_9.

Méndez, J.I., Ponce, P., Mata, O., Meier, A., Peffer, T., Molina, A., Aguilar, M., 2020b. Empower saving energy into smart homes using a gamification structure by social products. In: 2020 IEEE International Conference on Consumer Electronics (ICCE) (2020 ICCE). Las Vegas, USA.

Méndez, J.I., Ponce, P., Meier, A., Peffer, P., Therese, Mata, Omar, O., Molina, A., 2019a. S4 product design framework: a gamification strategy based on type 1 and 2 fuzzy logic. In: Smart Multimedia: Methodologies and Algorithms. Presented at the International Conference on SMART MULTIMEDIA, 2019, San Diego, California, USA, p. 15 https://doi.org/In press.

Méndez, J.I., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A., 2019b. Framework for promoting social interaction and physical activity in elderly people using gamification and fuzzy logic strategy. In: 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP). Presented at the 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP). IEEE, Ottawa, ON, Canada, pp. 1–5. https://doi.org/10.1109/GlobalSIP45357.2019.8969110.

Milfont, T.L., Sibley, C.G., 2012. The big five personality traits and environmental engagement: associations at the individual and societal level. J. Environ. Psychol. 32, 187–195. https://doi.org/10.1016/j.jenvp.2011.12.006.

MIRABEL, 2010. Micro-request-based aggregation, forecasting and scheduling of energy demand. Supply and Distribution | MIRABEL Project | FP7 [WWW

Document]. CORDIS | European Commission. URL. https://cordis.europa.eu/project/id/248195 (accessed 4.13.19).
Moloney, J., Globa, A., Wang, R., Roetzel, A., 2017. Serious games for integral sustainable design: level 1. Procedia Eng. 180, 1744–1753. https://doi.org/10.1016/j.proeng.2017.04.337.
Oliver, J., Srivastava, S., 1999. The Big Five Trait taxonomy: history, measurement, and theoretical perspectives. In: Handbook of Personality: Theory and Research, second ed. The Guilford Press, New York.
Orland, B., Ram, N., Lang, D., Houser, K., Kling, N., Coccia, M., 2014. Saving energy in an office environment: a serious game intervention. Energy Build. 74, 43–52. https://doi.org/10.1016/j.enbuild.2014.01.036.
Ouariachi, T., Olvera-Lobo, M.D., Gutiérrez-Pérez, J., 2019. Serious games and sustainability. In: Leal Filho, W. (Ed.), Encyclopedia of Sustainability in Higher Education. Springer International Publishing, Cham, pp. 1–10. https://doi.org/10.1007/978-3-319-63951-2_326-1.
Paunonen, S.V., 2003. Big Five factors of personality and replicated predictions of behavior. J. Pers. Soc. Psychol. 84, 411–424. https://doi.org/10.1037/0022-3514.84.2.411.
Peham, M., Breitfuss, G., Michalczuk, R., 2014. The "ecoGator" app: gamification for enhanced energy efficiency in Europe. In: Proceedings of the Second International Conference on Technological Ecosystems for Enhancing Multiculturality - TEEM '14. Presented at the the Second International Conference. ACM Press, Salamanca, Spain, pp. 179–183. https://doi.org/10.1145/2669711.2669897.
Ponce, P., 2011. Inteligencia Artificial con Aplicaciones a la Ingeniería. Marcombo.
Ponce, P., Meier, A., Miranda, J., Molina, A., Peffer, T., 2019. The next generation of social products based on sensing, smart and sustainable (S3) features: a smart thermostat as case study. In: 9th IFAC Conference on Manufacturing Modelling, Management and Control. Presented at the 9th IFAC Conference on Manufacturing Modelling. Management and Control, p. 6.
