# Internet of Behavior and Explainable AI Systems for Influencing IoT Behavior

Haya Elayan, Moayad Aloqaily, Fakhri Karray, and Mohsen Guizani


## Abstract

Pandemics and natural disasters over the years have changed the behavior of people, which has had a tremendous impact on all life aspects. With the technologies available in each era, governments, organizations, and companies have used these technologies to track, control, and influence the behavior of individuals for some benefits. Nowadays, the use of the Internet of Things (IoT), cloud computing, and Artificial Intelligence (AI) have made it easier to track and change the behavior of users through changing the behavior of IoT devices. This article introduces and discusses the concept of the Internet of Behavior (IoB) and its integration with Explainable AI (XAI) techniques to provide trusted and evident experience in the process of changing IoT behavior to ultimately influence user behavior. Therefore, We propose a system based on IoB and XAI that aims to influence user behavior and showcase its effectiveness in an electrical power consumption use case. Through our experiments, we are able to demonstrate a reduction in both power consumption and cost. The scenario results showed a decrease of 522.2 kW of active power based on the original historical average consumption over a 200-hours period. It also showed a total power cost saving of €95.04 for the same period.


## Introduction

Natural disasters and epidemics have affected people's lives for centuries. Tsunamis, the Spanish flu, HIV/AIDS, the COVID-19 pandemic, among others, have killed millions around the world and forced people to change their behaviors. These disasters have had a large impact on societies increasing mortality rate, causing economic damage, changing the behavior of individuals, causing social and economic disruption, and increasing political pressure and tensions, which compels developed countries to analyze them carefully.

While changing behavior appears to be a low-risk effect compared to mortality or economic disaster, it is powerful enough to result in similar risks. For example, in a study of the impact of social distancing on suicide rates apart from epidemiological deaths, results showed that a change in the social distancing index of ten units caused a 2.9 percent increase in the suicide rate [1]. Moreover, during the COVID-19 pandemic, scientists reported that wearing a mask could prevent approximately 130,000 deaths in the USA alone. Many behavioral aspects have been altered by the COVID-19 pandemic, such as customer interaction with brands, employee work procedures, and business engagement with consumers. All these and other examples have economic, technological, and physiological effects. Therefore, tracking people's behavior becomes crucial to help influence it toward positive outcomes when in adverse situations. For example, using machine learning for automated mask recognition is one way to get individuals to respect regulations and monitor negligence.

By 2023, it is predicted that the activities of 40 percent of the global population will be tracked digitally to influence human behaviors [2]. It is also projected that the IoT sensors market will reach $22.48 billion with 29.3 billion IoT devices to be available by 2023. Therefore, IoT would play a major role in detecting people's behavior.

Gote Nyman, a Psychology expert, was the first to announce the concept of the Internet of Behavior (IoB). In 2012, he said that if the human behavioral pattern is assigned to devices (e.g., IoT devices) with specific addresses, there will be an opportunity to benefit from the knowledge gained by analyzing the history of patterns in many fields including business, politics, societal, and healthcare. Behavior is a psychological characteristic that can determine a person's willingness to cooperate or collaborate. Despite the other characteristics: cognition, emotion, personality, and inter-Communication, behavior is responsible for the tendency to act and is highly dependent on the other four criteria. Therefore, by focusing on behavior, it is possible to gain the most insights on how to influence and treat people.

Attempting to influence and change user behavior is sensitive, as it may encounter resistance and other psychological factors related to comfort and trust. Emerging technologies such as Explainable AI (XAI) will help provide the user with the required understanding and trust of the results of any system that uses AI models. XAI aims to use methods/techniques to explain to the user what an AI model does and why, resulting in a better perception of the model's operation and decision making.

This article integrates the concepts of IoB and XAI to propose a trusted and understandable framework that addresses altering user behavior. Accordingly, we propose an IoB-based system that utilizes XAI in a use case scenario of household electrical power consumption. Our system aims to change user behavior into an eco-friendly behavior in order to reduce power consumption,

