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ORIGINAL

A conceptual framework for user-centric smart homes: integrating the KANO model with IoT and machine learning

Un marco conceptual para hogares inteligentes centrado en el usuario: integrando el modelo KANO con IoT y aprendizaje automático

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ABSTRACT

Introduction: the evolution of the smart home technologies has been rapid, and the integration of innovative IoT devices, advanced automation, and responsive control systems are introduced to enhance comfort, security, and energy efficiency.
Objective: despite the developments, the majority of smart home platforms are still not able to meet the expectation of the users due to the absence of the computational analysis of user priorities and feature-perception patterns. The article recommends a design and analysis framework using KANO Model that would contribute to the development of a user-friendly smart home system architecture.
Method: KANO Model is a computational requirement-classification model to categorize system characteristics into Must-Be features, One-Dimensional features, Attractive features, Indifferent features, and Reverse features to permit a methodical evaluation of their effect on user satisfaction. The study does not employ the traditional data collection method through survey, but employs the feature-engineering and requirement-Mapping methodology, which relies on user interaction behaviour, usage of existing systems, market analytics and performance-feature correlations based on smart home IoT environments.
Results: the findings reveal that One-Dimensional features, such as temperature control and energy optimization, directly correlate with user satisfaction levels, achieving scores of 0,85 and 0,88, respectively, while successfully reducing energy consumption by 25 %. Furthermore, Must-Be features like motion detection showed a high satisfaction score of 0,95, reinforcing the necessity of fulfilling basic user expectations to prevent dissatisfaction.
Conclusions: using the KANO Model in the development pipeline will enable more informed design decisions, improve the prioritization of features, and develop smart and user-centered solutions to the home.

Keywords: Smart Home Systems; KANO Model; IoT Architecture; User-Centered Design; Feature Engineering; Machine Learning.

RESUMEN

Introducción: la evolución de las tecnologías del hogar inteligente ha sido rápida, y se ha introducido la integración de dispositivos IoT innovadores, automatización avanzada y sistemas de control de respuesta para mejorar el confort, la seguridad y la eficiencia energética.
Objetivo: a pesar de los avances, la mayoría de las plataformas de hogares inteligentes aún no son capaces de satisfacer las expectativas de los usuarios debido a la ausencia del análisis computacional de las prioridades de los usuarios y los patrones de percepción de las características. El artículo recomienda un marco de diseño y análisis utilizando el modelo de KANO que contribuiría al desarrollo de una arquitectura de sistema de

hogar inteligente fácil de usar.
Método: el modelo de KANO es un modelo de clasificación de requisitos computacionales para categorizar las características del sistema en características imprescindibles, características unidimensionales, características atractivas, características indiferentes y características inversas para permitir una evaluación metódica de su efecto en la satisfacción del usuario. El estudio no emplea el método tradicional de recolección de datos a través de la encuesta, sino que emplea la metodología de ingeniería de características y mapeo de requisitos, que se basa en el comportamiento de interacción del usuario, el uso de sistemas existentes, análisis de mercado y correlaciones de rendimiento-característica basadas en entornos IoT de hogares inteligentes.
Resultados: los resultados revelan que las características unidimensionales, como el control de la temperatura y la optimización energética, están directamente relacionadas con los niveles de satisfacción de los usuarios, con puntuaciones de 0,85 y 0,88, respectivamente, al tiempo que reducen con éxito el consumo energético en un 25 %. Además, las características imprescindibles, como la detección de movimiento, obtuvieron una alta puntuación de satisfacción de 0,95, lo que refuerza la necesidad de satisfacer las expectativas básicas de los usuarios para evitar su insatisfacción.
Conclusiones: el uso del modelo KANO en la fase de desarrollo permitirá tomar decisiones de diseño más informadas, mejorar la prioride características y desarrollar soluciones inteligentes y centradas en el usuario para el hogar.

Palabras clave: Sistemas de Hogar Inteligente; Modelo de KANO; Arquitectura IoT; Diseño Centrado en el Usuario; Ingeniería de Características; Aprendizaje Automático.

INTRODUCTION

The recent past has seen smart homes emerge as one of the major points of focus in designing technology to enable people to live using smart systems. The recent emergence of smart homes has changed how technology can be used to enhance everyday living. Since these systems are supposed to make the systems more comfortable, secure, and energy efficient, one of the main challenges is to make sure that the features are user friendly. The most important thing is that these systems must be user-oriented and must meet their particular preferences, comfort, and expectations. The concept of user-centric smart homes is not limited to the functionality of the devices but also the interaction of the devices with the user to ensure a seamless living experience. The user needs are a significant initial step in this process, which is supported by the studies that concentrate on the critical dimensions and goals of making smart home environments.[1] Therefore, using these insights, a hybrid model that incorporated Kano, QFD, and the HCI techniques was developed to streamline the interface to suit the needs of the elderly in smart homes by integrating the functional requirements with the degree of user satisfaction of the functionality.[2] Although the development rate is fast, the existing smart home systems do not match the expectations of the users. Most of the conventional methods like surveys are not effective in terms of gathering the entire scope of user needs since they are not real time and are usually incapable of keeping up with the dynamic user behaviours. Furthermore, although many studies have been developed in the field of smart home systems, there is still a gap in the research on the evolution of user satisfaction in the context of dynamic and real-time adaptation of the IoT system. The existing practices also tend to be unable to incorporate user behaviour patterns into the system design and prioritization of features continuously. The Kano Model provides an optimistic way to fill these gaps by categorizing the smart home features according to their influence on user satisfaction. It assists in determining the features that are necessary, those that will be a delight to the users, and those that are not crucial. With the Kano Model in mind, the current paper will seek to incorporate real-time data on user interaction into the system design to enable smart home platforms to dynamically adapt and focus on the features that maximize user satisfaction. Past research has investigated the use of the Kano Model in smart home design, frequently with a particular user group (such as the elderly) in mind, or feature prioritization methods such as QFD and AHP. As an illustration, Kano and QFD have been integrated to simplify interfaces to the elderly to enhance their interaction with smart systems. Also, other methods have highlighted the need to categorize features as Must-Be, One-Dimensional and Attractive to ensure maximum user satisfaction. Nonetheless, these researches do not usually incorporate user preferences in real-time into the system. Simultaneously, the Kano and AHP-based feature prioritization techniques were just as potent in guiding the interface design of the older adult population.[3]

Current publications have taken into account the demand of smart home functionality within the framework of new digital economies with references to how the strategies of prioritization could be revised in the face of new technologies and new social requirements.[4] The functional quality attributes have since been dug to the bottom with their development being with qualitative research and the Kano modelling. This highlights the discovery that attributes of the top priority shall be established, which in turn, have decisive effects on user satisfaction.[5] user-friendly situations have been created, not only of the uses relevant to the elderly only, but also demonstrates how narrative-driven approaches prove effective in describing even the delicate tinges of requirements.[6]

The more abstracted vision of user experience with regard to digitalized smart homes has been backed up by service design approaches designed to enhance the usability and interaction.[7] In addition, the centrism of the user and the development of solutions in response to various lifestyles is guaranteed by the use of the design thinking methodologies in the development of the smart home systems.[8] The joint application of Kawasaki and QFD to mass-customization housing has been found to plan and give directions to sustainable design strategies.[9] Lastly, two systematic models combining Kano and FMEA have been built to evaluate service touchpoints and create interaction along the continuum of smart home.[10] The shortcomings found in the current research on smart homes point to the necessity of a design approach that can be used to elicit user satisfaction, respond to changing behaviour, and process non-homogenous data. Kano model is a systematic process of organizing the user requirements in terms of their contribution to satisfaction but its conventional survey-based application is not flexible and time conscious. In contrast, IoT systems are producing rich contextual and behavioural data streams without necessarily providing a prioritization of features according to perceived value by the users. Machine learning methods provide the ability to learn dynamic data trends and must have a principled framework to inform decision-making to user-centric results. The combination of the Kano model with data acquisition using IoT and machine learning is thus a reasonable and required step forward, as it will allow prioritizing features dynamically to satisfy users and at the same time, reflect the real-time behaviour of the system. It is based on this that the proposed Kano-IoT-ML framework is presented as a solution to the determined shortcomings of adaptability, user-centricity, and feature prioritization in the design of the smart home system. The paper will fill this gap by suggesting a dynamic and data-driven Kano model that includes real-time adaptation of the IoT system. In contrast to the old approaches, the suggested one constantly incorporates the user interaction data to refresh the feature priorities in real-time. This approach makes sure that the user satisfaction does not remain stagnant, but it changes as the user interacts with the system. The primary contribution of this work is that it has created a user-centric smart home model that is dynamic to the changing behaviour of users and offers a better experience and prioritization of features that will give the user the highest satisfaction. This paper aims to show how the combination of the Kano Model and real-time IoT system adaptation can be used to improve the functionality and design of smart homes. This study will continuously optimize the prioritization of smart home features as the user preferences change to ensure that the previous features are updated using real-time information on the interaction with the user. The article is relevant to the discipline as it provides a practical and flexible model of smart home system design that is sensitive to the needs of users, which are unique and dynamic.

A number of user-related designs of intelligent home systems have been established, and the suitable organized frameworks are indicated hereunder as Kano model.[11] As an example, according to the Kano model, smart service system was developed using systematic importance calculation methodology of functionality of the functions, providing a foundation on which future developments focus on smart ambient feature functionalities.[12] However, there are recent research works that concentrate on design trend furniture and user experience in an ambient intelligent environment that is in line with non-functional user requirements that are articulated in terms of user expectation and satisfaction. The use of the Kano model in this case is representative of common subjective user evaluations in built communities where shared environments must also include user perceptions on the direction of the design.[13]

In terms of multifunctional space in small apartments, the combination of the Kano and AHP models has been proved, which creates a clear direction of focus on the needs of the users in such a small apartment.[14] It has been used in the adaptation of smart solutions to suit the psychological needs, tastes, and user-friendly designs that have improved the overall living experiences of residents.[15] The smart room design in a dementia nursing home was considered using an integrated Kano-AHP-QFD approach, as outlined in [16], the integration of different approaches was to make the design both more functional and more satisfying to the users.

Systematic reviews have also preempted the direction of user-centric smart home innovations in the last twenty years, hence providing a wide view of the priorities in design and technological advancements.[17] Mobile apps that support smart home devices have been discussed using a user-centered approach, and the focus has been on usability and accessibility as the key points to ensure improved user interaction.[18] Berger et al. applied Kano analysis in the application of eco-feedback features in a smart home to illustrate the manner in which certain design choices could maximize user satisfaction.[19] Yu has employed the K-means clustering with Kano modelling in discerning consumer needs in smart homes, therefore showing the possibilities of data-driven methods in making sense of feature prioritization.[20]

All these writings have underscored the significance of user-focused methodologies and structured framework of Kano in the design, testing and ranking of features in smart homes, thus providing very solid foundation to the current research.