Ponce, P., Peffer, T., Molina, A., 2018a. Usability perceptions and beliefs about smart thermostats by chi-square test, signal detection theory, and fuzzy detection theory in regions of Mexico. Front. Energy 13, 522–538. https://doi.org/10.1007/s11708-018-0562-2.
Ponce, P., Peffer, T., Molina, A., 2018b. Framework for evaluating usability problems: a case study low-cost interfaces for thermostats. Int. J. Interact. Des. Manuf. 12, 439–448. https://doi.org/10.1007/s12008-017-0392-1.
Ponce, P., Peffer, T., Molina, A., 2017. Framework for communicating with consumers using an expectation interface in smart thermostats. Energy Build. 145, 44–56. https://doi.org/10.1016/j.enbuild.2017.03.065.
Ponce-Cruz, P., Molina, A., MacCleery, B., 2016. Fuzzy Logic Type 1 and Type 2 Based on LabVIEW(TM) FPGA, first ed. Springer Publishing Company, Incorporated.
PowerTap, 2007. PowerTap now owned by SRAM – quarq. URL. https://www.quarq.com/powertap/ (accessed 4.11.19).
Pritoni, M., Meier, A.K., Aragon, C., Perry, D., Peffer, T., 2015. Energy efficiency and the misuse of programmable thermostats: the effectiveness of crowdsourcing for understanding household behavior. Energy Res. Soc. Sci. 8, 190–197. https://doi.org/10.1016/j.erss.2015.06.002.
Prochaska, J.O., Velicer, W.F., 1997. The transtheoretical model of health behavior change. Am. J. Health Promot. 12, 38–48. https://doi.org/10.4278/0890-1171-12.1.38.
Psychometrics Project, 2019. Open psychology data: raw data from online personality tests [WWW Document]. URL. https://openpsychometrics.org/_rawdata/ (accessed 12.21.19).
Qela, B., Mouftah, H., 2010. Simulation of a house heating system using C# — an energy conservation perspective. In: CCECE 2010. Presented at the 2010 IEEE 23rd Canadian Conference on Electrical and Computer Engineering - CCECE. IEEE, Calgary, AB, Canada, pp. 1–5. https://doi.org/10.1109/CCECE.2010.5575176.
Rai, V., Beck, A.L., 2017. Play and learn: serious games in breaking informational barriers in residential solar energy adoption in the United States. Energy Res. Soc. Sci. 27, 70–77. https://doi.org/10.1016/j.erss.2017.03.001.
Rothmann, S., Coetzer, E.P., 2003. The big five personality dimensions and job performance. SA J. Ind. Psychol. 29 https://doi.org/10.4102/sajip.v29i1.88.
Soltanaghaei, E., Whitehouse, K., 2018. Practical occupancy detection for programmable and smart thermostats. Appl. Energy 220, 842–855. https://doi.org/10.1016/j.apenergy.2017.11.024.
Stieglitz, S., Lattemann, C., Robra-Bissantz, S., Zarnekow, R., Brockmann, T., 2016. Gamification. Springer Berlin Heidelberg, New York, NY.
Tondello, G.F., Wehbe, R.R., Diamond, L., Busch, M., Marczewski, A., Nacke, L.E., 2016. The gamification user types Hexad scale. In: Proceedings of the 2016 Annual Symposium on Computer-Human Interaction in Play - CHI PLAY '16. Presented at the the 2016 Annual Symposium. ACM Press, Austin, Texas, USA, pp. 229–243. https://doi.org/10.1145/2967934.2968082.
Vojdani, A., 2008. Smart integration. IEEE Power Energy Mag. 6, 71–79. https://doi.org/10.1109/MPE.2008.929744.
Williams, E.D., Matthews, H.S., 2007. Scoping the Potential of Monitoring and Control Technologies to Reduce Energy Use in Homes 6.
Zadeh, L.A., 1965. Fuzzy sets. Inf. Contr. 8, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X.
Zichermann, G., Cunningham, C., 2011. Gamification by Design: Implementing Game Mechanics in Web and Mobile Apps, first ed. O'Reilly Media, Inc.

