Data and Metadata. 2024; 3:.441
doi: 10.56294/dm2024.441

ORIGINAL

Building an IoB ecosystem for influencing energy consumption in smart cities

Construyendo un ecosistema IoB para influir en el consumo energético en ciudades inteligentes

Imane Moustati[1], Noreddine Gherabi[1], Mostafa Saadi[1]

[1]National School of Applied Sciences Khouribga, Sultan Moulay Slimane University. Khouribga, Morocco

Cite as: Moustati I, Gherabi N, Saadi M. Building an IoB ecosystem for influencing energy consumption in smart cities. Data and Metadata. 2024; 3:.441. https://doi.org/10.56294/dm2024.441

Submitted: 18-02-2024 **Revised:** 12-06-2024 **Accepted:** 11-10-2024 **Published:** 12-10-2024

Editor: Adrián Alejandro Vitón-Castillo

Corresponding author: Imane Moustati

ABSTRACT

Introduction: the Internet of Behaviors (IoB) represents a paradigm shift in integrating digital technologies with human behaviors, offering unprecedented insights and opportunities across various domains. This research paper explores the transformative potential of IoB and presents an innovative IoB framework applied to an energy consumption scenario.
Objective: we offer an innovative IoB ecosystem aimed at heightening citizens' responsibility and awareness regarding home energy consumption in smart cities.
Method: we propose a framework that elicits behavioral insights by leveraging smart meter data, clusters citizens based on similar energy consumption patterns using K-Means into groups, applies an LSTM-based prediction model to forecast their future energy consumption, and influences their behavior through a continuous personal reflection loop. Moreover, to foster trust, XAI principles are also integrated into our framework to ensure citizens comprehend and trust the IoB model's results.
Results: our proposed LSTM-based prediction model achieved, on the smart meters' dataset, high-performance results, an R^2 value equal to 0,986, a root mean squared error of 0,492 and a mean squared error equal to 0,242.
Conclusions: this paper presents how we can leverage the IoB and XAI into the energy sector. However, the IoB's potential is not restricted to a certain domain. It has a revolutionary influence across sectors, with the power sector standing out as one of the domains where the IoB has the potential to alter social practices.

Keywords: Internet of Behaviors (IoB); LSTM; Smart Meters; Energy Consumption Forecasting; Energy Consumption Behaviors.

RESUMEN

Internet of Behaviors (IoB) representa un cambio de paradigma en la integración de las tecnologías digitales con los comportamientos humanos, ofreciendo perspectivas y oportunidades sin precedentes en varios dominios. Este artículo de investigación explora el potencial transformador de IoB y presenta un ecosistema innovador de IoB destinado a aumentar la responsabilidad y la conciencia de los ciudadanos con respecto al consumo de energía en el hogar en ciudades inteligentes. Proponemos un marco que genera perspectivas conductuales aprovechando los datos de medidores inteligentes, agrupa a los ciudadanos en función de patrones de consumo de energía similares utilizando K-Means en grupos, aplica un modelo de predicción basado en LSTM para pronosticar su consumo futuro de energía e influye en su comportamiento a través de un ciclo continuo de reflexión personal. Nuestro modelo de predicción basado en LSTM propuesto logró, en un conjunto de datos de medidores inteligentes, un valor R^2 igual a 0,986 y un error cuadrático medio igual a 0,242. Para fomentar la confianza, los principios XAI también se integran en nuestro marco para garantizar que los ciudadanos comprendan y confíen en los resultados del modelo IoB.

Palabras clave: Internet de los Comportamientos (Iob); LSTM; Medidores Inteligentes; Previsión del Consumo Energético; Comportamientos del Consumo Energético.