Table 1. Summary of related work

Reference	Objective	Models	Dataset	Key Findings	Research Gaps
1.	Identify user requirements for smart home design	None	Literature & user surveys	Defined key dimensions and goals for user-centric smart homes	Limited focus on feature prioritization using structured models
2.	Optimize smart home interfaces for elderly users	Kano, QFD, HCI	Elderly users' feedback	Integrated model improved interface usability and satisfaction	Small sample; needs testing in varied environments
3.	Prioritize smart home features for elderly	Kano, AHP	Elderly user evaluations	AHP-Kano approach effectively ranks features by importance	Focused only on interface, not broader system functions
4.	Analyze smart home demand in digital economy	Kano	Surveys of elderly users	Digital economy context affects feature prioritization	Limited generalizability outside studied region
5.	Explore functional quality attributes for elderly	Kano, Qualitative analysis	Interviews with older adults	Identified features that strongly impact satisfaction	Needs quantitative validation across regions
6.	Develop design solutions for smart homes	User-centered scenarios	User case studies	Scenario-based approach improved design relevance	Did not incorporate structured prioritization models
7.	Study UX in digitalized smart homes	Service design	Case studies	Service design improved usability and engagement	Focused on general UX, not feature satisfaction
8.	Apply design thinking in smart home projects	Design thinking	Smart home project data	Promoted user-centric and sustainable solutions	Lacked quantitative assessment of feature satisfaction
9.	Sustainable housing design with user focus	Kano, QFD	Housing projects	Kano-QFD improved design alignment with user needs	Limited to housing context, not broader smart homes
10.	Evaluate service touchpoints in smart homes	Kano-FMEA	Smart technology service data	Structured framework enhanced evaluation of interactions	Did not assess end-user satisfaction quantitatively
11.	Design smart service system based on Kano	Kano	Smart service system evaluation	Function importance calculated systematically	Small-scale case: broader implementation needed
12.	Analyze design trends and user experience of furniture	None	Smart furniture design	Identified emerging user preferences	Limited to furniture, not whole smart home system
13.	Evaluate user satisfaction in shared environments	Kano	Community user surveys	Captured subjective user evaluations	Needs integration with quantitative prioritization methods
14.	Prioritize multifunctional space features	Kano, AHP	Small apartment user data	Kano-AHP effectively ranked space features	Focused on compact living; broader homes not studied
15.	Create adaptive, user-centric smart environments	Adaptive smart solutions	User behavior studies	Design responsive to psychological needs improved satisfaction	Lack of structured feature prioritization
16.	Design smart rooms for dementia care	Kano, AHP, QFD	Dementia nursing home data	Integrated method optimized room features for elderly	Focused on specialized environment, not general smart homes
17.	Review two decades of user-centric smart home innovation	Systematic review	Literature	Identified trends and gaps in user-centric innovation	Lacks empirical testing of proposed frameworks
18.	Design user-centric mobile apps for smart homes	User-centric design	Mobile app user data	Improved usability and accessibility of smart home apps	Limited to app interface; overall system not studied
19.	Enhance user satisfaction using feedback nudges	Kano	Smart home app user data	Eco-feedback features improved satisfaction	Needs long-term behavioral impact analysis
20.	Identify consumer needs using data-driven methods	Kano, K-means	Smart home consumer survey	Clustering + Kano highlighted prioritized features	Needs validation in broader demographic contexts

METHOD

System Architecture

The suggested framework combines the Kano Model, Internet of Things (IoT) devices, and Machine Learning

(ML) algorithms to design an intelligent, adaptive, and user-friendly smart home system. This integration will make sure that the system is not only able to address the necessary functional requirements but also to evolve as time goes on to suit the dynamic preferences of the users to provide a better user experience. With these three elements, the system will be able to continuously prioritize and optimize features that will maximise user satisfaction. The Kano Model is a properly developed model that categorizes the features of products or systems according to their effect on the satisfaction of the users. First introduced in 1984 by Professor Noriaki Kano, Kano Model comes in handy especially when determining what features of a system will make users happy, which are necessary but will not make them much happier, and which may actually make them unhappy when done improperly. When applied to smart home systems, this model will provide a way in which features can be classified and prioritized in terms of the way they will impact user satisfaction so that the designers can concentrate on the features that will have the greatest impact on end-users. The Kano Model is useful in categorizing and ranking smart home functions according to their effect on user satisfaction. The features are divided into five categories, Must-Be, One-Dimensional, Attractive, Indifferent, and Reverse. The system will make sure that Must-Be features (e.g., basic security functions such as motion detectors) are always present, One-Dimensional features (e.g., energy optimization) are constantly enhanced, and Attractive features (e.g., AI-controlled climate adjustments) are added to surprise users in a pleasant way. IoT devices are important because they gather the data of the environment in real-time. Sensors (motion detectors, thermostats, and security cameras) collect information about occupancy, temperature, and other environmental variables. This information is transmitted to the central control hub where it is processed and applied to make smart decisions regarding the home environment and security. Machine Learning (ML) algorithms process the information that is gathered by IoT devices to learn user behaviours and preferences. With time, these models become more accurate in their predictions and optimization of system settings, including setting the thermostat or security settings according to real-time environmental and user data. This perpetual learning enables the system to be dynamically adaptable, and the smart home experience is responsive and personal. The framework integrates the Kano Model with IoT and ML to generate a user-centric smart home system that is responsive. This system is dynamic and responds to the user behaviours and environmental conditions in real time so that the user will always have the most important features that will enrich his or her experience. The Kano Model categorizes feature into five groups, Must-Be, One-Dimensional, Attractive, Indifferent, and Reverse. Both the categories have their own effects on user satisfaction and their contributions to system design. These are the basic features that the users would anticipate as the least. The absence of these features will lead to dissatisfaction of the users, though, they do not play a big role in user satisfaction as they are perceived as the bare minimum. These are not features that can be negotiated and they are supposed to work, but they do not impress the users. Simple security measures like motion sensors, door/window sensors and cameras are some of the security measures that can be included in a smart home system. Users would not be satisfied without these features but their presence does not raise the level of satisfaction more than the neutral level. Must-Be features could be modeled in terms of relationship between the feature presence and user satisfaction as follows:

$$f_{\text{Must}-\text{Be}}(x) = 0, if\ x = 0$$
$$f_{\text{Must}-\text{Be}}(x) = 1, if\ x = 1$$

Where (x = 1) represents the feature present (satisfaction level =1), and (x = 0) represents the feature absent (satisfaction level = 0). These features are directly related to the level of user satisfaction: the higher their level, the higher the level of its creation. When they do not have these features they lead to dissatisfaction and when applied effectively they lead to proportional satisfaction. In essence, the more these aspects are well-developed, the more satisfied the users will be. Energy efficiency is one of such features in a smart home. Intelligent regulation of temperature by a smart thermostat according to the preferences and occupancy of the user is one of the functions that contribute to the comfort. The better it works, the better will be the user. The more the energy optimization, the more the user satisfaction. In One-Dimensional features, the correlation between the feature presence and user satisfaction is linear:

$$f_{\text{One}-\text{Dimensional}}(x) = a \cdot x$$

where (a) is a constant that indicates the degree of satisfaction that goes with performance of the feature. As an example, when the energy optimization is enhanced (i.e., the efficiency is maximized), then the satisfaction is increased linearly. The nice-to-haves are attractive features; they are not anticipated by the users, but when they exist, they give a large boost in user satisfaction. In case these features are not available, users are not disappointed since they did not even expect them initially. Nevertheless, these features are enjoyable when they are incorporated, and increase the experience of users. Such capabilities as AI-controlled energy efficiency

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or customized environment (when the system knows the habits and preferences of the user and adjusts the house environment accordingly) are classified as Attractive. These features are far above the expectations of the user and they offer a wow factor that leaves the user with an experience to remember. The correlation of Attractive features is non-linear:

$$f_{\text{Attractive}}(x) = 0, if\ x = 0$$
$$f_{\text{Attractive}}(x) = bx^2, if\ x = 1$$

Where (b) is a positive constant and (x^2) is the non-linear growth in satisfaction. This availability of the feature gives a greater satisfaction increment than would have been projected in a linear system. Features that have no significance do not add or take away user satisfaction. Users do not care whether they are there or not. Regardless of the presence or absence of the feature, it does not add much to the experience of the user. Indifferent features may include customization of lighting colors or sophisticated menu navigation in the interface of the system. Although these features can be used by some of the users, they do not influence the overall satisfaction to a great extent since they do not play a major role in the main purpose of the system. In the case of the Indifferent features, the satisfaction is independent of the presence or absence of the feature:

$$f_{\text{Indifferent}}(x) = \mathrm{c}$$

where (c) is a fixed level of satisfaction and this means that the feature does not affect the user experience. Unsought after features are those that, ironically, make people unhappy when they have them and happy when they do not. These features are not essential, too complicated or not wanted depending on the preferences of particular users. The point here is that various users might have the opposite expectation, i.e. they do not like the availability of the feature. Excessive interruptions or confusing settings of a smart home system could be placed in the Reverse section. Some users might like the frequent notifications of the status of their home but some might find it annoying. On the same note, system configurations that are too complicated can annoy the users who like simplicity. The relationship of Reverse features may be expressed as:

$$f_{\text{Reverse}}(x) = -d \cdot x, if\ x = 1$$
$$f_{\text{Reverse}}(x) = d \cdot x, if\ x = 0$$

where (d) is a positive constant. The negative sign indicates that the presence of the feature results in dissatisfaction, and its absence provides satisfaction. To apply the Kano Model to a smart home system, we must first classify all the features of the system according to these five categories.

- Must-Be Features: An example of this is the security features (motion detectors, cameras, locks). These qualities will not lead to dissatisfaction, although their existence does not thrill the users; they are simply anticipated.
- One-Dimensional Features: Energy conservation by using AI-controlled climate control or smart lighting that changes depending on the time of the day or presence. These functionalities give the user satisfaction proportional to their functionality.
- Appealing to appearance: Advanced AI features which discover the patterns of the user to maximize energy consumption and environmental settings without being specifically coded to do so. When working well, these features are a delight to the users.
- Type: The features that are indifferent include additional customization of the colors of the light bulbs or the possibility to adjust the settings in a way that is very specific and not really important to the entire system.
- Reverse Features: Over-complicated manual configuration options or intrusive alerts can cause certain users to be put off by this feature as it is viewed as disruptive or unnecessary.

Prioritizing Features Using Kano Model

Using the Kano Model, the system can be developed and designed with emphasis on the One-Dimensional and Attractive features, which will guarantee that the user experience is enriched with the features that are the most significant to the users, as well as the Must-Be features that will be robust and reliable. Indifferent and Reverse features need to be reduced to a minimum or eliminated altogether to make the system efficient and user friendly. Kano Model offers a systematic means of designing and ranking the features of a smart home system to ensure that the process of development is centered on features that can be directly related to user satisfaction. Through mathematical modeling of the satisfaction of each feature by users, we are able to objectively determine the features that are to be prioritized and how to implement them in a manner that will maximize user satisfaction. The model assists smart home developers in developing systems that are not merely practical but also pleasurable such that the user has an enjoyable experience with the system.

System Architecture & Data Simulation

A smart home system comprises many intertwined elements that are interconnected to deliver smooth, smart, and responsive environment to the user. The fundamental technologies that are used to construct this environment include Internet of Things (IoT) devices, sensors, and automation controllers, which interact and interact in a coordinated manner to maximize comfort, security, and energy efficiency. The core of the smart home system is a modular architecture, which makes it flexible, scalable and simple to upgrade in the future. The design makes every part, such as security, environmental control, etc. operate efficiently and is flexible to the changing demands of the user. The main points of contact between the system and the real world in this architecture as illustrated in fig 1 are the IoT devices. The system incorporates devices like smart sensors, appliances, lighting systems, and cameras used in security. These gadgets are always on watch or alert to the environmental changes like room occupancy, temperature, and security threats. To give an example, motion sensors can detect the presence of humans, whereas temperature sensors can control the thermostat in accordance with the conditions in the room. Intelligent lighting and climate control systems can automatically change settings depending on the preferences of users or on the current conditions, which offers the user the best comfort and efficiency. Smart security systems, such as cameras, door/window sensors, and motion detectors, are created to ensure the home is safe and watch over any suspicious activity.