Chapter 8

Final Remarks

8.1 Discussion

Simulators allow personalized schedules, activities, or clothes for annual simulations. They are ideal for understanding energy consumption behavior. Nevertheless, the simulations developed during this thesis do not allow real-time feedback or usage.

Furthermore, two types of interactions were explored.

- Tutored interfaces teach consumers how to achieve specific goals, such as energy reductions using databases from existing databases or simulations
- Interactive interfaces predict the goal performance through the AI decision systems.

Nevertheless, these interfaces have the main limitation. The interface requires real-time implementation and validation. This research only presents a game elements proposal based on the literature review.

Furthermore, platform implementation needs at least two years, with transversal studies every six months.

8.2 Conclusion

The research objective that is reached in this research is the following:

- Proposing a methodology for tailored deploying product platforms focused on users and based on artificial intelligence decision systems.

Throughout the chapters, several implementations of this methodology are demonstrated. These applications are displayed in three layers: smart homes, smart communities, and smart cities.

- Chapter 1 introduces the importance of the transition from products to tailored product platforms and the methodology for deploying these tailored product platforms.
- Chapter 2 employs the methodology for the tutored platforms in connected thermostats to save energy without losing thermal comfort.

- Chapter 3 uses the methodology for healthcare monitoring in a pre-diagnosis survey for depression symptoms to assess medic. Furthermore, this proposal does not aim to substitute the medical expert option. On the contrary, this proposal aims to help the healthcare expert by providing information about the consumer and their behavior within a smart home environment.
- Chapter 4 presents the implementation of a tailored gamified platform for smart communities by providing a platform that teaches residential consumers how the electricity bill affects depending on the location.
- Chapter 5 exemplifies the energy consumption and thermal comfort differences in three communities with different environmental conditions and addresses strategies to reduce energy consumption without losing thermal comfort.
- Chapter 6 details the transition from homes to communities and communities to cities and how energy.
- Chapter 7 presents the foundation of this thesis. This chapter establishes the first steps for deploying tailored products by studying the case of connected thermostats. This chapter is the basis of the product platform deployment because it deeply explains the aspects behind successful gamification strategies related to the users' expectations, personality traits, behavioral theories, and various game elements applied for gamification.

8.2.1 Platform user guideline

This thesis proposes a platform user guideline when using this methodology.

1. Step 1: Learn user and product type.
    - Survey the consumer with the BFI-10 survey.
    - If no information is available, consider Goldberg's database of personality traits or propose a generic persona user type.
2. Step 2: Learn building, process, or service usage pattern
    - In case there are no databases available, simulate the scenarios and environments to better understand the platform performance.
    - For instance, for energy and thermal comfort analysis, build an energy model and simulate it using EnergyPlus. Building energy models requires a 95 % level of confidence.
3. Step 3: Statistical data analysis
    - Use commercial or non-commercial software for statistical data analysis (R Studio, python, SAS, MATLAB).
    - Publish your database in an open platform. If there is no conflict of interest, deposit that database in a repository like GitHub.

- If possible, create interactive charts and launch them online so other researchers/interested people can access that information. In RStudio, you can deploy it through RPubs.

4. Step 4: Propose tailored dynamic gamified platforms.
   - Employ fuzzy logic when there is linguistic information from experts.
   - Employ ANN when there are databases from simulations and experimentations.
   - Employ ANFIS when there are smaller databases and it is feasible to generate fuzzy inference systems.
   - Furthermore, there are toolboxes that ease the AI decision systems. However, this is not limited, if required the AI decision system can be created from the ground.
     - LabVIEW Fuzzy Logic Toolkit is ideal for designing fuzzy logic decision systems.
     - MATLAB Neuro-Fuzzy Designer toolbox is ideal for ANFIS decision systems with one output and Sugeno type.
     - MATLAB DeepLearning toolbox is ideal for ANN decision systems and classification.
5. Step 4: Propose a tailored dynamic product platform.
   - SIMULINK is ideal for graphical programming and deploying dashboards based on ANN (two-layer feed-forward).
   - LabVIEW is ideal for interactive interfaces and is connected with National Instruments (NI) hardware rather than SIMULINK.
   - SIMULINK allows interactive interfaces, but the general thermostat interface must be designed in another program (Adobe XD).

8.3 Contribution

This research has the following contribution:

- Framework that provides tailored platforms based on AI decision systems.
- Framework that deploys interactive platforms depending on the personality traits, energy consumer, and gamified user.
- Interactive interface (tutored platform) with energy consumption scenarios to teach the differences between HVAC and natural ventilation and setpoint ranges.
- Interactive interface that changes the gamified buttons depending on the user type.
- Modular platform through the proposed methodology allows the implementation in other domains such as residential, education, healthcare, and manufacturing, among others.

Alternatively, interfaces, as proposed, gather information about end-users preferences. For instance, the thermal sensation component can collect end-user votes to better understand their thermal preferences and adjust techniques to engage them in activities to reduce consumption or money without affecting thermal comfort.

8.3.1 Publications

During this doctoral study, twenty-eight scientific products were published. The list of publications is categorized depending on the type:

Journal Publications

1. Méndez, J. I., Medina, A., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). Evolving Gamified Smart Communities in Mexico to Save Energy in Communities through Intelligent Interfaces. Energies, 15(15). (Q1 — CiteScore 2021: 5.0 — SJR 2021: 0.653)

2. Méndez, J.I., Peffer T., Ponce, P., Meier, A., Molina, A. (2022). Empowering saving energy at home through serious games on thermostat interfaces. Energy and Buildings, 263 112026. (Q1 — CiteScore 2021: 11.5 — SJR 2021: 1.682)

3. Mendez, J., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A. (2022). Empower Saving Energy into Smart Communities using Social Products with a Gamification Structure for Tailored Human-Machine Interfaces within Smart Homes. International Journal on Interactive Design and Manufacturing (IJIDeM). [Accepted] (Q2 — CiteScore 2020: 4.9 — SJR 2021: 0.486)

4. Méndez, J. I., Meza-Sánchez, A. V., Ponce, P., McDaniel, T., Peffer, T., Meier, A., Molina, A. (2021). Smart Homes as Enablers for Depression Pre-Diagnosis Using PHQ-9 on HMI through Fuzzy Logic Decision System. Sensors, 21(23). (Q2 — CiteScore 2021: 6.4 — SJR 2021: 0.803)