Digital Object Identifier:
10.1109/MNET.009.2100500

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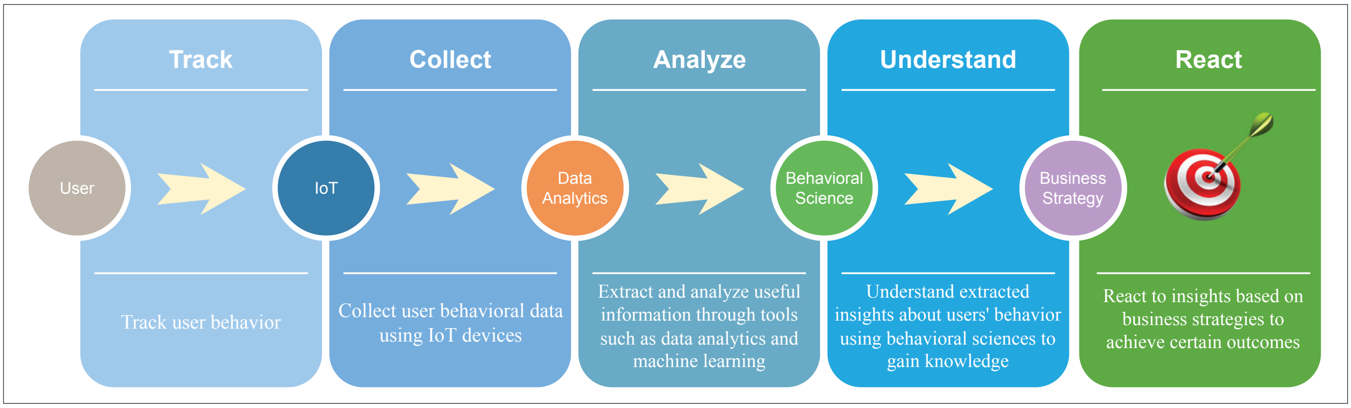


FIGURE 1. IoB Workflow Steps.

and therefore, reduce energy waste and cost. The proposed framework integrates Internet of Things (IoT), Artificial Intelligence (AI), Data Analytics, Behavioral Science, and XAI techniques to achieve user and business benefits. To the best of our knowledge, this is the first attempt to investigate the concept of IoB, its workflow, benefits, challenges, and current industrial directions. The contributions of this article can be summarized as follows:

- We propose a trusted and comprehensible IoB-XAI-based system that attempts to influence and change user behavior to achieve benefits for users and businesses.
- We present a use case scenario of electrical power consumption behavior to influence consumer behavior and raise awareness to control and reduce the power consumption process.
- We discuss and compare the main characteristics of related work in the power consumption area to provide readers with a state-of-the-art understanding of the use case scenario.
- We highlight potential developments and future directions of the proposed system to open up new research avenues to explore.

## Internet of Behavior (IoB): IoT Devices

IoB is using devices to collect a massive amount of human behavioral data and turn it into valuable insights to improve user experience by changing user behavior, interests, and preferences. The increasing number of IoT devices along with the massive amount of data they provide has made it possible to improve the IoB process in terms of speed, ease, and efficiency.

IoB attempts to appropriately understand data and use this understanding to create new products, promote current products, redesign the value chain, increase profits, or reduce costs. Therefore, user behavior in the IoB workflow will be tracked first using connected devices, as shown in Fig. 1. The IoT devices' generated data will be collected and then analyzed using data analytics and machine learning algorithms. The analytics phase will yield useful information that must be properly understood from a behavioral science perspective. Finally, the knowledge gained will be used to develop business strategies and influence users' behavior, thus, achieving a specific goal.

As shown in Fig. 2, the IoB process is descriptive yet proactive. It tracks and analyzes a user behavior in order to detect and accordingly influence important psychological variables to achieve the needed objective. This usually introduces a wide set of benefits and accompanied challenges.

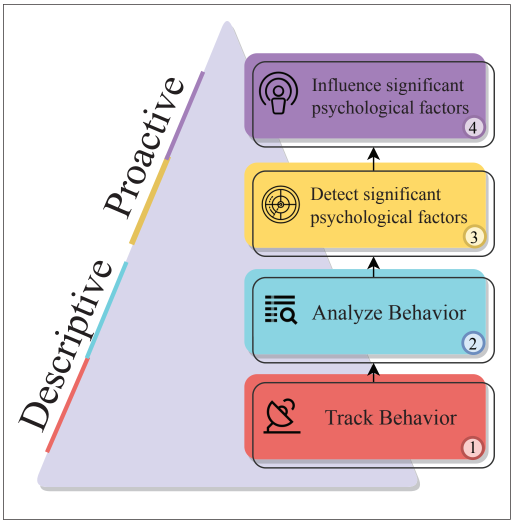


FIGURE 2. The IoB Process.

### IoB Benefits

IoB is a new concept in today's emerging technologies. It is being used in many applications for several benefits, however, without much knowledge about it in the research community. Therefore, in this sub-section, we summarize the key benefits of IoB.