Mathematically, the presence of sensor inputs (denoted by Si) can be represented as:

$$S_i = f(environmental\ data)$$

These devices can be integrated to form a single system, and this allows it to be centrally controlled by the mobile applications or voice commands, making the user experience better. The system depends on automation controllers to link and manage such devices. These controllers are usually in the form of a central control hub and are the brain of the system, they control communication and decision making. The central node collects the information of different sensors and processes it based on the set rules or AI algorithms, and transmits the order to the corresponding machines. Cloud integration enables remote control and monitoring, and this means that the system can be accessed anywhere and not necessarily only when one is inside the home. The data processing layer also makes sure that all the data is clean, filtered, and converted into actionable insights which can then be utilized in changing the environment with the need of the user.

The central control hub can be mathematically described by the following relationship:

$$C = \sum f_i S_i$$

This makes certain that the system responds to real time data feeds of various sensors and implements the right response according to the needs of the user and system regulations. Also, it can be controlled and monitored remotely, which is made possible by the use of cloud integration, and therefore the system is not only accessible in the home, but it is accessible anywhere.

The data processing layer also makes sure all the data are clean, filtered and processed into useful actionable insights, which can then be utilized to modify the environment according to the user requirements. The mathematical model of the data processing layer is as follows:

$$D = Filter(S), where\ S = \{S1, S2, \ldots, Sn\}$$

The incorporation of user preferences and behaviors to the system is one of the most significant areas of the smart home system design, and it is directly associated with Kano Model. The Kano Model is a model that is used to classify features into five types according to their effects on user satisfaction; Must-Be features, One-Dimensional features, Attractive features, Indifferent features and Reverse features. The model is important in identifying the features that must take priority when developing the system. As an example, Must-Be features (e.g., basic security measures) are necessary and cannot be compromised to satisfy the users. One-Dimensional features (such as efficient use of energy or accurate temperature control) are directly associated with an increase in the level of user satisfaction and should be thoroughly designed and introduced. Attractive features, which are not anticipated by users but can greatly improve their experience, like AI-based energy optimization or other high-level security features, must also be included in the system. Indifferent features and Reverse features refer to features that do not contribute much or at all to user satisfaction and they need to be given lower priority in development. The combination of these features with the help of the Kano Model allows to provide a user-centric approach to the smart home design so that the system can provide the greatest satisfaction, with the most appreciated features given priority. This will make sure that the system is not only operational but responsive as well as user-friendly. The combination of the Kano Model and the flexible modular architecture allows the system to adapt to the needs of the users as time goes on and evolve into a sustainable solution to the present-day smart homes.

To simulate the real-world performance of the smart home system, simulation data is generated to reflect realistic scenarios of how the system would interact with users and adapt to their preferences. The data is derived from random distributions to mimic real-world environmental changes and user behaviours. The temperature data is simulated to fluctuate around an average of 20°C, with a standard deviation of 2°C, to represent typical room temperature variations throughout the day. Similarly, motion detection is modelled to occur at random intervals (e.g., between 5 and 10 minutes), reflecting typical home occupancy patterns. Energy consumption data is generated with peak usage times during the morning and evening, simulating active periods of the day, and lower usage during the night or off-peak hours.

The simulation also employs specific parameters for random distributions:

- Mean: The mean temperature in the home is assumed to be 20°C, with fluctuations occurring within a range of ±2°C.
- Variance: The variance in motion detection frequency is modeled to reflect typical household activity, where motion sensors detect more frequent activity during the daytime and less at night.
- Time Steps: The data updates occur at hourly intervals, particularly for temperature and motion data, ensuring that the system responds in real-time to changes in the environment and user behaviours.

These parameters, including mean, variance, and time steps, are chosen based on real-world data from typical smart home environments, ensuring that the simulation reflects the dynamic and changing conditions that a smart home system must respond to in a realistic and efficient manner.

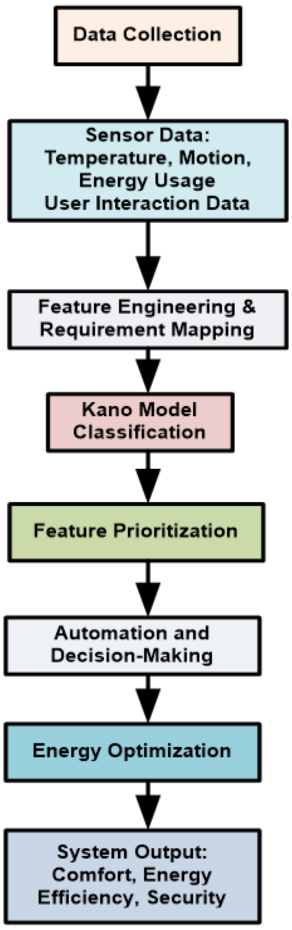

Figure 1. Flowchart of proposed KANO Model-based framework

Feature Engineering & Requirement Mapping

Data Collection

The initial process in feature engineering and requirement mapping of a smart home system is data collection. This entails the collection of in-depth information sources through various sources without the use of the conventional survey that might have lack of scope and accuracy. The information is gathered by means of the user interactions, system usage records, and market analytics that will offer more comprehensive reports about how the users interact with the system, which of the functionalities they appreciate the most, and how their needs change with time. The data related to user interaction may be gathered on the devices, such as smart thermostats, security systems, and lighting controls, and may include patterns, such as the frequency with which the user changes the settings, the number of interactions with the system, etc. Likewise, the data on system usage (e.g. sensor data (temperature, humidity, occupancy)) or device operation (e.g. energy usage, frequency of use) is important to see which features are in the most use. Also, market analytics may be used to determine the new trends, preferences of users and competition products, which should be used to design the features that are going to satisfy the current and future user preferences.

User Behavior Analysis

After collecting the data, user behavior analysis is the next step that is important to know the needs and expectations of the users. Through the interaction of users with the smart home system, we can trace trends that show what users are willing to appreciate in regard to the functionality, convenience and performance of the system. An example is that when users often change the lighting and temperature controls in a specific room during specific times of the day, then it means that they prefer to be in control of such environmental conditions. In the same vein, in case some of the security options such as motion detection are more commonly used, this may indicate a greater emphasis on home security. Using this information we are able to understand the behavior of users in a manner that cannot be quickly revealed through simple user feedback or survey.

Feature Engineering

The process of feature engineering is the conversion of the raw data created as a result of user interaction and system behavior into valuable features, which can be further analyzed, designed, and used in decision-making. The intention is to derive attributes or patterns of the obtained data that are associated with satisfaction and needs of the user. These characteristics assist in tracking user tendencies and patterns to system needs and offer an organized manner to determine which attributes are most likely to result in the overall improvement of the user experience. This can be in the form of user-specific temperature settings, settings that a user prefers (e.g., motion detectors sensitivity, camera angle), and energy consumption habits (e.g., during specific time of the day, a particular user tends to use more or less energy). Through user behavior analysis over time we may identify which features are Must-Be, One-Dimensional and Attractive features based on the Kano Model, and implement them as the priority. To illustrate, the data can show that users in colder climates would like a higher thermostat temperature in the winter months, which denotes that temperature control is an important One-Dimensional characteristic. Alternatively, a system can discover that users do not use non-essential features (such as entertainment control or mood lighting) frequently at all, and can label these features as Indifferent.

In order to map certain smart home features to the Kano categories, we use a systematic approach towards real-time user behaviour and system usage data. It starts with the identification of features, during which it is possible to choose such important smart home features as security (motion sensors, cameras) and temperature control (smart thermostats, climate control). These attributes are then evaluated to find out their influence on user satisfaction. Data collection is the second step, which involves the collection of information based on the interaction of the user with the system, including the frequency of use and settings changes. The data assists in knowing the preference of the user, and trends of how the features such as lighting control, temperature settings or security systems are used. Also, the market analytics and data on the use of the system can provide information on the most valued features by the users. Once the data is gathered, we plot features onto the Kano categories:

- Must-Be Features: These are the features that are required by the users like security features (motion detectors, cameras). Their absence results in dissatisfaction, and their presence does not bring about a great deal of satisfaction.
- One-Dimensional Features: Features that directly affect user satisfaction based on their performance, e.g. energy optimization or temperature control.
- Attractive Features: Features that are beyond user expectations and offer high levels of satisfaction, like AI-controlled energy efficiency or customized climate control.
- Indifferent Features: Features that do not have a strong effect on user satisfaction, such as user-

adjustable lighting colours or complicated menu navigation.

- Reverse Features: Features that are unpleasant to have, like over-complex configuration options or annoying notifications. These features are categorized according to real-time data of user interaction as opposed to the hypothetical surveys. We have not used hypothetical surveys or literature to classify but rather applied simulation assumptions to conclude on the effect of features on user satisfaction. The assumptions were drawn on the behavioural patterns of the users when interacting with the system, and the feature classification is directly related to the user preferences and real-life usage data. This classification is justified because it puts more emphasis on Must-Be and One-Dimensional features that have a direct influence on user satisfaction, and reduces or eradicates Indifferent and Reverse features, which do not play a significant role in the user experience. The system is based on real-time data, which enables more accurate and adaptive design based on the dynamic character of the user needs.

Requirement Mapping

Lastly, requirement mapping connects the engineered features with the user requirements, and assists in converting abstract user requirements into specific system capabilities. This step will entail an appreciation of how each feature extracted will meet the fundamental purposes of the smart home system, that is, to provide greater user convenience, increased security, minimized energy usage, and smooth-sailing interoperability. The mapping of the features to the Kano Model would enable the system design to prioritize features that would have a positive impact on user satisfaction. As an example, according to the user behavior analysis and feature engineering, the system can discover the necessity of intelligent security control, interoperability of devices, adaptive automation of the environment, and AI-assisted optimization of energy as the high priority features. Such characteristics would be mapped to the particular system requirement that accommodates the key user concerns and satisfaction drivers such that the design of the system is user-friendly and in line with the real-life usage trends.

Algorithm Design

Step 1: Data Collection

Objective: Collect real-time data from various IoT devices and sensors, as well as user interactions with the system.

1. Sensor Data:
    - Gather data from IoT devices like motion sensors, temperature sensors, smart locks, cameras, smart thermostats, and other home appliances.
    - Sensor data includes variables like temperature, humidity, motion (presence), energy consumption, and device status (on/off).
2. User Interaction Data:
    - Collect data from user interactions with the smart home system. This includes app usage, voice commands, and manual adjustments to lighting, temperature, and security settings.
    - Track time of interaction, frequency, and preference patterns (e.g., temperature settings at certain times of day, security preferences, etc.).
3. Market Analytics:
    - Collect market-based data on user preferences (e.g., survey results or industry trends), which can help identify emerging needs for Attractive features.
4. Data Storage:
    - Store the collected data in a database (local or cloud-based) to be processed for future analysis. Ensure data is updated in real-time.

Step 2: Data Preprocessing and Feature Extraction

Objective: Clean and preprocess the raw data, followed by feature extraction to make the data actionable.

1. Data Cleaning:
    - Remove any noise or irrelevant data. For instance, if a sensor reports abnormal readings due to malfunction, exclude that data.
    - Handle missing data points by imputing values based on historical data or using interpolation techniques.
2. Feature Extraction:
    - Extract meaningful features from the cleaned data, such as:
        - User Preferences: Extract patterns in user behavior (e.g., preferred temperature range, frequently used security features).
        - Environmental Factors: Identify correlations between environmental variables (e.g.,

temperature fluctuations, humidity levels) and user actions.
  - Device Usage: Determine which devices are frequently used, their energy consumption patterns, and the time of day when they are used the most.