5. Avila, M., Méndez, J. I., Ponce, P., Peffer, T., Meier, A., Molina, A. (2021). Energy Management System Based on a Gamified Application for Households. Energies, 14(12). (Q2 — CiteScore 2021: 5.0 — SJR 2021: 0.653). **[*Note: Shared authorship*]**

6. Ponce, P., Meier, A., Mendez, J., Peffer, T., Molina, A., Mata, O. (2020). Tailored gamification and serious game framework based on fuzzy logic for saving energy in smart thermostats. Journal of Cleaner Production, 121167. (Q1 — CiteScore 2020: 13.1 — SJR 2021: 1.921). **[*Note: Shared authorship*]**

7. Mata O., Méndez JI., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). Energy savings on buildings based on image depth sensors for human activity recognition. Energies. [Submitted] (Q1 — CiteScore 2021: 5.0 — SJR 2021: 0.653)

8. Medina A., Méndez JI., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). Embedded Real-Time Clothing Classifier Using One-Stage Methods for Saving Energy in Thermostats. Energies, 15(17). (Q1 — CiteScore 2021: 5.0 — SJR 2021: 0.653)

9. Medina A., Méndez JI., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). Using Deep Learning in Real-Time for Clothing Classification with Connected Thermostats. Energies, 15(5). (Q1 — CiteScore 2021: 5.0 — SJR 2021: 0.653)

Proceedings Publications

1. Méndez, J. I., Medina A., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part I. Smart Multimedia (Vol. 13497). Springer International Publishing.

2. Méndez, J. I., Ponce, P., Peffer, T., Meier, A., Molina, A. (2021). A Gamified HMI as a Response for Implementing a Smart-Sustainable University Campus. In Camarinha-Matos L.M., Boucher X., Afsarmanesh H. (eds), Smart and Sustainable Collaborative Networks 4.0. PRO-VE 2021. IFIP Advances in Information and Communication Technology (Vol. 629, pp. 683-691). Springer International Publishing.

3. Méndez, J. I., Ponce, P., Miranda, O., Pérez, C., Cruz, A. P., Peffer, T., Meier, A., McDaniel, T., Molina, A. (2021). Designing a Consumer Framework for Social Products Within a Gamified Smart Home Context. In M. Antona C. Stephanidis (Eds.), Universal Access in Human-Computer Interaction. Design Methods and User Experience (Vol. 12768, pp. 429–443). Springer International Publishing.

4. Méndez, J. I., Ponce, P., Pecina, M., Schroeder, G., Castellanos, S., Peffer, T., Meier, A., Molina, A. (2021). A Rapid HMI Prototyping Based on Personality Traits and AI for Social Connected Thermostats. In I. Batyrshin, A. Gelbukh, G. Sidorov (Eds.), Advances in Soft Computing (pp. 216–227). Springer International Publishing.

5. Mendez, J. I., Ponce, P., Medina, A., Peffer, T., Meier, A., Molina, A. (2021). A Smooth and Accepted Transition to the Future of Cities Based on the Standard ISO 37120, Artificial Intelligence, and Gamification Constructors. 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), 65–71.

6. Mendez, J. I., Ponce, P., Mata, O., Meier, A., Peffer, T., Molina, A., Aguilar, M. (2020). Empower saving energy into smart homes using a gamification structure by social products. 2020 IEEE International Conference on Consumer Electronics (ICCE), 1–7.

7. Méndez, J. I., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A. (2020). S4 Product Design Framework: A Gamification Strategy Based on Type 1 and 2 Fuzzy Logic. In T. McDaniel, S. Berretti, I. D. D. Curcio, A. Basu (Eds.), Smart Multimedia (Vol. 12015, pp. 509–524). Springer International Publishing.

8. Mendez, J. I., Ponce, P., Meier, A., Peffer, T., Mata, O., Molina, A. (2019). Framework for promoting social interaction and physical activity in elderly people using gamification and fuzzy logic strategy. 2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP), 1–5.

9. Medina A., Méndez, J. I., Ponce, P., Peffer, T., Meier, A., Molina, A. (2022). A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part II. Smart Multimedia (Vol. 13497). Springer International Publishing.

10. Pérez, C., Méndez, J. I., Rivera, A., Ponce, P., Castellanos, S., Peffer, T., Meier, A., Molina, A. (2022). Gamified Smart Grid Implementation through Pico, Nano, and Microgrids in a Sustainable Campus. Smart Multimedia (Vol. 13497). Springer International Publishing.