**Quality of Experience, Increased Profit:** IoB helps companies resolve issues in improving sales while keeping their customers satisfied at the same time (a win-win strategy). For example, online fashion retailer apps can use the clicks and search history of users to suggest personalized discounts and offer packages.

**Task Automation:** IoB helps replace outdated fashion tactics like time-consuming and unfavorable customer surveys, thus reducing tedious tasks.

**Target Customers:** IoB provides the opportunity to identify valuable customers based on their interests and which customer segments to target and invest in. For instance, a smartwatch company may find through tracked data that males aged 20-30 who do not exercise regularly are more likely to purchase its smartwatch to make themselves more committed to exercise.

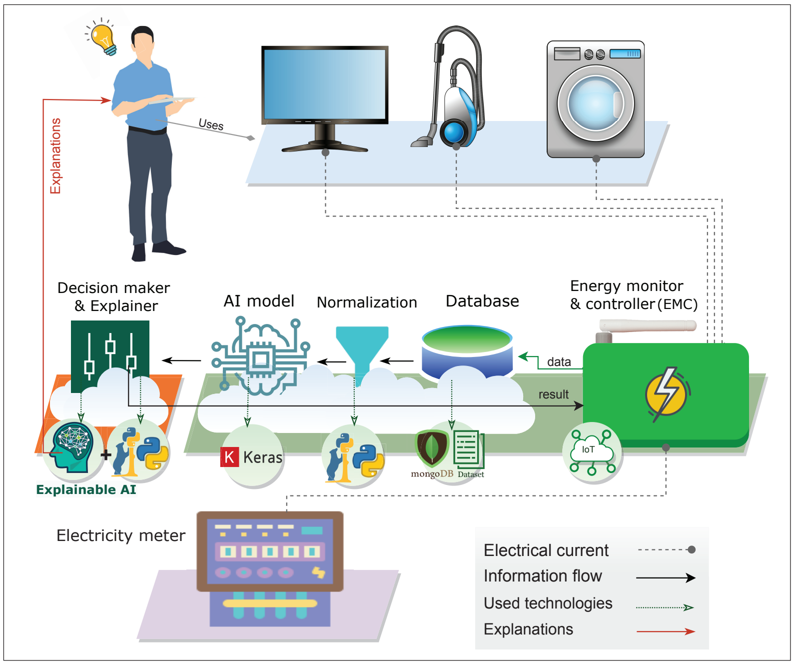


FIGURE 3. The proposed system workflow applied to a household energy consumption use case.

**Accuracy:** IoB provides the ability to track and study the unobtainable behavior of how customers interact with products and services in order to notice what typically goes unnoticed.

**Real-Time Interactions:** IoB helps provide real-time interactions via notifications or alerts to customers about targeted offers, sales, and/or advertisements. For example, social media apps provide real-time feeds and ads based on the viewing patterns, amount of time spent in one account, interest in specific content, or search and chat analysis.

## IoB Challenges

**Security:** Dealing with sensitive and real-time data always creates security concerns for any service user. In IoB, it is necessary to demonstrate a high level of security and protection to users, as their behavioral data is expected to be prone to attacks. The data sensitivity motivates cybercriminals to access, reveal, collect and benefit from the data.

**Ethical Use:** Behavioral data is a sensitive and personal data type, and its collection, storage, or analysis must be accompanied by transparency and ethical use. Users have the right to be aware of this process as well as to know that their privacy is preserved and protected from misuse. Another aspect of ethical use is not following the principle "the end justifies the means." Companies, in most cases, aim for more profit regardless of the impact on users and the accompanied risk of changing user behaviors in critical areas such as health. Finally, companies must ensure that users' consent is obtained when their data is collected and used for any purpose.

**Ostrich Effect:** The ostrich effect is a phenomenon that occurs when the rational mind believes something is important and the emotional mind expects it to be painful. People understand the power and benefits of using IoB, however, they may be uncomfortable about the tracking process due to trust issues, which results in avoiding or rejecting the IoB technology and process. Therefore, when companies implement IoB, it is not enough to work on process understanding by users. They also have to work on removing the discomfort of using this technology.

## XAI for IoB

IoB challenges may create resistance on the part of users as it tries to influence and change their behavior and track their data. Using AI models in IoB to analyze users' data provides an opportunity to leverage XAI techniques to make the operations of IoB-based systems more understandable to the user, and thus, more trustworthy.