INTRODUCTION

The Internet of Behaviors (IoB) has emerged as a transformative paradigm, transcending the conventional realms of connectivity by placing human behavior at its core. In aiming to understand, influence, and optimize human actions through the vast web of interconnected devices and using psychological knowledge, IoB holds unparalleled potential for societal impact.(1) Unlike IoT, which primarily focuses on device communication and data exchange, IoB provides us with a more inclusive vision of humans that is different from other disciplines, such as software engineering (SE), human-computer interaction (HCI), and human-in-the-loop (HITL).(2) The core concept of IoB is based on the ideas of i) building intelligent linked systems, such as IoT infrastructures, to monitor and forecast human behaviors; ii) adjusting the system to real-world behaviors; and iii) influencing people's decisions and actions inside a loop.(2) By intertwining digital technologies with behavioral science, IoB endeavors to enhance decision-making, foster responsibility, and influence constructive actions. The IoB's promise is not confined to a singular domain but extends its transformative touch across industries.(3) Various tentatives have been established to study the benefit and effect of IoB in different application domains, and the energy sector stands out prominently among the domains where IoB's potential is poised to revolutionize societal practices. In the context of the energy sector, IoB emerges as a transformative force, offering unprecedented opportunities for optimizing energy consumption behaviors. By comprehensively analyzing behavioral patterns, IoB enables tailored recommendations, interventions, and adaptive strategies that resonate with individual preferences. This personalized approach not only enhances energy efficiency but also fosters a sense of ownership and awareness among users. Consequently, IoB holds the promise of not just optimizing resource utilization but also catalyzing a cultural shift towards sustainable and eco-conscious energy practices.

The landscape of IoB applications has witnessed remarkable growth, reflecting the increasing integration of human-centric data into digital systems. Initiatives have been taken to apply IoB concepts in various sectors. Chin-Feng Lai et al.(4) set the stage for advancements in IoB-driven respiratory rate monitoring. They aimed to create a more effective respiratory rate measurement system by proposing an IoB-enhanced method that uses low-resolution continuous thermal images and advanced image processing techniques. Ossama Embarak(5) showed that remarkable improvement in academic performance can be achieved by monitoring students' academic success using IoT and IoB. Also, Wanus Srimaharaj et al.(6) used the concepts and traits of the IoB and human brainwaves and offered an ML model to assess cognitive performance. Through an IoB framework, Zhang Guangyuan et al.(7) comprehended the relationship between air pollution incidents and residents' daily activities and investigated how changes in air pollution influenced people's daily activities. Haya Elayan et al.(8) proposed a system to control electricity consumption and reduce power consumption in households. Youcef Djenouri et al.(9) introduced a deep-learning-based framework for IoB, studied a connected vehicle scenario, and assisted in comprehending users and influencing their behavior in this sector. Other researchers(10) extended the investigation of driving behaviors to driving habits and inspected deviating behaviors, which can become anomalous driving habits, to prevent their transformation. Hind Bangui et al.(11) proposed a self-adaptation DL model for trust management in the IoB context, and aimed to provide runtime evidence for trust building in interaction among IoB elements. They considered Pay-How-You-Drive vehicle insurance to showcase their work.

This research paper introduces an IoB ecosystem meticulously designed to elevate the awareness, responsibility, and behavioral patterns of citizens in smart cities concerning their energy consumption. We propose an IoB framework that utilizes IoT data from meters in homes, clusters citizens based on similar consumption behavior using the k-Means algorithm, applies a Long Short-Term Memory (LSTM)-based model to predict their next energy consumption, decides whether or not to alert citizens about their consumption, and uses a mobile application so that users can continually reflect on their energy consumption behavior, influence their behavior, and deliver personalized educational content and recommendations to enhance their awareness and social responsibility. To foster trust, Explainable Artificial Intelligence (XAI) principles are integrated, ensuring citizens comprehend and trust the IoB model's outcomes. With an acute focus on reducing waste and promoting efficiency, our proposed framework represents a harmonious integration of advanced technologies, citizen engagement, and sustainable practices.

The remaining content of this paper is organized as follows: in Section 2, we discuss the transition from

https://doi.org/10.56294/dm2024.441

the IoT era to the IoB era. Section 3 presents a detailed explanation of the proposed IoB ecosystem and the workings of each of its components. A thorough discussion of the security threats and challenges is presented in Section 4. A discussion and future directions are presented in Section 5, and Section 6 gives the conclusion.