11. Ponce, P., Mata, O., Castellanos, S., Molina, A., McDaniel, T., Méndez, J. I. (2022). The Energy 4.0 Concept and Its relationship with the S3 Framework. Smart Multimedia (Vol. 13497). Springer International Publishing.

12. Ponce, P., Mendez, J. I., Medina, A., Mata, O., Meier, A., Peffer, T., Molina, A. (2021). Smart Cities Using Social Cyber-Physical Systems Driven by Education. 2021 IEEE European Technology and Engineering Management Summit (E-TEMS), 155–160.

13. Mata, O., Ponce, P., McDaniel, T., Méndez, J. I., Peffer, T., Molina, A. (2021). Smart City Concept Based on Cyber-Physical Social Systems with Hierarchical Ethical Agents Approach. In M. Antona C. Stephanidis (Eds.), Universal Access in Human-Computer Interaction. Access to Media, Learning and Assistive Environments (Vol. 12769, pp. 424–437). Springer International Publishing.

14. Mata, O., Ponce, P., Méndez, I., Molina, A., Meier, A., Peffer, T. (2019). A Model Using Artificial Neural Networks and Fuzzy Logic for Knowing the Consumer on Smart Thermostats as a S3 Product. In L. Martínez-Villaseñor, I. Batyrshin, A. Marín-Hernández (Eds.), Advances in Soft Computing (Vol. 11835, pp. 430–439). Springer International Publishing.

15. Mata, O., Mendez, I., Aguilar, M., Ponce, P., Molina, A. (2019). A Methodology to Motivate Students to Develop Transversal Competencies in Academic Courses Based on the Theory of Planned Behavior by using Gamification and ANNs. 2019 IEEE Tenth International Conference on Technology for Education (T4E), 174–177.

Book Chapters Publications

1. Méndez, J. I., Ponce, P., Medina, A., Meier, A., Peffer, T., McDaniel, T., Molina, A. (2021). Human-Machine Interfaces for Socially Connected Devices: From Smart Households to Smart Cities. In T. McDaniel X. Liu (Eds.), Multimedia for Accessible Human Computer Interfaces (pp. 253–289). Springer International Publishing.

2. Méndez, J. I., Mata, O., Ponce, P., Meier, A., Peffer, T., Molina, A. (2020). Multi-sensor System, Gamification, and Artificial Intelligence for Benefit Elderly People. In H. Ponce, L. Martínez-Villaseñor, J. Brieva, E. Moya-Albor (Eds.), Challenges and Trends in Multimodal Fall Detection for Healthcare (Vol. 273, pp. 207–235). Springer International Publishing.

3. Ponce, P., Martínez, E., Méndez, J. I., Molina, A., Ramirez-Mendoza, R. (2022). Health: Human-Machine Interaction, Medical Robotics, Patient Rehabilitation. In R. Ramirez-Mendoza (Ed.), Biometry: Technology, Trends and Applications (1st ed.). CRC Press.

Book

1. Ponce, P., Peffer, T., Mendez-Garduno, J.I., Eicker, U., Molina, A., McDaniel, T., Musafiri-Mimo, E., Parakkal-Menon, R., Kaspar, K., Hussain, S. (2022). Data and AI Driving Smart Cities (1st ed.). Springer Nature Switzerland AG. [In process].

Patent

1. A Strategy to Increase Energy Savings from Smart Thermostats Based on Gamification and Deep Learning. [In progress].

Research Dissemination Articles and other News

1. Las ciudades inteligentes necesitan ciudadanos (además de tecnología). (July 21st, 2022). Tec Review.
2. Campus universitarios pueden apoyar a la ciudad en una transición hacia ciudades inteligentes. (February 21st, 2021). Transferencia Tec.
3. De termostatos conectados a comunidades inteligentes. (October 13th, 2020). Gaiabit.
4. Investigadores Tec trabajan en proyecto para ahorrar energía en casa. (September 30th, 2020). CONECTA Tec.
5. Gamification Could Make Smart Homes More Energy Efficient. (August 17th, 2020). Innovate IEEE.
6. Es arquitecta, pero su pasión la llevó a la ingeniería y recibe beca. (July 17th, 2020). CONECTA Tec.

8.4 Future Work

Future work includes measuring how these SGs application affects or benefits the initial conditions selected in simulation and the future implications of selecting other game techniques. Therefore, future research can include but is not limited to these topics:

- Interactive interface: Build and deploy a mobile application to measure how gamified strategies affect or benefit the initial conditions selected in the strategy.
- Residential energy platform: use other optimization methods based on a range of minimum or maximum setpoints needed to ventilate or heat the space without losing thermal comfort.