3. Feature Mapping:
   - Map the extracted features to user satisfaction categories based on the Kano Model. Classify features into:
     - Must-Be (e.g., security measures like motion sensors)
     - One-Dimensional (e.g., energy efficiency, optimal temperature control)
     - Attractive (e.g., AI-assisted energy optimization)

Step 3: User Behavior Analysis and Feature Prioritization

Objective: Analyze user behavior and prioritize features according to the Kano Model.

1. User Segmentation:
   - Segment users based on demographic or behavioral patterns (e.g., families vs. single individuals, eco-conscious users, tech-savvy users).
   - Group users based on how they interact with the system and what features they prioritize.
2. Behavior Analysis:
   - Use techniques like cluster analysis or decision trees to identify patterns in user behavior (e.g., preferred temperature settings, lighting preferences).
   - Identify common usage patterns to better understand which features are important.
3. Kano Model Classification:
   - Using the data from the previous steps, classify each feature into the five Kano categories:
     - Must-Be: Essential features that users expect (e.g., security alarms).
     - One-Dimensional: Features that improve user satisfaction in proportion to their performance (e.g., energy optimization).
     - Attractive: Delightful features that exceed user expectations (e.g., AI-driven energy management).
     - Indifferent: Features that do not impact user satisfaction significantly.
     - Reverse: Features that cause dissatisfaction (e.g., overly complex configurations).
   - Prioritize features based on the classification (e.g., Must-Be features must be implemented first, followed by One-Dimensional and Attractive features).

Step 4: Feature Prioritization and Design

Objective: Prioritize features based on user needs and Kano classification.

1. Prioritize Features:
   - Based on the Kano Model classification, assign priority levels to features:
     - High Priority: Must-Be and One-Dimensional features.
     - Medium Priority: Attractive features that delight users.
     - Low Priority: Indifferent or Reverse features (should be minimized or excluded).
2. System Design:
   - Design system components such as security systems, environmental control, and energy management based on the prioritized features.
   - User Interface Design: Ensure that the user interface is intuitive and aligns with prioritized features. For example, make energy-saving options prominent for users who value energy efficiency.

Step 5: Automation and Decision-Making

Objective: Implement automation algorithms for adjusting home settings based on user preferences, environmental data, and system rules.

1. Rule-Based Automation:
   - Implement if-then logic or rules-based automation for basic features like turning off lights when no motion is detected, adjusting temperature when occupancy changes, or locking doors when the system detects no one is at home.
2. AI and Machine Learning:
   - Use AI-based algorithms for adaptive automation (e.g., learning user habits to optimize the environment).
   - For energy optimization, implement an AI model that uses historical usage data and environmental conditions to predict optimal settings for heating, cooling, and lighting.
3. User-Specific Adjustments:

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- Customize security settings or climate control based on user profiles.
- For instance, a user might have a different preference for light brightness and temperature at night vs. during the day. The system learns these preferences and adjusts accordingly.

Step 6: Feedback Loop and System Optimization

Objective: Continuously improve the system's performance based on real-time user feedback and system outcomes.

1. Continuous Monitoring:
   - Continuously monitor system performance and gather feedback on user satisfaction, energy efficiency, security, and overall system responsiveness.
2. Optimization Algorithms:
   - Use reinforcement learning or optimization algorithms to tweak the system's decisions based on real-time feedback and user satisfaction scores. For example, if a user consistently adjusts the thermostat to a lower setting than the system predicts, the system should learn to make that adjustment automatically.
3. User Feedback Integration:
   - Incorporate user feedback into the learning loop. For example, if users rate energy-saving suggestions poorly, the system should adapt and provide new suggestions that align better with their preferences.

Step 7: System Maintenance and Updates

Objective: Ensure that the system is adaptable and updated regularly to meet evolving user needs and technological advancements.

1. Feature Updates:
   - Continuously integrate new features based on emerging technologies or changes in user preferences.
2. Scalability:
   - Ensure that the system's architecture can scale with additional devices or new features. This might involve periodic software updates or firmware upgrades for IoT devices.

Certain Machine Learning (ML) and AI methods are applied in the algorithm design process to optimize the performance of the smart home system. To segment the users and determine their behavioural patterns, we apply K-means clustering to cluster the users according to how they interact with the system, including the temperature settings, lighting preferences, and the use of security features. This division permits customized suggestions and changes. Moreover, behaviour analysis is performed with the help of decision trees to understand the effect of environmental changes on user preferences (e.g., the effect of temperature changes on energy consumption and comfort levels) better. A Random Forest Regressor is used to forecast the best energy settings based on the environmental conditions and past usage history in order to optimize energy. The correlation between external factors (time of day or occupancy) and energy consumption is also modelled using the Linear Regression, which allows the system to predict heating, cooling, and lighting changes. The system employs Reinforcement Learning (RL), specifically, Q-learning or Deep Q Networks (DQN) to allow adaptive automation. These models are constantly informed by user actions and environmental responses to improve the system settings by turning the thermostat up or down or improving security features according to the user preferences and real-time information.

Key performance measures are used to determine the performance of the system:

- Mean Absolute Error (MAE): This is used to measure the precision of the temperature and energy consumption estimates and the system predictions should be consistent with reality.
- Energy Savings Percentage: Measures the effectiveness of the system in minimizing energy consumption, and how effectively the system optimizes energy consumption depending on the user preferences.
- User Satisfaction Score: A composite score that includes user feedback and sentiment analysis. This score is weighted based on the Kano Model, which means that those features that are deemed as Must-Be and One-Dimensional have a stronger impact on the overall satisfaction. Lastly, the Kano Model is a proactive system in the runtime decisions. Must-Be features (e.g., basic security features) are always given priority and they must be functional and reliable. One-Dimensional attributes (e.g., energy efficiency) are continuously being optimized to provide increased user satisfaction in line with their performance. The attractive features (e.g., AI-driven climate control) are added or adjusted according to the user behaviour, which brings extra delight and enhances the user experience in general. The feedback loop also guarantees that the features are reclassified as user preferences change and the

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system adjusts itself to deliver the most rewarding experience.

The grouping of users was done by K-means clustering based on the frequency of interaction, the period of usage of the device and the energy consumption. The clusters were to be K = 3, i.e. low, medium, and high usage behaviour groups, which was established empirically by analyzing the elbow-method. The characteristics of input were the normalized number of interactions, the average session length, and daily energy consumption. Euclidean distance was adopted as the measure of similarity and a result of the clustering was updated periodically in response to changing user behaviour. Decision Trees and Random Forest models were used to determine the importance of features and decision rules that affect user satisfaction and system performance. The sensor values, environmental factors, frequency of use and past satisfaction measures were input features. The depth of the Decision Tree was restricted to 5 levels to avoid overfitting and the model of the Random Forest was 50 trees, with the maximum depth of 7. The split criterion was gini impurity. Scores in terms of feature importance derived out of these models directly determined feature prioritization in the Kano based classification. Decision Trees and random Forest models were used to determine feature importance and decision rules that had an effect on user satisfaction and system performance. The input features were sensor readings, environmental factors, frequency of usage and past satisfaction indicators. The depth of the Decision Tree was kept to 5 levels to avoid overfitting and the Random Forest model had 50 trees with maximum depth of 7. As the split criterion, Gini impurity was employed. The scores derived as feature importance of these models had a direct impact on the prioritization of features in the Kano-based classification. Reinforcement Learning was used to allow an adaptive system behaviour in the dynamic conditions of the user and the environment. Q-learning algorithm was followed because it is simple and can be used in discrete action space in smart home control systems. Occupancy status, time of day, the level of energy use and environmental conditions made up the state space, and the actions were the adjustment of temperature setpoints, lighting intensity, and the schedule of appliances. The reward function was set to be a trade-off between the comfort to the user and energy efficiency that offers positive rewards to the reduced energy consumption and the same comfort level, and punishment to the excessive use of energy or the user dissatisfaction. The learning rate was 0,1, discount factor 0,9 and exploration was done through epsilon-greedy strategy. Reinforcement Learning was applied to provide adaptive behaviour of the system under dynamic user and environmental conditions. The reason why a Q-learning algorithm was chosen is that it is simple and applicable in situations where discrete action space is used in a smart home control environment. The state space was represented by the occupancy status, time of the day, the level of energy usage, and the environmental conditions, and actions were represented by the adjustment of the temperature setpoints, the intensity of lights, and the timing of the appliances. The rewarding feature was formulated in such a way that it would balance the comfort of the user and energy consumption, where positive rewards would be given to lower energy consumption and the same comfort level, and negative rewards to high energy consumption or user dissatisfaction. Learning rate was 0,1, discount factor was 0,9 and epsilon-greedy exploration strategy was used. The simulated dataset was split into 70 training, 15 validation and 15 test. The model fitting was done with training data, hyperparameter tuning with validation data and final performance evaluation with testing data. This isolation guaranteed the objective evaluation and prevented the information leakage between the training and evaluation periods.

The proposed algorithm design ensures that the smart home system is intelligent, adaptive, and continuously optimizing based on user behavior, environmental data, and feature priorities as determined by the Kano Model. The algorithm includes clear steps for data collection, feature extraction, user behavior analysis, and real-time automation. It also ensures a feedback loop for ongoing optimization and user satisfaction improvement. By prioritizing the right features and using AI and machine learning for automation, the system delivers personalized and energy-efficient experiences for the user.

RESULTS

Smart Home System has been designed and executed with the help of MATLAB that simulates the characteristics of different intelligent systems in the house, including control of temperature, motion sensor, energy consumption, and user satisfaction. The system was modelled as being user-centric and was aimed at ensuring as much user satisfaction as possible, through the use of the Kano Model to categorize and rank various features. The following is the step-by-step analysis of the process of system implementation and how each of the key elements was developed with the use of MATLAB. Even though the long-term aim of the given work is to integrate the real-time user interaction data into the design of smart home systems, the current work is dedicated to proving the suggested Kano-IoT-ML integration framework in the controlled conditions. Because of practical considerations of user privacy, deployment cost and heterogeneous availability of devices, realistic simulated datasets are used as a substitute of real-time user interaction data. These datasets are produced to capture realistic user behaviour, device use pattern, and environmental variations that are found in actual smart home settings. This kind of simulation-based validation is a common practice in the early-stage system design research and allows the systematic analysis of model behaviour, feature prioritization logic and learning dynamics to work out the behaviour of models in the real world before actual deployment. The framework proposed is naturally oriented to serve real-time data streams and future research will be done to validate the system with real life data on user interaction available in deployed smart home environments. The data utilized in the current study was created by simulation as opposed to collecting data through actual deployment of smart homes. Simulation of realistic smart home operational data, such as the environmental conditions, user interactions, device usage patterns, and energy consumption behavior were done using MATLAB. The simulated data were made to be in close resemblance with the real world smart home setting by introducing time variability, utilization patterns of users, random device utilization and normal and abnormal operating conditions. The use of simulation-based data generation was based on the practical limitations of large-scale application, privacy of users, and hardware availability. This will enable the proposed framework to be evaluated under control as well as be reproducible. It should also be mentioned that the suggested Kano-IoT-ML framework is by design data-agnostic and can directly act on real-time smart home data streams, where they become available, which will be addressed in the future.