Transsitioning from IoT era to IoB era

The advent of IoB marks a pivotal transition from the traditional realm of IoT to a new era characterized by the intricate interplay between human behaviors and digital technologies. IoB represents a paradigm shift that extends beyond the mere connectivity of devices to delve into the rich tapestry of human actions and interactions with these connected systems. Unlike IoT, which primarily focuses on device communication and data exchange, IoB places human behavior at its core, leveraging data from wearable devices, social interactions, and contextual cues to glean insights into individual and collective actions. This evolution recognizes the profound impact of human-centric data on shaping the digital landscape. The key differentiator between them lies in IoB's emphasis on understanding, analyzing, and influencing human behavior through the data generated by connected devices or gathered from online platforms. It transcends the technicalities of IoT by delving into the motivations, preferences, and decision-making processes of individuals, thus unlocking a deeper understanding of user needs and facilitating more personalized and context-aware interventions. While the IoT mainly interacts with the data and information levels in the DIKW pyramid, its design principle is information-centered, uses data to learn information, and its data nature is mainly non-behavior data; the IoB extends the DIKW pyramid from information level to knowledge and then the wisdom level,[1] it is intention-centered and based on human-behavior focused data, and utilizes human behavior data to infer human intention. This transition empowers applications in various application domains, particularly the energy sector, with unprecedented capabilities. By harnessing behavioral insights, the IoB can facilitate precise demand forecasting, personalized energy consumption recommendations, and the cultivation of sustainable habits.

Influencing energy consumption in smart cities: a use case study

In this section, we explain the built IoB ecosystem to promote energy consumption responsibility among citizens and reduce waste. In this ecosystem, the system will push its users to reflect on their energy consumption behaviors and, thus, update their behaviors accordingly. The system workflow is illustrated in figure 1. The smart meters (sensors) in the smart city homes will collect behavioral data on homes' energy consumption, and then this behavioral data will be stored in a NoSQL database. After data storage, a phase of data processing and normalization, described below, is necessary to take full advantage of its hidden information. Next, citizens will be grouped into clusters based on similar consumption patterns. This will aid in approaching them with effective personalized mechanisms. The AI model we propose below will utilize information from previous steps to predict the next hourly energy consumption. Once the predictions are available, a decision-maker and influence engine (DMIE) will compare the value with an already established threshold, which can be the mean value of the same day in the same period of the past three years, or an agreed-on value, for instance, the cluster's members have voted on through the dedicated mobile application. The vote frequency can be adjusted to take into consideration the seasonal fluctuations in temperature and energy utilization. In case the predicted value exceeds the threshold, the DMIE will alert the cluster members using the mobile application through pop-up alerts and notifications. The DMIE will also act as an influence engine by incorporating behavioral techniques to influence users' behavior. It can use the application to push educational content at a convenient time to inculcate energy consumption responsibility in citizens. The mobile application will also have a leaderboard with a changeable cluster ranking based on every cluster achievement. Thereby developing the citizenship of users and their sense of collaboration and responsibility. The DMIE can also analyze individuals' consumption behavior and generate vouchers, with amounts respectively increasing with the cluster's achievements, to reward their efforts and encourage them to maintain their tendencies. Through these active interactions (actuators), users continually reflect on their behaviors and update their energy consumption, creating a reflection loop and aiding in reducing energy loss and developing the energy efficiency of their city.

Dataset

To implement the use case, an Electricity Customer Behaviour Trial dataset has been used [12]. In order to gather data for a cost-benefit analysis of a nationwide rollout, the Commission for Energy Regulation (CER) in Ireland launched the Smart Metering Project in 2007, intending to conduct trials to evaluate the effectiveness of Smart Meters, their impact on consumers' energy consumption, and the economic case. The Smart Metering Electricity Customer Behaviour Trials (CBTs) involved around 6000 households and businesses in Ireland between 2009 and 2010. For more than a year, samples of the energy consumption of 6000-meter IDs were taken once every thirty minutes, every day of the week.