Describing the AI-based system process, workflow, impact, and outcomes using user-friendly mathematical and analytical proofs, as well as covering the user concerns about the system processes and results will give users a better understanding of the system and raise awareness of its impact. As a result, it will become possible to mitigate the problems of trust and the impact of resistance.

# Eye on Industry

In this section, we will discuss examples of IoB applications from different industries.

## Healthcare

Nowadays, smartphones allow many software companies to build and promote different applications that care about users' health, where they can easily use smartphone sensors to track biometrics and healthy behavior. For instance, the *Beddit* health app tracks sleep patterns, heart rate, and breathing rate. After analyzing the tracked behavior, the app sends alerts, notifications, and tips to improve the user's sleep and motivates him/her to achieve daily goals to reach a more positive health-related outcome [3].

During the COVID-19 pandemic, many countries have developed health smartphone apps for citizens to control the spread of the virus. The *China Health Code Alipay* app, for example, tracks a user's travel history, contact history, and body biometrics such as temperature. Then, a colored QR code is generated to identify his/her health status. Accordingly, some restrictions may apply to the user and affect his/her behavior, such as permitting travel or quarantining at home or in a central location [4].

## Transportation

Even in transportation, IoB can be applied for the shared benefit of both drivers and passengers. After a long history of disputes with drivers and a high turnover rate, Uber is trying to resolve these issues and settle disputes in its favor by influencing driver behavior using gamification. Uber has tricks like loss aversion, recognition, and intrinsic motivation to reward drivers or make them fear losing their winnings [5]. Another example is presented by the car manufacturing firm, Ford, which is expanding its reach by joining forces with Argo AI to develop autonomous vehicles that adapt and behave differently to road infrastructure designs and driving behaviors. This technology is being tested in many locations in the USA such as the streets of Miami, Washington, and others [6].

| Ref. | Algorithm | Dataset | Goal | Proposed Method |
|---|---|---|---|---|
| [7] | CNN LSTM | Short-term individual households power consumption for Australian customers | Predicting the individual household electrical load. | Focusing on deep learning model architecture |
| [8] | LSTM | Monthly electricity consumption in a Korean region | Forecasting the annual electricity consumption based on the history of the last three years. | Focusing on deep learning model architecture |
| [9] | CNN ResNet | Electrical meters of a nonresidential building in Switzerland | Forecasting building load using Resnet to enhance the ability of learning | Focusing on deep learning model architecture |
| [10] | CNN LSTM | Individual household electric power consumption In France / Appliances Energy Prediction | Predicting electricity consumption at various distribution and transmission systems' levels. | Building a framework of two steps: data cleaning and model building |
| [11] | CNN LSTM | Household power consumption by Korea Electric Power Corporation. | Accelerating a deep learning model deployment after power data stream training | Building a framework for a power flow edge cloud system |
| [12] | Deep RL | Electrical submeters recorded by Pecan Street. Inc | Optimizing home energy management by taking a series of actions | Focusing on deep RL architecture |
| [13] | Deep RL | Electrical submeters recorded byPecan Street. Inc | Scheduling energy consumption for household appliances | Building a framework for the interaction of power grid and households using a stochastic game |
| Proposed Model | LSTM | Individual household electric power consumption In France | Influencing electricity consumption behavior by automatically controlling the amount of power and providing explained processes to the user. | Building an IoB and XAI-based framework of four steps: Data collection, storage, and normalization,AI model, Decision making, and XAI |

TABLE 1. Related work comparison.

## IoB and XAI For Power Consumption Reduction: A Use Case Scenario

This section proposes a use case scenario of a system for household electrical power consumption. The system aims to influence the electricity consumption behavior of a house by automatically controlling the amount of global active power in a way that the user understands and trusts through leveraging the intersection of IoB and XAI. Global active power control will reduce energy consumption which will, in return, reduce waste and cost of excessive energy usage.

Figure 3 demonstrates the proposed system workflow. As a first step, the electrical current is passed through an energy monitor and controller device (EMC) to record how much electricity each IoT device is consuming. After that, the data is transmitted from the EMC to a cloud database to be stored and normalized. This phase will be discussed later. Then, the normalized data is used to train an AI model that will predict the global active power that may be consumed in the next hour by the household, based on the previous household consumption behavior. The model will be discussed in detail below. The prediction result is passed to a decision maker and explainer to determine how much energy appliances should use. Then, the results are returned to the EMC to control the consumption in the next hour if it is above a certain threshold in order to reduce it. In the case of a controlling power consumption, the explainer would send explanations to the user to clarify the process and give a better understanding of how the system works. The Decision Maker and Explainer will also be discussed below.