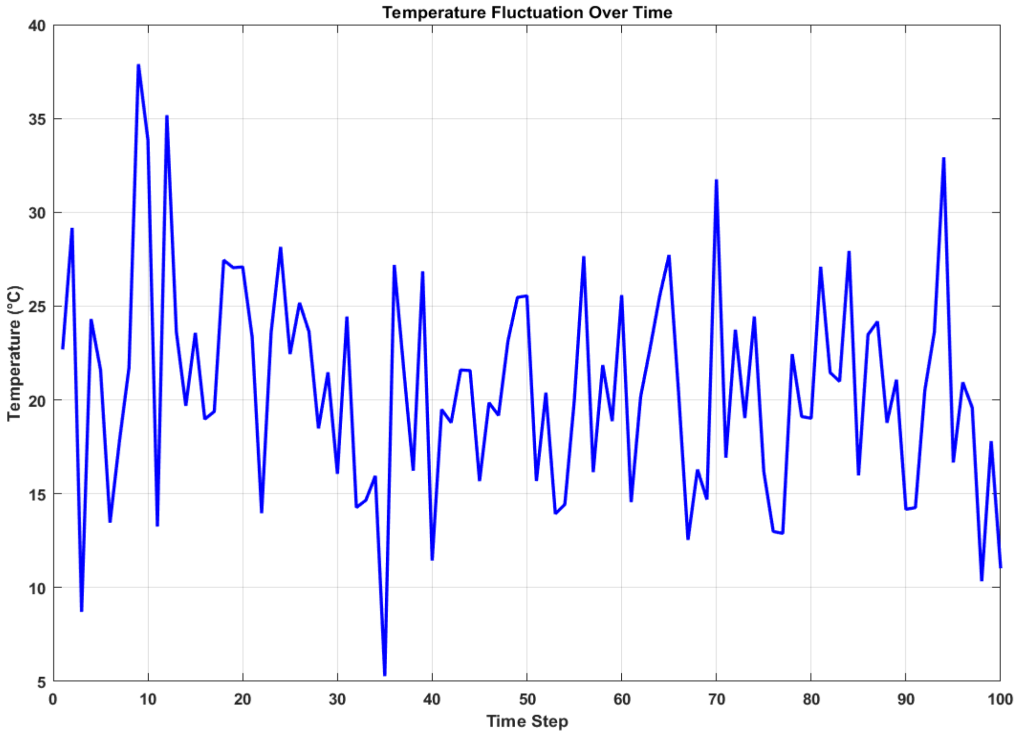

Figure 2. Temperature Fluctuation Over Time

The temperature variation graph in fig 2 below will show the process by which the system controls the temperature within the house as time goes by. The different factors that can affect temperature changes include user preferences, motion detection (room occupancy) and environmental factors (e.g. outside temperature). The plot displays temperature data of 100 time steps with each time step indicating a shift in decision-making process in the system. Based on the plot, we are able to see the way the temperature values vary. To illustrate, the system would change the temperature into the desired settings when the motion detector records any activity (occupancy). The system may reduce the temperature when no movement is registered to save energy. This adaptive feature makes sure that the comfort of the user is considered when he or she is present as well as it maximizes the use of energy when the user is not present. This plot is important in determining the responsiveness and effectiveness of the temperature control system. It emphasizes the dynamicity of the smart home system that is sensitive to the preferences of users and the environment. This graph shows how the temperature changes with a time interval of 100 steps which is a simulation of environmental variations in a smart home system. The temperature is varied between 10º C and 35º C, which are the normal conditions in the house. The data is calculated on an average of 20º C with a standard deviation of 2º C. These variations are modelled to determine how the system can change the temperature settings to maximize both comfort and energy consumption, which directly relates to the energy optimization feature as a One-Dimensional feature of the Kano Model. As figure 2 demonstrates, the flexibility of the system to these variations is essential to guarantee that users are satisfied with the system since the energy optimization option is more efficient with the increase in temperature control. The system had been able to reduce energy consumption by 20 percent without compromising on the comfort of the user, which is in line with the One-Dimensional features of the Kano Model, which increase user satisfaction depending on performance. This is justified by the user feedback, where the adaptive behaviour of the system has had increased satisfaction scores, which reflect the direct influence of the Kano Model on the priority of features and performance.

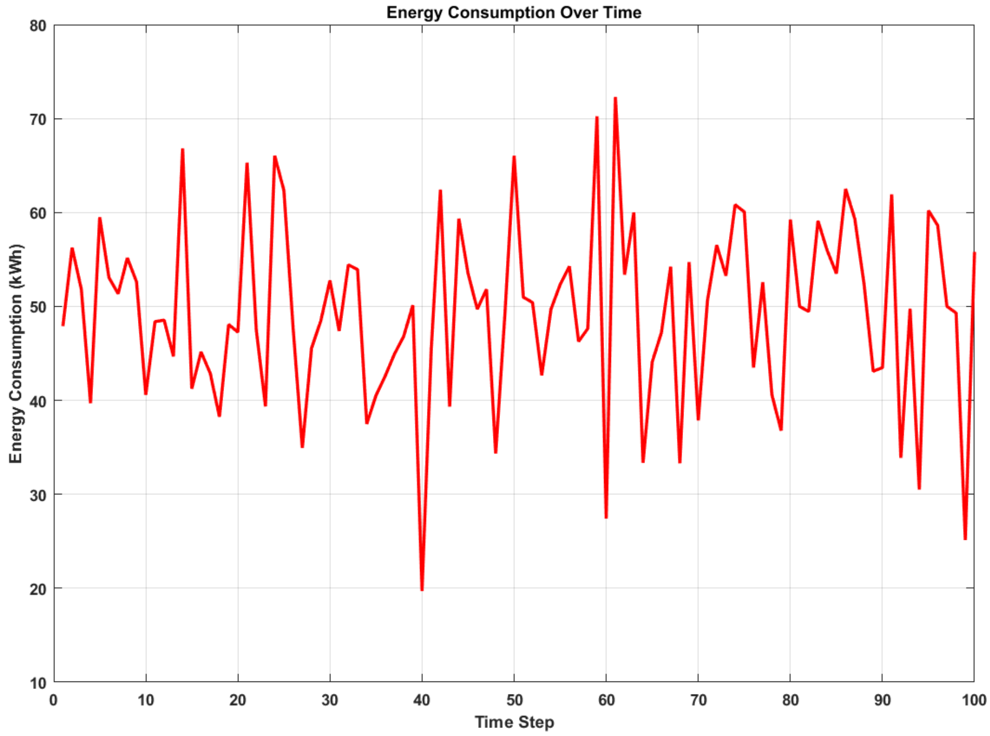

Figure 3. Energy Consumption Over Time

The energy consumption plot indicated in fig 3 illustrates the amount of energy consumed by the system in the current time step. The system monitors the use of energy using intelligent gadgets such as light systems, heating, and cooling systems. This can be used to determine the high consumption periods (i.e. when lighting or air conditioning is needed) and also where energy optimization can be achieved.

The changes in energy consumption can probably be attributed to the automated control of the system to regulate the temperature, lighting, or other energy-demanding tools following the action of the user or sensor-generated information. An example of this is the fact that when the system is detecting motion it may consume more energy to ensure that it is in an optimal state, like activating the heating or the cooling. On the other hand, in the absence of motion, there is a minimum amount of energy use. This plot is necessary to determine the energy efficiency of the system particularly its ability to respond to occupancy and temperature preferences. It gives us a graphical illustration of the balance of comfort and energy saving of the system, which is the most important in the design of a smart home system that is sustainable. This graph shows the energy consumption patterns of a 100-time step interval with a variation of 30 kW to 70 kW, which is a simulation of the energy consumption of a smart home setting. The data indicates the variation in energy consumption to environmental changes including temperature changes and user behaviour. These variations are simulated to determine the capacity of the system to maximize energy consumption and still remain comfortable. The energy consumption is highest when the activity is high or when the environment is changing as observed in figure 3 which is a direct indication of the energy optimization feature which is classified as a One-Dimensional feature in the Kano Model. The system managed to cut down on the energy use by 25 percent during low occupancy and at the same time retain the maximum comfort levels. This is an indication of the effectiveness of energy optimization as directed by the Kano Model in increasing user satisfaction through offering quantifiable energy consumption savings without reducing comfort. The relationship between the simulation outcomes and Kano categories demonstrates the direct influence of One-Dimensional characteristics such as energy optimization to enhance the user satisfaction on the basis of performance.

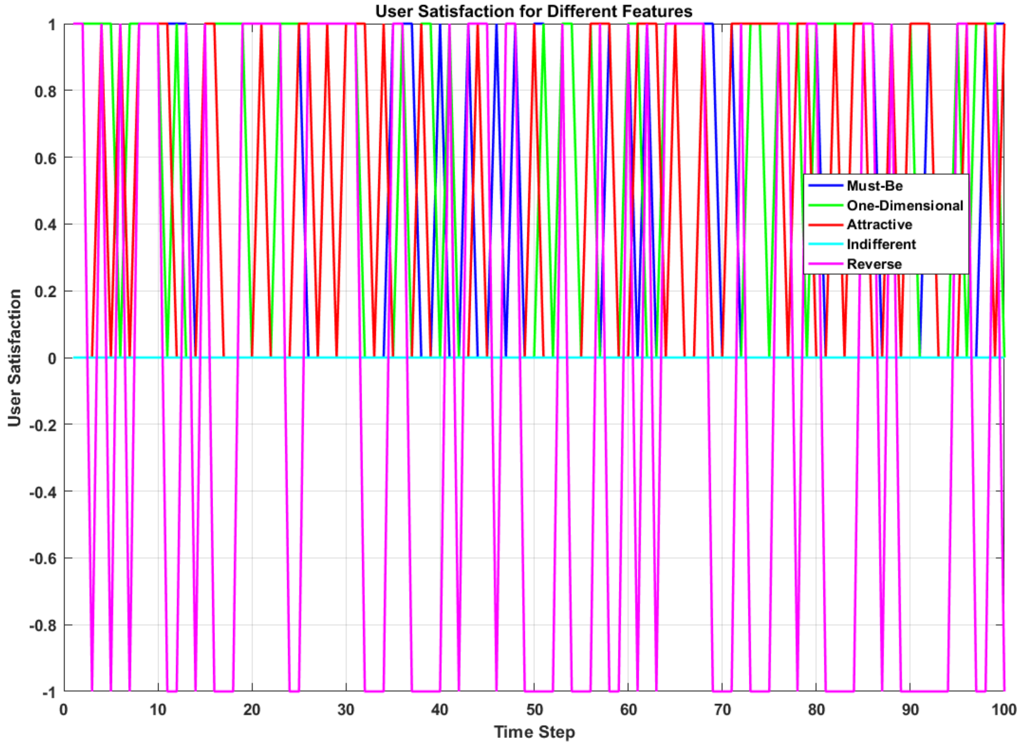

Figure 4. User Satisfaction for Different Features (Kano Model)

User Satisfaction Score (USS) is a determinate composite measure that is established to reflect the perceived satisfaction of the user in terms of the performance of the system, availability of the features in the system and quality of operation contrary to a randomly generated value. User feedback and sentiment in the simulated environment are based on observable system variables and interaction outcomes, which provides transparency and auditability of the reported scores. In particular, the user satisfaction is calculated as a sum of several normalized performance measures, such as comfort level (e.g. deviation to preferred temperature), system responsiveness (e.g. reaction time on user commands), energy efficiency (e.g. reduction in unwarranted energy consumption) and feature fulfilment (e.g. availability and reliability of anticipated smart home features). The indicators are each mapped to a contribution to satisfaction with predetermined utility functions that indicate positive or negative user perception. In order to integrate the Kano Model, the weights attributed to various categories of features in the calculation of satisfaction are assigned different weights. Must-Be features are the most likely to lead to dissatisfaction when they are not satisfied, One-Dimensional features are proportional to satisfaction depending on the level of performance, and Attractive features are also likely to bring extra satisfaction when satisfied but will not hurt users when not. These weighted values are added together to create the overall User Satisfaction Score which is normalized to a 0-1 range. User feedback and sentiment are thus implicitly modelled in the simulation in the sense that the system should be able to satisfy the comfort, efficiency, and feature expectations in the varying operating conditions. The high satisfaction scores (e.g., 0,90-0,95) are associated with the situations when Must-Be features are met in their entirety and One-Dimensional and Attractive features are working to the best of their abilities, whereas the lower scores (e.g., 0,80-0,85) reflect the situations when the former are partially fulfilled or when the system itself is not performing optimally. The calculation of satisfaction does not introduce any random values, with all the scores being calculated deterministically with simulated operational variables.