https://doi.org/10.56294/dm2024.441

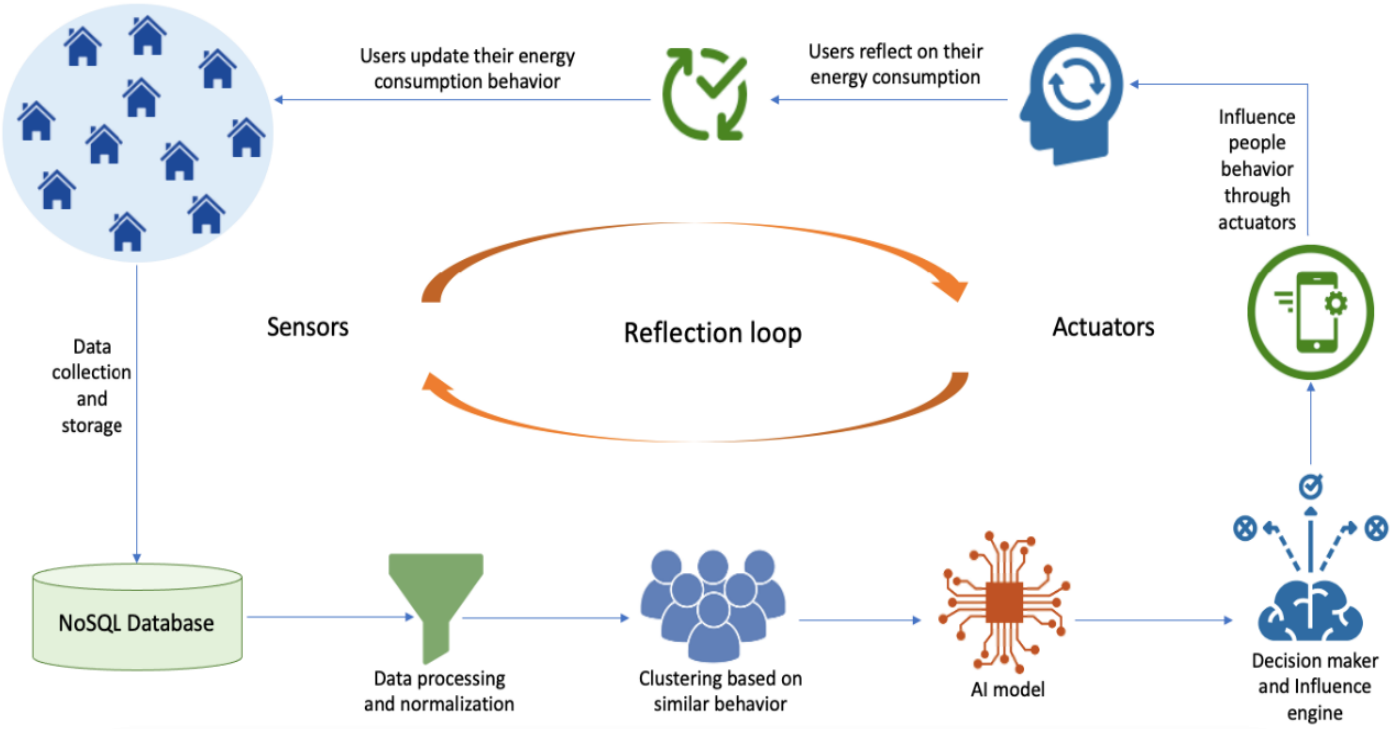

Figure 1. System workflow

Data preprocessing and normalization

First, within the IoB context, the gathered behavioral data is massive and mainly unprocessed. Therefore, to handle it, a suitable database is needed. Cloud-based NoSQL databases or regular NoSQL databases, like DynamoDB, MongoDB, etc., are well suited for time series data and the unstructured and semi-structured nature of IoB data. They can handle large volumes of diverse and dynamic data generated by various sources, besides offering excellent data storage and retrieval capability, essential for real-time data gathering and transmission. Since IoB data is unstructured, there is a chance that it will be inconsistent or incomplete. For this reason, the data normalization step is necessary to pre-process and normalize the data and put it in an appropriate format, excluding noise and abnormalities.