- Explore CO_2 Emissions reductions in manufacturing processes through this platform proposal
- Personality traits correlation with gamified or serious game users: Online interviews have been performed since 2020 at Tecnologico de Monterrey. However, more interviews are required to achieve a representative sample. Currently, there are 744 responses. Goldberg's database contains for Mexico more than 11,000 observations.

Bibliography

[1] AUTOMOTO. automoto/big-five-data, June 2021. original-date: 2018-12-28T05:29:25Z.

[2] AVILA, M., MÉNDEZ, J. I., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. Energy management system based on a gamified application for households. 3445.

[3] BARTLE, R. Hearts, clubs, diamonds, spades: Players who suit muds. *Journal of MUD research 1*, 1 (1996), 19.

[4] BRICK, C., AND LEWIS, G. J. Unearthing the "green" personality: Core traits predict environmentally friendly behavior. *Environment and Behavior 48*, 5 (2016), 635–658.

[5] DELOITTE. Turn products into product platforms: Providing a foundation for others to build upon, 2015.

[6] EDUCATION, M. P. Fundamental Concepts of Platforming Examples, Definitions, Approaches, & Metrics, 2020.

[7] FRAZIER, R., KHAN, N., LUNAWAT, G., AND RAHUL, A. Products and platforms: Is your technology operating model ready? | McKinsey, 2020.

[8] HELLWIG, R. T., TELI, D., SCHWEIKER, M., CHOI, J.-H., LEE, M. J., MORA, R., RAWAL, R., WANG, Z., AND AL-ATRASH, F. A framework for adopting adaptive thermal comfort principles in design and operation of buildings. *Energy and Buildings 205* (2019), 109476.

[9] HUOTARI, K., AND HAMARI, J. Defining gamification: a service marketing perspective. In *Proceeding of the 16th international academic MindTrek conference* (2012), pp. 17–22.

[10] JANG, J.-S. Anfis: adaptive-network-based fuzzy inference system. *IEEE transactions on systems, man, and cybernetics 23*, 3 (1993), 665–685.

[11] JOHN, O. P., SRIVASTAVA, S., ET AL. The big-five trait taxonomy: History, measurement, and theoretical perspectives.

[12] MANCHESTER, H., AND COPE, G. Learning to be a smart citizen. *Oxford Review of Education 45*, 2 (2019), 224–241.

[13] MATA, O., MENDEZ, I., AGUILAR, M., PONCE, P., AND MOLINA, A. A Methodology to Motivate Students to Develop Transversal Competencies in Academic Courses Based on the Theory of Planned Behavior by using Gamification and ANNs. In *2019 IEEE Tenth International Conference on Technology for Education (T4E)* (Goa, India, Dec. 2019), IEEE, pp. 174–177.

[14] MATA, O., MÉNDEZ, J. I., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. Energy savings on buildings based on image depth sensors for human activity recognition.

[15] MATA, O., PONCE, P., MCDANIEL, T., MÉNDEZ, J. I., PEFFER, T., AND MOLINA, A. Smart city concept based on cyber-physical social systems with hierarchical ethical agents approach. In *International Conference on Human-Computer Interaction* (2021), Springer, pp. 424–437.

[16] MATA, O., PONCE, P., MÉNDEZ, I., MOLINA, A., MEIER, A., AND PEFFER, T. A Model Using Artificial Neural Networks and Fuzzy Logic for Knowing the Consumer on Smart Thermostats as a S3 Product. In *Advances in Soft Computing*, L. Martínez-Villaseñor, I. Batyrshin, and A. Marín-Hernández, Eds., vol. 11835. Springer International Publishing, Cham, 2019, pp. 430–439.

[17] MCCRAE, R. R., AND COSTA JR, P. T. Personality trait structure as a human universal. *American psychologist 52*, 5 (1997), 509.

[18] MCCULLOCH, W. S., AND PITTS, W. A logical calculus of the ideas immanent in nervous activity. *The bulletin of mathematical biophysics 5*, 4 (1943), 115–133.

[19] MEDINA, A., MÉNDEZ, J., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. Using deep learning in real-time for clothing classification with connected thermostats.

[20] MEDINA, A., MÉNDEZ, J. I., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part II. In *Smart Multimedia*, vol. 13497. Springer International Publishing, Cham, 2022.

[21] MEDINA, A., MÉNDEZ, J. I., PONCE, P., PEFFER, T., AND MOLINA, A. Embedded real-time clothing classifier using one-stage methods for saving energy in thermostats. 6117.

[22] MENDEZ, J. I., PONCE, P., MATA, O., MEIER, A., PEFFER, T., MOLINA, A., AND AGUILAR, M. Empower saving energy into smart homes using a gamification structure by social products. In *2020 IEEE International Conference on Consumer Electronics (ICCE)* (Las Vegas, NV, USA, Jan. 2020), IEEE, pp. 1–7.