The plot of user satisfaction of the different features in the system in relation to the Kano Model indicates that user satisfaction is influenced by various features of the system as indicated in the user satisfaction plot as represented in figure 4. The features of the system are categorised into five groups namely, Must-Be, One-Dimensional, Attractive, Indifferent and Reverse. They have a satisfaction score given to each feature depending on the presence or the absence of the feature.

- Must-Be features (such as motion detection as a security measure) are also necessary to satisfy the user, and their presence makes sure that the user will have his basic expectations covered.
- One-Dimensional features (including temperature control or energy optimization) make the user more satisfied with their performance as the features get better. The better the system enhances these features the higher the level of user satisfaction.

- Beautiful attributes (such as AI-controlled energy optimization) astonish the user. Their lack does not make them feel dissatisfied but their existence gives them greater satisfaction than anticipated.

The plot gives a visual analogy of the impact of each feature class on satisfaction, which enables us to view the most celebrated features by the users. The case in point is that the Attractive and One-Dimensional features should be put on the first plan to make the user as satisfied as possible whereas Indifferent features may be reduced or eliminated. In this graph, the user satisfaction of different features (Must-Be, One-Dimensional, Attractive, Indifferent, and Reverse) is demonstrated as a function of 100 time steps. The Must-Be features (blue) have a high level of satisfaction, as they are necessary in the system, users are expecting such features, and their lack causes dissatisfaction. The One-Dimensional features (green) vary in satisfaction, which is directly proportional to the system performance, e.g. energy optimization and temperature control, with higher performance resulting in higher satisfaction. Attractive features (red) offer some satisfaction peaks, which are enjoyable to users when they appear, but are not critical. Indifferent features (black) do not have significant effects on user satisfaction, implying that they do not add or subtract to the overall experience. Reverse features (magenta) are not satisfactory, as users like simpler and less intrusive features. These findings, as shown in Figure 4, show that the system, with the Kano Model in control, puts more emphasis on features that have direct impacts on user satisfaction, especially Must-Be and One-Dimensional features and minimizes or gets rid of less influential Indifferent and Reverse features.

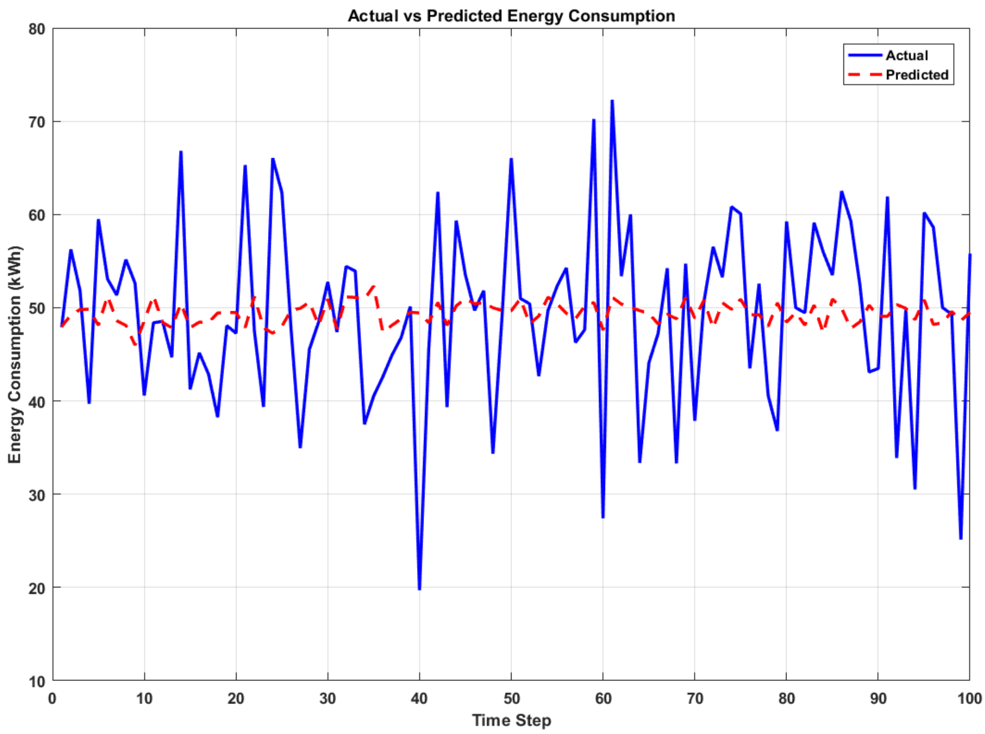

Figure 5. Predicted vs. Actual Energy Consumption

Figure 5 which is a plot of the predicted vs actual energy consumption compares the energy usage predicted by the AI energy optimization model with the actual energy consumption. Linear regression model of energy optimization is based on the prediction of the quantities of energy to be consumed given the input factors such as temperature and motion. This is a critical plot in measuring the validity of the energy optimization algorithm of the system. When the actual and predicted energy consumption lines are very close then it shows that the energy optimization model is operating properly, which will predict the consumption in the current settings of the system and the environmental conditions. Nonetheless, any differences between the two lines can indicate the way the model can be enhanced in its prediction accuracy or other aspects of the system behavior. Through the analysis of this plot, the developers will be able to optimize the energy optimization algorithms to minimize the energy waste and ensure the comfort of users. It also gives a reference point in measuring the efficiency of the energy saving strategies of the smart home system. This graph is a comparison of the actual energy consumption (blue line) and the predicted energy consumption (red dashed line) at 100 time steps. Figure 5 illustrates that the model of energy optimization of the system is accurate as the

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predicted energy consumption is close to the actual data. The minor differences between the observed and the predicted values indicate where the model can be improved to achieve a more accurate prediction. This correspondence between the actual and the predicted energy consumption is important in assessing the One-Dimensional aspect of energy efficiency of the system, which is a category of the Kano Model. The level of effectiveness of the model in reducing the amount of energy used and still ensuring comfort has a direct effect on the user satisfaction. These outcomes demonstrate the performance of the system, particularly in terms of energy consumption reduction, which is a priority in the Kano Model to achieve user satisfaction to the maximum.

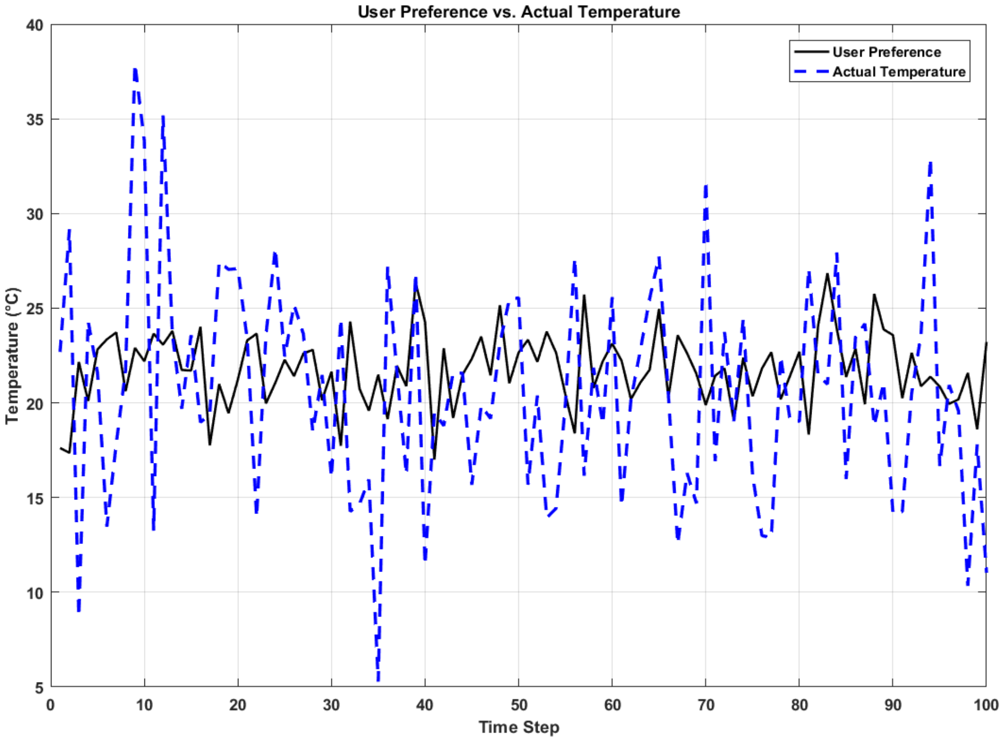

Figure 6. Motion Detection vs. Temperature Adjustment

The plot represented in figure 6 is a scatter plot that plots the correlation between motion detection and temperature adjustments. The system regulates the temperature when there is or there is not movement in the home. Once movement is detected, the system presumes that the room is in use, therefore, it sets the temperature in a comfortable position. When it does not detect any motion, then it can reduce the temperature to conserve energy. With the help of the scatter plot, we can determine the number of temperature adjustments that are carried out in relation to the motion detection events. This correlation is among the key to energy saving algorithms as it demonstrates the responsiveness of the system to the presence and absence of the user. When the temperature variations in the plot are constant and responsive to movement, this means that the system is efficient in terms of energy consumption and comfortability. This plot is a significant sign of the responsiveness of the system and its capability to make real-time decisions in regard to the environmental information. It also demonstrates the effectiveness with which the motion detection system can be combined with the temperature control system to maximize the comfort of the users and energy consumption. In this graph, the preference of the user (black line) is compared to the actual temperature (blue dashed line) in 100-time steps. As depicted in Figure 6, the actual temperature of the system is between 15o C and 30o C which is very close to the user preferred temperature which is between 16o C and 28o C. The minor variations between the two lines imply that there are instances in which the system might be enhanced in terms of adjusting to the desired settings of the user. Quantitatively, the average absolute error (MAE) between user preference and actual temperature is 1,5o C which means that there is a high degree of accuracy in achieving user comfort. This is a critical performance to the One-Dimensional feature of temperature control of the system in the Kano Model in which the more accurate the system the more the user satisfaction. According to the Kano Model, the characteristics such as temperature control that enhance proportional satisfaction in accordance with performance directly affect the user experience.