### Related Work on Power Consumption

Before discussing the proposed system flow in detail, a set of related proposals in the electrical power consumption area will be discussed. Table 1 shows a summary of the previous work on power consumption and compares them against the proposed system. Studies [7–9], used deep learning algorithms including long short-term memory (LSTM), convolutional neural network (CNN), or both to predict the electrical consumption [10, 11]. However, they focused their contribution on the architecture of the proposed model. Syed *et al.* [10] have proposed to predict the power consumption through proposing a framework consisting of data cleaning and model building steps. Whereas Kim *et al.* [11] aimed to accelerate the deployment process of deep learning models using a proposed edge-cloud framework.

On the other hand, [12] and [13] applied Deep Reinforcement Learning (DL) algorithms to perform tasks related to the process optimization of power consumption. While Liu *et al*. [12] focused on the proposed RL model structure, Chung *et al*. [13] proposed a stochastic game framework that controls the interaction between the consumed power and household.

The proposed model of this article presents a comprehensive framework consisting of all technology needed to form a successful IoB/XAI model, which will reduce the power consumption by using the IoB and XAI to influence users' behaviors. First, the LSTM algorithm will be used to build a power consumption prediction model, and then the power consumption process will be controlled. Meanwhile, the workflow will be explained to users to ensure their understanding and a smoother behavior change process.

### Dataset

An individual household electric power consumption dataset available online has been used to implement the use case [14]. It contains measurements of one household's electrical power consumption per minute for approximately four years, collected in a house located in France. The data has been re-sampled to get the total consumption per hour, which reduced the dataset size from 2,075,259 to 34,589. The dataset was divided into 50 percent trained samples and 50 percent test samples. The dataset includes the following features: Date, Time, and Voltage, Global active power: Household global active power, Global reactive power: Household global reactive power, Global intensity: Household global current intensity in ampere, Sub-metering 1: Energy of the

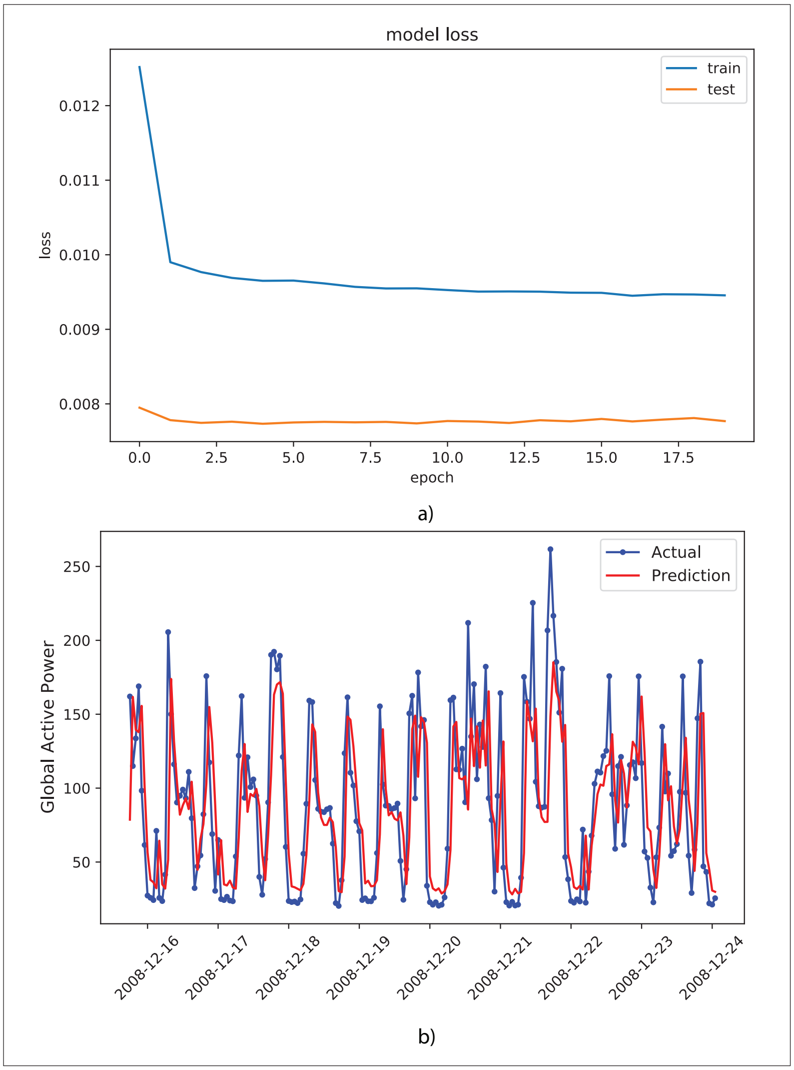


FIGURE 4. Summary of model performance in terms of quantitative loss and qualitative visual inspection: a) Comparison of the model's training and testing losses; b) Comparison of the model's predicted output consumption and the true measured consumption.

kitchen, Sub-metering 2: Energy of the laundry room, and Sub-metering 3: Energy of the electric water heater and the air conditioner.