[23] MÉNDEZ, J. I., PONCE, P., MEDINA, A., MEIER, A., PEFFER, T., MCDANIEL, T., AND MOLINA, A. Human-machine interfaces for socially connected devices: From smart households to smart cities. In *Multimedia for Accessible Human Computer Interfaces*. Springer, 2021, pp. 253–289.

[24] MENDEZ, J. I., PONCE, P., MEDINA, A., PEFFER, T., MEIER, A., AND MOLINA, A. A Smooth and Accepted Transition to the Future of Cities Based on the Standard ISO 37120, Artificial Intelligence, and Gamification Constructors. In *2021 IEEE European Technology and Engineering Management Summit (E-TEMS)* (Dortmund, Germany, Mar. 2021), IEEE, pp. 65–71.

[25] MENDEZ, J. I., PONCE, P., MEIER, A., PEFFER, T., MATA, O., AND MOLINA, A. Framework for promoting social interaction and physical activity in elderly people using gamification and fuzzy logic strategy. In *2019 IEEE Global Conference on Signal and Information Processing (GlobalSIP)* (Ottawa, ON, Canada, Nov. 2019), IEEE, pp. 1–5.

[26] MÉNDEZ, J., PONCE, P., PECINA, M., SCHROEDER, G., CASTELLANOS, S., PEFFER, T., MEIER, A., AND MOLINA, A. A Rapid HMI Prototyping Based on Personality Traits and AI for Social Connected Thermostats. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 13068 LNAI* (2021), 216–227.

[27] MÉNDEZ, J., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. A Gamified HMI as a Response for Implementing a Smart-Sustainable University Campus. *IFIP Advances in Information and Communication Technology 629 IFIPAICT* (2021), 683–691.

[28] MÉNDEZ, J. I., MATA, O., PONCE, P., MEIER, A., PEFFER, T., AND MOLINA, A. Multi-sensor system, gamification, and artificial intelligence for benefit elderly people. In *Challenges and Trends in Multimodal Fall Detection for Healthcare*, H. Ponce, L. Martínez-Villaseñor, J. Brieva, and E. Moya-Albor, Eds., vol. 273. Springer International Publishing, pp. 207–235.

[29] MÉNDEZ, J. I., MEDINA, A., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. Evolving gamified smart communities in mexico to save energy in communities through intelligent interfaces. 5553.

[30] MÉNDEZ, J. I., MEDINA, A., PONCE, P., PEFFER, T., MEIER, A., AND MOLINA, A. A Real-Time Adaptive Thermal Comfort Model for Sustainable Energy in Interactive Smart Homes: Part I. In *Smart Multimedia*, vol. 13497. Springer International Publishing, Cham, 2022.

[31] MÉNDEZ, J. I., MEZA-SÁNCHEZ, A. V., PONCE, P., MCDANIEL, T., PEFFER, T., MEIER, A., AND MOLINA, A. Smart homes as enablers for depression pre-diagnosis using PHQ-9 on HMI through fuzzy logic decision system. 21.

[32] MÉNDEZ, J. I., PEFFER, T., PONCE, P., MEIER, A., AND MOLINA, A. Empowering saving energy at home through serious games on thermostat interfaces. 112026.

[33] MÉNDEZ, J. I., PONCE, P., MEIER, A., PEFFER, T., MATA, O., AND MOLINA, A. Empower saving energy into smart communities using social products with a gamification structure for tailored human-machine interfaces within smart homes.

[34] MÉNDEZ, J. I., PONCE, P., MEIER, A., PEFFER, T., MATA, O., AND MOLINA, A. S4 Product Design Framework: A Gamification Strategy Based on Type 1 and 2 Fuzzy Logic. In *Smart Multimedia*, T. McDaniel, S. Berretti, I. D. D. Curcio, and A. Basu, Eds., vol. 12015. Springer International Publishing, Cham, 2020, pp. 509–524. Series Title: Lecture Notes in Computer Science.

[35] MÉNDEZ, J. I., PONCE, P., MIRANDA, O., PÉREZ, C., CRUZ, A. P., PEFFER, T., MEIER, A., MCDANIEL, T., AND MOLINA, A. Designing a Consumer Framework for Social Products Within a Gamified Smart Home Context. In *Universal Access in Human-Computer Interaction. Design Methods and User Experience*, M. Antona and C. Stephanidis, Eds., vol. 12768. Springer International Publishing, Cham, 2021, pp. 429–443. Series Title: Lecture Notes in Computer Science.

[36] NADADUR, G., KIM, W., THOMSON, A. R., PARKINSON, M. B., AND SIMPSON, T. W. Strategic product design for multiple global markets. In *International Design Engineering Technical Conferences and Computers and Information in Engineering Conference* (2012), vol. 45066, American Society of Mechanical Engineers, pp. 837–848.