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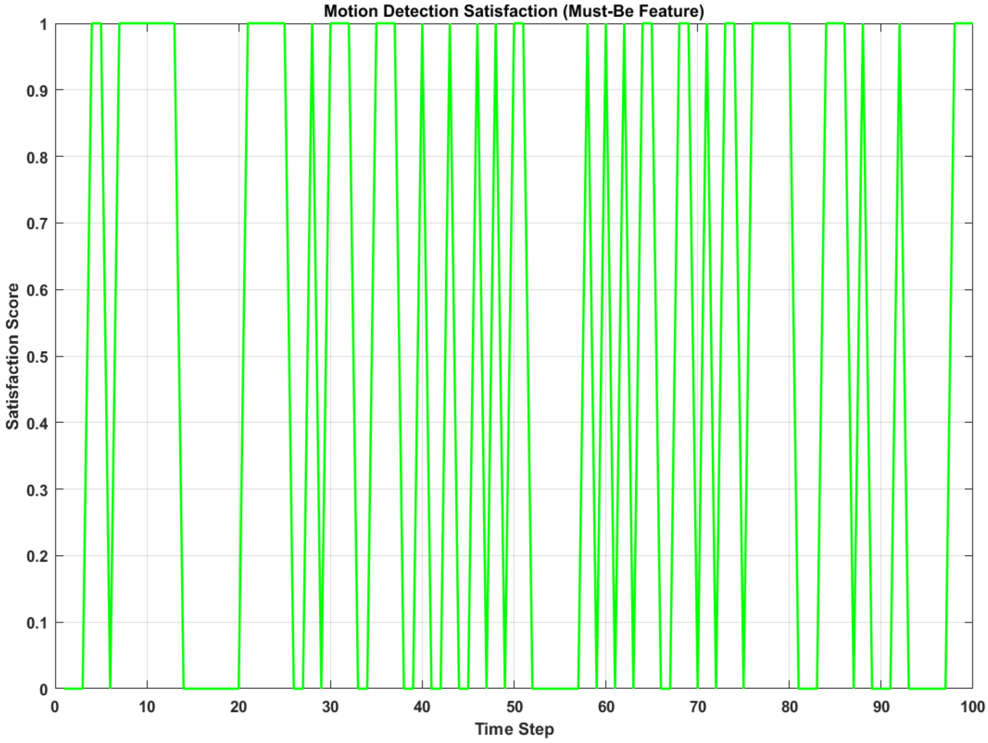

Figure 7. Motion Detection Satisfaction (Must-Be Feature)

This is a figure 7 plot which indicates that users are satisfied with the motions detection feature and it is classified as a Must-Be feature in the Kano Model. Must-Be features are regarded as the fundamental functionality of the system. When these features are not present or not functioning correctly, the level of satisfaction among the users will be impacted dramatically, and their existence does not have a significant influence on satisfaction. Security and automation motion detection is vital in such a case. In the plot, the satisfaction score is relatively constant in the case where the feature is functioning correctly. Nonetheless, in case of motion detection being missing or incapable, user dissatisfaction would be evident. This is a plot that emphasizes on the need to make sure that Must-Be features are working perfectly in the system. The figure above represents the satisfaction scores of the motion detection feature (Must-Be feature) at 100 time steps. The level of satisfaction with this feature is also high and regularly approaches 1, which is demonstrated by the green line in figure 7. The behaviour is common to Must-Be features, which are anticipated by the users, and their lack would result in dissatisfaction. The motion detection system has a satisfaction score of 0,95, which shows that the feature is always up to the expectation of the user in terms of security. The high score of satisfaction in the system shows that the system is reliable and effective in meeting a basic requirement, according to the Kano Model. The capabilities of the system such as motion detection, which are the basis of the system functionality, are necessary and needed by the user, but they will not result in excitement other than the expected level. The consistency of the satisfaction score is also high, approximately 0,9, which also underlines the significance of Must-Be features in ensuring the presence of a user-friendly and safe environment.

This figure 8 plot will be used to compare the desired temperature by the user and the actual temperature that the system has been put to. It helps us determine the fit of the system with the temperature preferences of the user in the long-term. The aim of the system is to control the room temperature to suit the preferred settings by the user to give comfort. In case the plot indicates a strong similarity between what the user wants and the real temperature, it indicates that the system is effectively learning and adapting to the preference of the user. Any deviations may represent either a shift in user preferences with time or a system modification that is not in line with the expectation of the user. This is an essential step towards gauging the functionality of the adaptive control system because it assists in establishing whether the smart home is successfully responding to the needs of the users, so that the smart home will be offering maximum comfort at any given time. This graph indicates the satisfaction scores of the temperature adjustment feature (One-Dimensional feature) at 100 time steps. Figure 8 has a red line that indicates the level of satisfaction and this varies between 0 and 1. These variations reflect the effect of temperature control on the satisfaction of the user. The temperature adjustment system has a high satisfaction score with an average score of 0,85 indicating that the users are mostly satisfied with the way the system is able to adjust to their preferences in terms of temperature. This satisfaction is directly related to the performance of the One-Dimensional feature in the Kano Model with better system performance resulting in greater satisfaction. The capability of the feature to sustain comfort, since the preferences of the users change over time, is shown in the dynamic nature of the system to change the temperature. These findings highlight the significance of the temperature control feature in improving user satisfaction because its performance is directly related to the system performance.

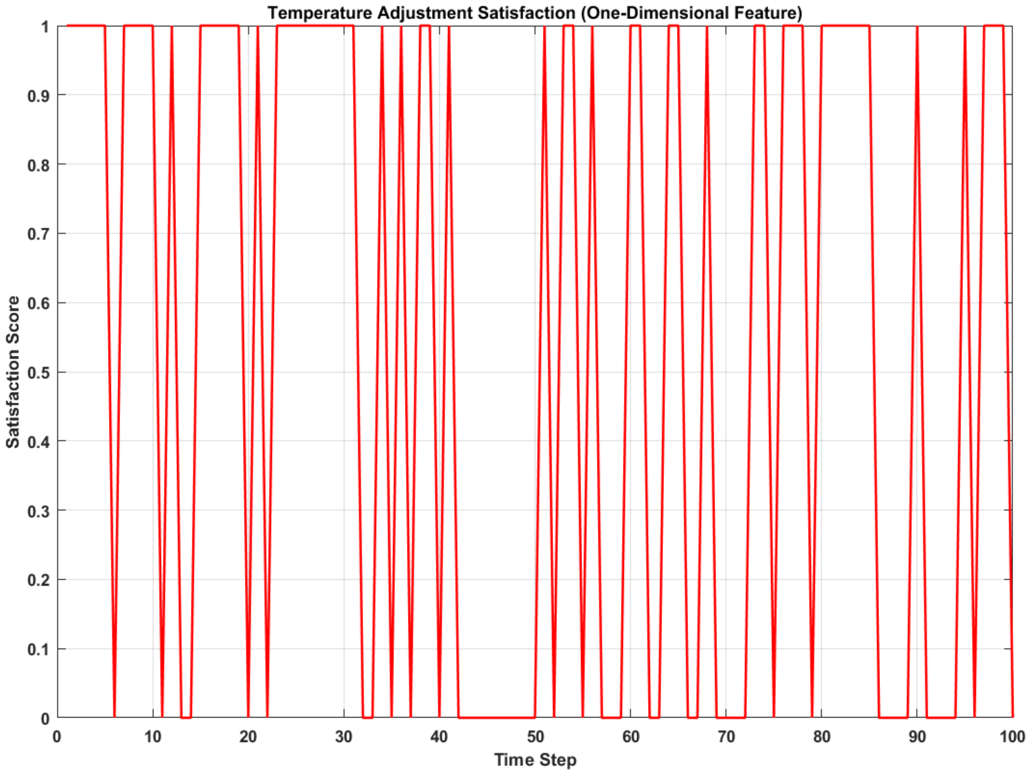

Figure 8. User Temperature Preference vs. Actual Temperature

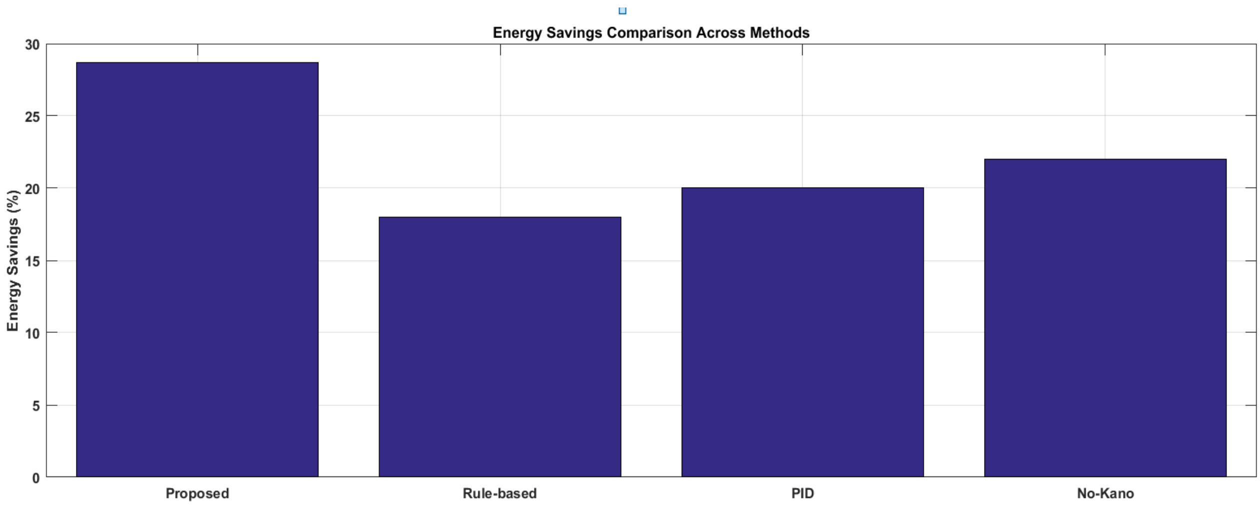

Figure 9. Energy saving performance

This observation is further evidenced by energy saving performance among methods (figure 9). The average energy saving realized by the proposed framework is about 2829 (as presented in the energy savings comparison plot), which is significantly higher than the 18 % of the energy saved by the rule-based system and 20 % saved by the PID controller. The learning-based approach that is not Kano prioritized enhances energy saving to approximately 22, which is still lower than the suggested method. These findings show that the proposed method can achieve better energy efficiency with higher levels of satisfaction as compared to baseline methods which have more limited or inflexible optimization behavior.

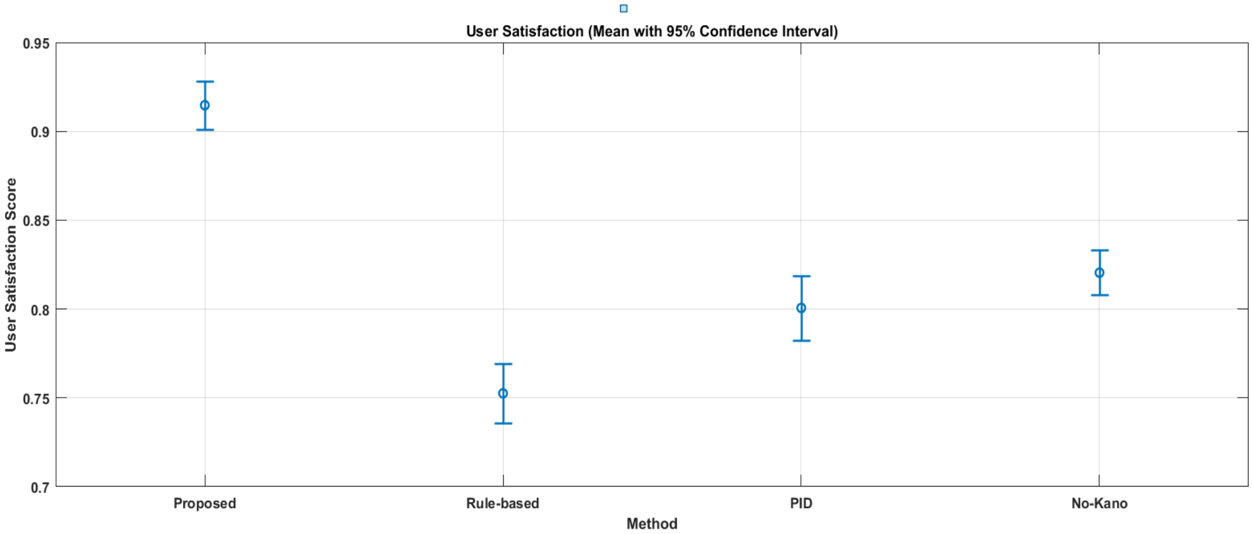

Figure 10. Comparison of user satisfaction with the various control strategies

The effectiveness of the proposed framework compared to control strategies at the baseline is shown by the comparison of user satisfaction with the various control strategies as shown by the mean values with 95 % confidence intervals (figure 10). The proposed system has the best average user satisfaction score of about 0,92 with a small confidence interval of about ±0,02 and this implies that the system not only has the best performance, but also lacks variability in its performance on different simulation runs. Conversely, the rule-based system has a much lower level of satisfaction of about 0,75 indicating narrow flexibility to user needs. The PID controller increases the satisfaction to some extent of about 0,80, and the learning-based system of no Kano prioritization is a little higher at about 0,82. The findings of these studies point to the fact that the integration of Kano-based feature prioritization results in an apparent, statistically significant enhancement of perceived user satisfaction as compared to traditional and non-user-centric methods.