Before applying our prediction model to the data, a phase of preprocessing and normalization is necessary. The dataset has consumption data gathered from multiple smart meters that will be clustered based on common electricity behavior. First, the time series data is imported, cleaned, and aggregated at an hourly level instead of a half-hourly level. Then, a min-max normalization into the [0,1] interval is applied to make input features at comparable ranges. After reading, cleaning, and transforming the data, the K-Means algorithm, which is a well-established clustering technique, is used to identify groups with common electricity consumption behavior. The clustering procedure was based on behavioral measures like the intra-day energy usage percentage by smart meters, which is segmented into five segments (7h-9h, 9h-13h, 13h-17h, 17h-21h, 21h-7h), the intra-week usage percentage of each smart meter, and the average yearly, monthly, and weekly energy usage. After clustering the data, we will focus on one cluster, apply our prediction model to it, and draw conclusions. The dataset has values of energy consumption in KW and was divided into 80 % train samples and 20 % test samples.

Energy consumption prediction model

In the energy sector, time-series forecasting is a valuable tool. It can be used hourly for predicting demand peaks and production redundancy, daily for forecasting energy consumption and consequent optimization of scheduling and allocation, weekly for predicting energy purchase policies and maintenance schedules, and monthly or annually for forecasting network balancing, strategic planning, and production.

In this study, we utilize a time-series-based dataset. Thus, adding sequence dependence complexity to input features. We chose to employ a Long-Short Term Memory (LSTM) network to predict future energy consumption. LSTMs, which are a type of recurrent Neural Networks (RNN), are mainly employed in time series problems due to their capability of successfully manipulating large amounts of historical data while eliminating the most common issues with RNNs, which are the vanishing and exploding gradient.

To have a reliable prediction of the overall energy consumption of the chosen cluster, we built a recurrent deep-learning model based on LSTM. It is a layered model composed of one LSTM layer and one Dense layer, along with the input and output layers, with weights transmitted from each layer to the following one. We built our model using the Keras library, used Adam as an optimization algorithm, and ran it for 50 epochs with 40 batches each.

In order to further enhance our model's prediction results, we added lag features to it. We incorporated information from multiple past time steps as additional features, providing the model with a broader context of historical data to allow it to capture temporal dependencies and patterns more effectively. We used a temporal window of lagged values equal to 180. Adding additional lag features is beneficial since they are stored in uniquely weighted vectors, thus allowing for separate contributions. Also, if patterns in the data go beyond the temporal dependencies captured by the LSTM's internal memory, providing lag data as additional features can help the model capture external relationships or seasonality.