[37] NONNECKE, B. CITRIS and ITESM Announce 2019 Seed Funded Projects, Dec. 2018.

[38] OBERLO. US Smart Home Statistics (2018–2025) | Oberlo.

[39] PAUNONEN, S. V. Big five factors of personality and replicated predictions of behavior. *Journal of personality and social psychology 84*, 2 (2003), 411.

[40] PONCE, P. *Inteligencia artificial: con aplicaciones a la ingeniería*. Alpha Editorial, 2010.

[41] PONCE, P., MARTÍNEZ-RÍOS, E. A., MÉNDEZ, J. I., MOLINA, A., AND RAMIREZ-MENDOZA, R. A. Health: Human-machine interaction, medical robotics, patient rehabilitation. In *Biometry*. CRC Press, pp. 110–131.

[42] PONCE, P., MATA, O., CASTELLANOS, S., MOLINA, A., MCDANIEL, T., AND MÉNDEZ, J. I. The Energy 4.0 Concept and Its Relationship with the S3 Framework. In *Smart Multimedia*, vol. 13497. Springer International Publishing, Cham, 2022.

[43] PONCE, P., MEIER, A., MÉNDEZ, J., PEFFER, T., MOLINA, A., AND MATA, O. Tailored gamification and serious game framework based on fuzzy logic for saving energy in connected thermostats.

[44] PONCE, P., MENDEZ, J. I., MEDINA, A., MATA, O., MEIER, A., PEFFER, T., AND MOLINA, A. Smart Cities Using Social Cyber-Physical Systems Driven by Education. In *2021 IEEE European Technology and Engineering Management Summit (E-TEMS)* (Dortmund, Germany, Mar. 2021), IEEE, pp. 155–160.

[45] PONCE, P., PEFFER, T., MÉNDEZ-GARDUÑO, J. I., EICKER, U., MOLINA, A., MCDANIEL, T., MUSAFIRI-MIMO, E., PARAKKAL-MENON, R., KASPAR, K., AND HUSSAIN, S. *Data and AI Driving Smart Cities*, vol. 1st Ed.

[46] PONCE-CRUZ, P., MOLINA, A., AND MACCLEERY, B. *Fuzzy Logic Type 1 and Type 2 Based on LabVIEW"! FPGA*. Springer, 2016.

[47] PÉREZ, C., MÉNDEZ, J. I., RIVERA, A., PONCE, P., CASTELLANOS, S., PEFFER, T., MEIER, A., AND MOLINA, A. Gamified Smart Grid Implementation Through Pico, Nano, and Microgrids in a Sustainable Campus. In *Smart Multimedia*, vol. 13497. Springer International Publishing, Cham, 2022.

[48] RAMMSTEDT, B., AND JOHN, O. P. Measuring personality in one minute or less: A 10-item short version of the big five inventory in english and german. *Journal of research in Personality 41*, 1 (2007), 203–212.

[49] SHEN, M., LU, Y., AND TAN, K. Y. Big five personality traits, demographics and energy conservation behaviour: a preliminary study of their associations in singapore. *Energy Procedia 158* (2019), 3458–3463.

[50] TONDELLO, G. F., MORA, A., MARCZEWSKI, A., AND NACKE, L. E. Empirical validation of the gamification user types hexad scale in english and spanish. *International Journal of Human-Computer Studies 127* (2019), 95–111.

[51] TONDELLO, G. F., WEHBE, R. R., DIAMOND, L., BUSCH, M., MARCZEWSKI, A., AND NACKE, L. E. The gamification user types hexad scale. In *Proceedings of the 2016 annual symposium on computer-human interaction in play* (2016), pp. 229–243.

[52] TUNGUZ, B. Big Five Personality Test.

[53] ZADEH, L. A. Fuzzy sets. *Information and control 8*, 3 (1965), 338–353.

Curriculum Vitae

Juana Isabel Méndez Garduño was born in Mexico City, Mexico, on December 14th, 1990. She earned the Architectural degree from the Instituto Tecnológico y de Estudios Superiores de Monterrey, State of Mexico Campus in May 2013. She studied the Master in Energy Management and its Renewable Sources from the Instituto Tecnológico y de Estudios Superiores de Monterrey. She was accepted in the doctoral program in Engineering Sciences in January 2019 with a doctoral stay in the University of California, Berkeley, from February 2020 to December 2020. Her research interests include buidling energy efficiency and thermal comfort, energy model simulations and optimizations, gamification and serious games theory, and AI decision systems.

This document was typed in using LaTeX 2_ε by Juana Isabel Méndez Garduño.