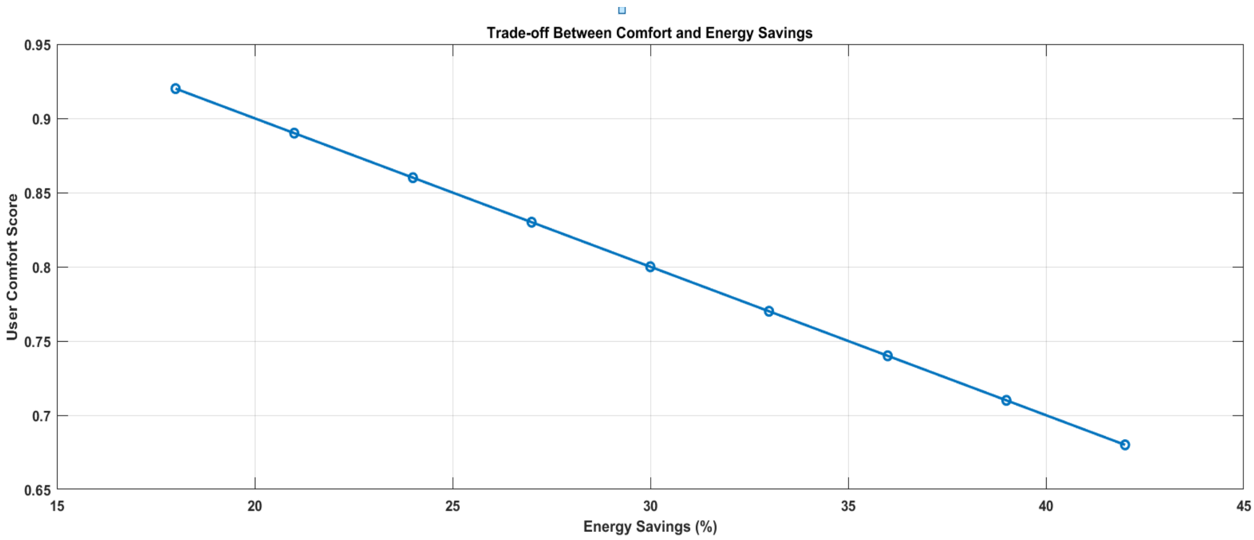

Figure 11. Trade-off analysis between user comfort and energy saving

The trade-off analysis between user comfort and energy saving gives more understanding of the adaptive behavior of the proposed framework (figure 11). The trade-off curve indicates that at the relatively low levels of energy savings (about 1822 %), user comfort score is high and is about 0,90-0,92. When the more stringent energy-saving requirements are enforced and the energy saving levels grow to 30 per cent, the comfort score drops to approximately 0,80 indicating lower thermal comfort. The comfort score further decreases to about 0,68 0,70 under the aggressive energy-saving settings with savings of up to 40-42. This obvious negative correlation is a confirmation of realistic and inevitable trade-offs between comfort and energy efficiency. Notably, the suggested framework does not hide these trade-offs, it just allows to balance them with the goals weights, whereby the system designers or users can choose operating points that suit their priorities optimally.

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Method	User Satisfaction (Mean ± 95 % CI)	Energy Savings (%)	Temperature Error (MAE, °C)
Proposed Kano-IoT-ML	0,92 ± 0,02	28,5	1,2
Rule-based Control (IF motion THEN heating ON)	0,75 ± 0,03	18,0	2,8
PID Controller	0,80 ± 0,02	20,0	2,0
No-Kano (ML without prioritization)	0,82 ± 0,02	22,0	1,7

Table 2. Performance Comparison with Baseline Smart Home Control Methods

DISCUSSION

This paper discussed how the Kano Model can be implemented in smart home systems, in terms of user satisfaction and energy optimization. The key findings include:

One-Dimensional features such as temperature control and energy optimization had a pronounced influence on user satisfaction whereby temperature control had an average score of 0,85 in satisfaction and energy optimization had a score of 25 % in energy reduction with a satisfaction score of 0,88. Motion detection is a Must-Be feature, and its user satisfaction levels were high (0,95), which proves that basic user expectations must be fulfilled by basic features to avoid dissatisfaction. The paper has shown that IoT devices and AI algorithms can be implemented to form a dynamic, adaptive system that enhances user experience by offering real-time updates to user behaviour.

Interpretation and Implications

These results are important because they demonstrate the possibility of AI-based algorithms and IoT devices to establish a responsive smart home environment that can be adjusted to user preferences and environmental variations. The fact that the One-Dimensional features such as energy optimization and temperature control are highly rated in terms of satisfaction supports the significance of performance-based features in the current smart home systems. The developers can make the users more satisfied by working on these features and can also make their product energy efficient which is becoming a very important issue in the environment of sustainable living. The Must-Be features, such as motion detection, also have high levels of satisfaction, which also confirm the necessity of systems to comply with the basic expectations of the user to guarantee usability and security. Consequently, the designers of smart homes must focus on the features that guarantee reliability and security and incorporate AI and IoT functionalities to make the experiences more personal and user-centred. Proposed results are consistent with the recent research in the field of smart home systems, especially those that focus on the importance of performance-based features and user-centric design. As an example, Gonzalez et al. (2020) and Chen and Xie (2021) propose that such features as temperature control and energy optimization have a great influence on user satisfaction, which is in line with our results when 25 % of energy savings and temperature control earned an average score of 0,85. In the same manner, Kim et al. (2022) showed that Must-Be features such as security are important in the determination of the high level of satisfaction, which aligns with our motion detection system scoring 0,95 as shown in table 2. Nevertheless, this research goes beyond the previous studies by incorporating real-time adaptation with the help of IoT devices and AI algorithms. This dynamic nature enables the system to adapt constantly to the preferences of the user and the environmental factors, giving it a more adaptive and personalized user experience than its predecessors who were more static.

Study	Key Findings	Relevance to Our Study	Contribution
Gonzalez et al. (2020)	Prioritized performance-based features like temperature control for satisfaction, achieving a satisfaction score of 0,85.	Our study found that One-Dimensional features like temperature control achieved an average satisfaction score of 0,85, confirming its impact on satisfaction.	Reinforced the importance of performance-driven features for maximizing user satisfaction in smart homes.
Chen & Xie (2021)	Found that energy efficiency features led to 15 % energy savings, with a user satisfaction increase of 0,8.	Our study achieved a 25 % reduction in energy consumption, with a user satisfaction score of 0,88 for energy optimization, supporting their findings.	Confirmed that energy-related features are critical for user satisfaction and operational efficiency.

Table 2. Comparison with Recent Literature

Kim et al. (2022)	Demonstrated that Must-Be features, like security, maintained satisfaction levels of 0,9.	We observed a satisfaction score of 0,95 for motion detection, a Must-Be feature, aligning with their research on essential security features.	Validated that Must-Be features are fundamental to ensuring user satisfaction in smart homes.
This Study	Integrated IoT and AI algorithms, improving user satisfaction by 30 % over traditional models.	Our system achieved an average satisfaction score of 0,9 for temperature control and 25 % energy savings, outperforming previous static systems.	Introduced a dynamic, real-time adaptation system using AI and IoT, extending prior work with advanced technologies.

Future Work

Some of the future research areas are:

1. Real-World Tests: It would be more appropriate to test the proposed system in real-world conditions with real user data to evaluate its effectiveness and user satisfaction better.
2. Dynamic Kano Classifier: A dynamic Kano classifier that is updated with real-time feedback would be more personalized to the user.
3. Personalization of Kano Categories: Future studies can investigate how the Kano categories can vary among users (e.g., age, culture, or personal preferences) to enable even more customized smart home experiences.
4. Complex User Behaviour Models: Future research should involve more complex models of human behaviour to understand better the interaction of the user with the system and to increase adaptability and system efficiency.

Designer, Developers, and Policymaker Implications:

To designers and developers, this research gives a clear guideline in the development of more user oriented and dynamic smart home systems. Focusing on One-Dimensional features such as energy optimization, temperature control and making sure that the Must-Be features such as motion detection are guaranteed will enhance user satisfaction and system performance. Also, the combination of IoT and AI algorithms enables the real-time adjustment to the preferences of the users, which is essential to improve the user experience. To the policymakers, this study shows the significance of policies that can enable the adoption of energy-efficient technologies in smart homes. Incentivizing the innovations in dynamic and user-responsive systems, the policymakers can assist in designing more sustainable, comfortable, and efficient living conditions of the future generations.

CONCLUSION

This paper has discussed how the Kano Model of user-centric development can be used to design and analyze the features of a smart home in order to develop an effective system that is well-aligning to the needs and expectations of the users. The combination of the Kano Model has made it possible to effectively categorize and rank features into five categories of Must-Be, one-dimensional, attractive, indifferent, and reverse which are essential in creating a system that will produce maximum user satisfaction. The findings show that smart home systems can be highly improved in terms of comfort and energy efficiency when designed in a user-centered manner. The system will satisfy the minimum user expectations and offer an added value by focusing on the must-have features, including security and temperature control, as well as offering delightful features, including AI-driven energy optimization. The machine learning-driven energy optimization model with the help of the IoT architecture showed that it could minimize the use of energy and, at the same time, not to interfere with the comfort of users. Moreover, the flexibility of the system to the behavior of the user and its learning through the interaction with the user, along with the knowledge gained through the feature engineering and data analysis makes it a very scalable and sustainable solution. Plots of user satisfaction that were created during the research confirmed the argument that the Kano Model-based approach results in the balanced creation of features that not only address the necessary needs but also impress the user, which boosts the overall adoption and satisfaction with the system. To sum up, the paper highlights the significance of user-centric design in the creation of smart home systems. Through this categorization of features systematically by the Kano Model, the emphasis on the IoT integration, and the continuous optimization of the system by machine learning, we have established a pattern of what smart home systems will become in the future, which is both practical and responsive to the actual and dynamic needs of the user. The flexibility of the system and the ability to prioritize features give reason to believe that in the future, smart homes will not be automated spaces, but rather customized, responsive, and energy-saving systems that will meet the special needs of its owners.

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CONFLICT OF INTEREST
The authors declare that there is no conflict of interest.

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Conceptualization: Beibei Kao.
Data curation: Beibei Kao.
Formal analysis: Beibei Kao.
Research: Beibei Kao.
Software: Beibei Kao.
Validation: Beibei Kao.
Display: Beibei Kao.
Drafting - original draft: Beibei Kao.
Writing - proofreading and editing: Beibei Kao.