### Database and Data Normalization

The electrical power consumption data is acquired from smart energy monitoring sensors connected to the Internet. An advanced type of smart monitoring sensor can detect the type of each appliance by just connecting the monitor to the electricity meter, without the need to connect multiple monitoring sensors to each appliance. This helps centralize the system and reduce the cost of its installation.

The acquired data is huge and in its raw format. Therefore, it requires a proper database to handle it. For example, MongoDB is one of the NoSQL databases that can handle this data as it is document-oriented. MongoDB can deal with semi-structured data, which is suitable for the presented use case as most IoT data exists in semi-structured or unstructured formats. Moreover, it has a high performance in data storage and retrieval, which is necessary for second-by-second data acquisition and transmission.

Due to the possibility of incomplete, unstructured, and inconsistent data in IoT, the data normalization phase is needed to normalize and pre-process the data to render it in a suitable format that is free of noise and outliers. Additionally, the normalization phase handles data loss that may occur due to a disconnect or dropout, thus it deals with missing values by adding data averaging or removing these values entirely. Moreover, it scales features using scaling methods like MinMax-Scaler to map data to the same range.

### Power Consumption Prediction Model

The dataset used in this scenario is time-series-based data. Time-series prediction problems are one of the difficult types of predictive modeling problems because they add sequence dependence complexity amidst input features. The long short-term memory network (LSTM) is a type of Recurrent Neural Network (RNN) used in time-series problems because it can successfully train huge structures with eliminating major problems, such as vanishing gradients.

An LSTM-based sequential deep learning model was built to predict the hourly power consumption. It allows building a layered model, with each layer having weights corresponding to the following layer. The Keras library was used for coding the model structure. The model was constructed using one LSTM layer, one Dense layer, and trained for 20 epochs with the Adam optimizer. The model was trained on a machine with the following specifications: Intel CPU@2.3GHz, 2 cores, RAM 13GB, and Disk 70GB.

### Decision Maker and Explainer

The EMC will track the power consumption of appliances per hour and pass the tracked data to a cloud database to be stored and normalized. Then, the AI model will use the data to analyze the consumption behavior and predict the power consumption for the next hour. Based on prediction and historical data patterns, the decision maker will decide the amount of power that should be used in the next hour. To personalize the user experience, the decision maker will make the decision based on the historical user's behavior and pattern. Therefore, the decision will be made by comparing the predicted consumption with the historical average consumption at specific times related to the prediction hour, taking into account influences of seasonal and occasional factors.

The explainer is responsible for applying XAI techniques to describe the AI model, its impact, biases, and outcomes to the user. The purpose is to use a set of processes and methods to allow the user to understand and trust the results generated by the model, as the consumption is controlled based on the AI model prediction.

By passing the model and the dataset to the explainer cloud platform, the explainer will attempt to cover the following concerns to the user about the system behavior through its model and data using data annotation and deep learning algorithm annotation: model prediction process, model success and failure, and model confidence in decision making. The data annotation describes statistical information of the dataset, such as feature distribution and correlation. While the algorithm annotation shows the characteristics of the model and whether it is biased toward certain features or outliers. The results will be sent to the user whenever they are requested from the explainer cloud platform using any Internet-connected device.

Using the XAI explainer platforms such as IBM AI Explainability 360 will help provide explanations for various user concerns by providing the dataset and the built model for the open-source toolkit, then selecting the type of consumer to customize the explanations [15]. Finally, it forms different questions that cover the user's concerns and offers explanations and insights through the answers. For example, in the power consumption use case, samples of question-answer pairs could be as follows:

- Why is the power consumption controlled? The predicted power consumption based on the last hour consumption is 100 kW, while your historical average is 55 kW.
- What appliance consumes the most energy? Appliance "A" is the most consuming device.
- How was the energy consumption distributed during this decision? Appliance "A" consumed 23 Wh, appliance "B" consumed 13 Wh, and appliance "C" consumed 15 Wh.

Accordingly, the entire system works to influence the users' consumption behavior in their favor by saving the energy from waste, saving the cost of wasted energy, and increasing users' awareness to improve their consuming behavior. As a result, the workflow creates a ''collective wisdom" and more responsible habits that affect not only an individual but also the society as a whole.

## Use Case Results

**Model Performance:** The model loss indicates how weak the model's predictions are. A loss close to zero means that the model's prediction is perfect and the model's performance is good. The proposed model loss started with a training loss of 0.0125 and a testing loss of 0.0079. Both of them continued to decline, reaching a training loss of 0.0095 and a testing loss of 0.0078. Figure 4a illustrates the loss performance over epochs.

Figure 4b shows a snapshot of the model's perdition results for the global active power and the actual global active power values of 200 samples. As shown, the prediction follows the actual values' pattern, while the error rate is low.

**Energy Saving:** Since the proposed system predicts the global active power for the next hour and controls the amount of used power to a certain threshold, a certain amount of energy will be saved. The system will control the power if the prediction is above the average consumption of the same hour of the same month and the same weekday for the past four years. If the prediction is lower than the average, the system will not trigger the next action. The system has been tested on 200 samples from the testing data to compute the amount of saved energy. As shown in Fig. 5, the system issued warnings (red squares) on 27 hours from 200 predicted hours, where the consumption was above the historical average power consumption. The total saved power amount for the 27 hours was of 522.2 kW.

**Cost Saving:** As the system is tested on 200 samples and saved 522.2 kW of the global active power, the power cost was also reduced to result in cost savings. In France, the price of electricity in kilowatt-hours for households is 0.182 euros.

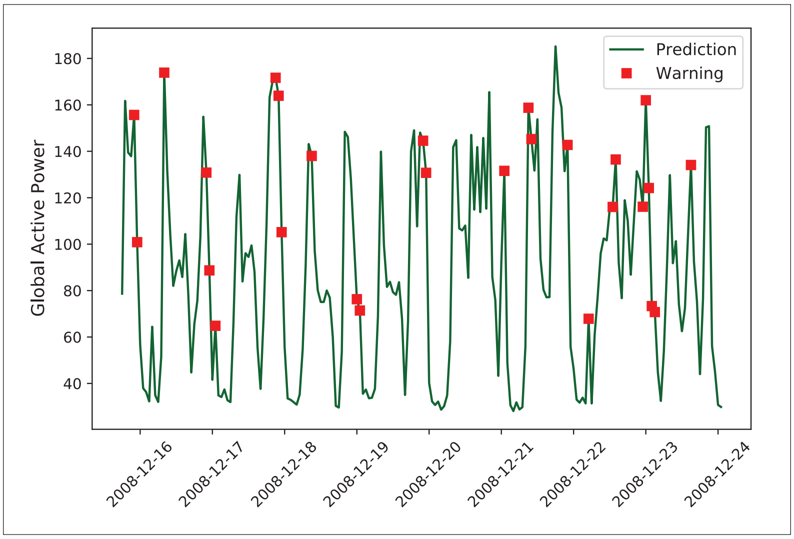


FIGURE 5. System warnings.

Therefore, the system will save €95.04 for a period of 200 hours.

**Global Intensity Reduction:** The energy intensity indicates the quantity of energy required per unit output or activity to produce a product or service. A high intensity indicates a high energy used to provide a service, and a low intensity indicates a lower energy to provide a service. This affects the price or cost of the energy conversion as a low energy intensity indicates a low cost of energy conversion into the gross domestic product (GDP). In the dataset, the global intensity is positively correlated with the global active power by 99 percent, making them both move in tandem, and implying that if the global active power decreases, the global intensity will also decrease.

To sum up, the proposed system in this use case scenario managed to reduce 522.2 kW of house global active power over a 200-hours period, while helping to reduce €95.04 from wasted power cost. Moreover, the reduction of the global active power affected the global intensity positively, which will benefit the community as well.

## Future Directions

For future directions, there are various open issues and areas of potential development that need to be investigated and tested. Incorporating a user feedback subsystem into the proposed system is important for improving the learning and prediction of the AI model and the overall system. It is also important to measure the user satisfaction factor. This will help improve the experience, fix emerging issues, and keep the user more engaged.

Another potential development area is building a distributed version of the proposed system. The aim is to compare the distributed version to the current centralized version and test its impact on both technical and user experience aspects, such as its effect on network efficiency, cost, data storing processes, and system failures.

Moreover, sending out instructive notifications to users to teach them about the optimal behavior to follow is also a considerable approach in product and system design. Users' responses and use of instructive notices will speed up the process of changing behavior

Users' responses and use of instructive notices will speed up the process of changing behavior and make the process easier, clearer, and more ingrained.

and make the process easier, clearer, and more ingrained. Furthermore, emphasizing the use of different AI/ML learning techniques is another development area to reduce the complexity of the AI model and increase its accuracy.

Finally, integrating technologies that add more control over security and data privacy is significant. The application of different security schemes, techniques, and technologies for different levels and processes of the system from data transmission to its storage and use will add more value to the system.

## Conclusion

Since IoT devices are increasingly being used in, tracking, understanding, and influencing users' behavior to achieve material and moral profits has become a reality. To the best of knowledge, this article is the first attempt to investigate the concept of IoB, its workflow, benefits, challenges, and current industrial directions. It also proposes a trusted and comprehensible tracking-analyzing-influencing behavior system using IoB and XAI. Moreover, the article presents an IoB and XAI-based framework in a use-case of an electrical power consumption system that works for the benefit of individuals, power companies, and society to save energy waste and cost. The collected results demonstrated that the proposed system was able to save 522.2 kW of wasted power and €95.04 in cost.

## References


[1] S. Stack and I. R. Rockett, "Social Distancing Predicts Suicide Rates: Analysis of the 1918 Flu Pandemic in 43 Large Cities, Research Note," *Suicide and Life-Threatening Behavior*, 2021.

[2] "Gartner Top Strategic Predictions for 2020 and Beyond," https://www:gartner:com/smarterwithgartner/gartner-topstrategic- predictions-for-2020-and-beyond/; accessed: 8-3-2022.

[3] "Beddit Sleep Monitor," https://www:beddit:com/; accessed: 8-3-2022.

[4] "In Coronavirus Fight, China Gives Citizens a Color Code, With Red Flags," https://www:nytimes:com/2020/03/01/business/chinacoronavirus-surveillance:html; accessed: 8-3-2022.

[5] "How Uber Uses Psychological Tricks to Push Its Drivers' Buttons," https://www:nytimes:com/interactive/2017/04/02/technology/uber-drivers-psychological-tricks:html; accessed: 8-3-2022.

[6] "Autonomous Vehicles — Smart Vehicles for a Smart World," https://www:ford-mobility:eu/autonomous-vehicles; accessed: 8-3- 2022.

[7] M. Alhussein, K. Aurangzeb, and S. I. Haider, "Hybrid cnnlstm Model for Short-Term Individual Household Load Forecasting," *IEEE Access*, vol. 8, 2020, pp. 180 544–57.

[8] C.-G. Lim and H.-J. Choi, "Deep Learning-Based Analysis on Monthly Household Consumption for Different Electricity Contracts," *Proc. 2020 IEEE Int'l. Conf. Big Data and Smart Computing (BigComp)*, IEEE, 2020, pp. 545–47.

[9] J. Wang *et al.*, "Building Load Forecasting Using Deep Neural Network With Efficient Feature Fusion," *J. Modern Power Systems and Clean Energy*, vol. 9, no. 1, 2021, pp. 160–69.

[10] D. Syed *et al.*, "Household-Level Energy Forecasting in Smart Buildings Using a Novel Hybrid Deep Learning Model," *IEEE Access*, vol. 9, 2021, pp. 33 498–33 511.

[11] S.-H. Kim, C. Lee, and C.-H. Youn, "An Accelerated Edge Cloud System for Energy Data Stream Processing Based on Adaptive Incremental Deep Learning Scheme," *IEEE Access*, vol. 8, 2020, pp. 195 341–58.

[12] Y. Liu, D. Zhang, and H. B. Gooi, "Optimization Strategy Based on Deep Reinforcement Learning for Home Energy Management," *CSEE J. Power and Energy Systems*, vol. 6, no. 3, 2020, pp. 572–82.

[13] H.-M. Chung *et al.*, "Distributed Deep Reinforcement Learning for Intelligent Load Scheduling in Residential Smart Grids," *IEEE Trans. Industrial Informatics*, vol. 17, no. 4, 2020, pp. 2752–63.

[14] "Individual Household Electric Power Consumption Data Set," https://archive:ics:uci:edu/ml/datasets/individual+-household+electric+power+consumption; accessed: 8-3-22.

[15] "AI Explainability 360," https://www:ibm:com/blogs/research/ 2019/08/ai-explainability-360/; accessed: 8-3-2022.


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