Model performance evaluation

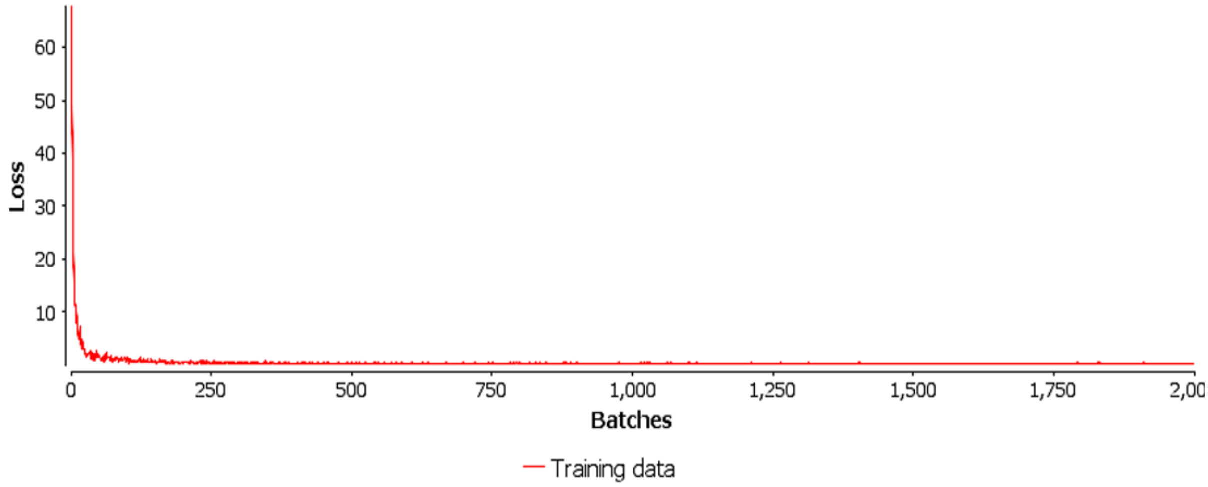

Figure 2. Model training loss using MSE

Our proposed model showed high-performance results, ensuring high levels of prediction for future energy consumption values. In ML, a loss function represents how correctly our model can predict the outcome we expect. We chose to use the mean squared error as a loss function in our study. A large number for the loss indicates that our model performed badly. A low loss value indicates that the model functioned successfully. Figure 2 and figure 3 show the loss results of our proposed model over batches, with the mean squared error (MSE) configured as the loss function. The experimental results in Table 2 show the model's performance based on different statistical measures. It can be seen that our model achieved a superior R^2 value equal to 0,986, a mean absolute error equal to 0,359, and a mean squared error equal to 0,242. Figure 4 illustrates the differences between the predicted hourly energy consumption amount and the actual value. It can be seen that the proposed model highly mimicked the actual data values over time.

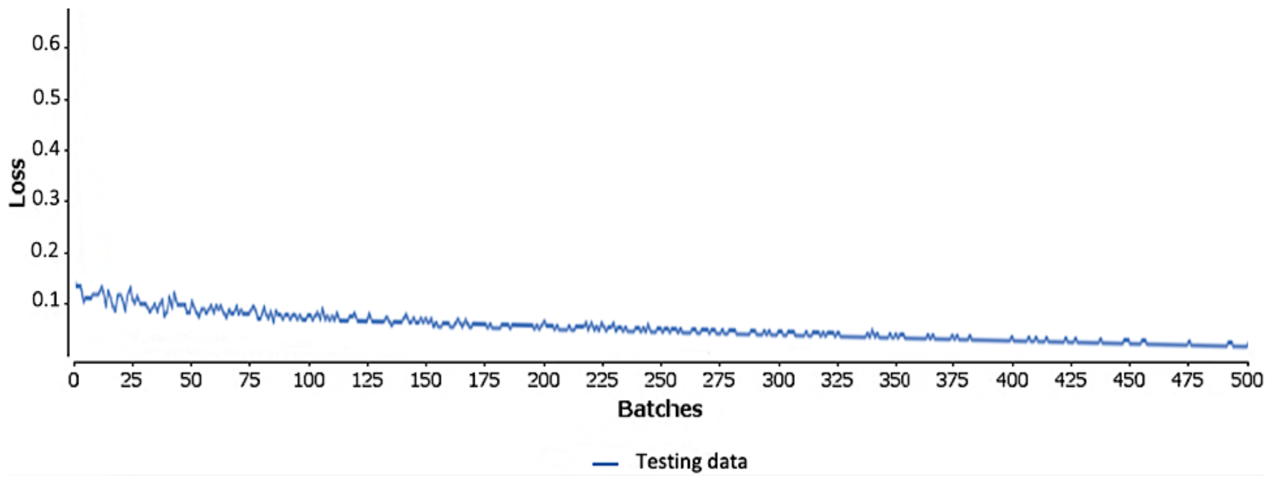

Figure 3. Model testing loss using MSE

https://doi.org/10.56294/dm2024.441

Table 2. The model performance

Measures	R^2	Mean absolute error (MAE)	Mean squared error (MSE)	Root mean squared error (RMSE)	Mean signed difference (MSD)	Mean absolute percentage error (MAPE)
Model performance	0,986	0,359	0,242	0,492	0,318	0,06

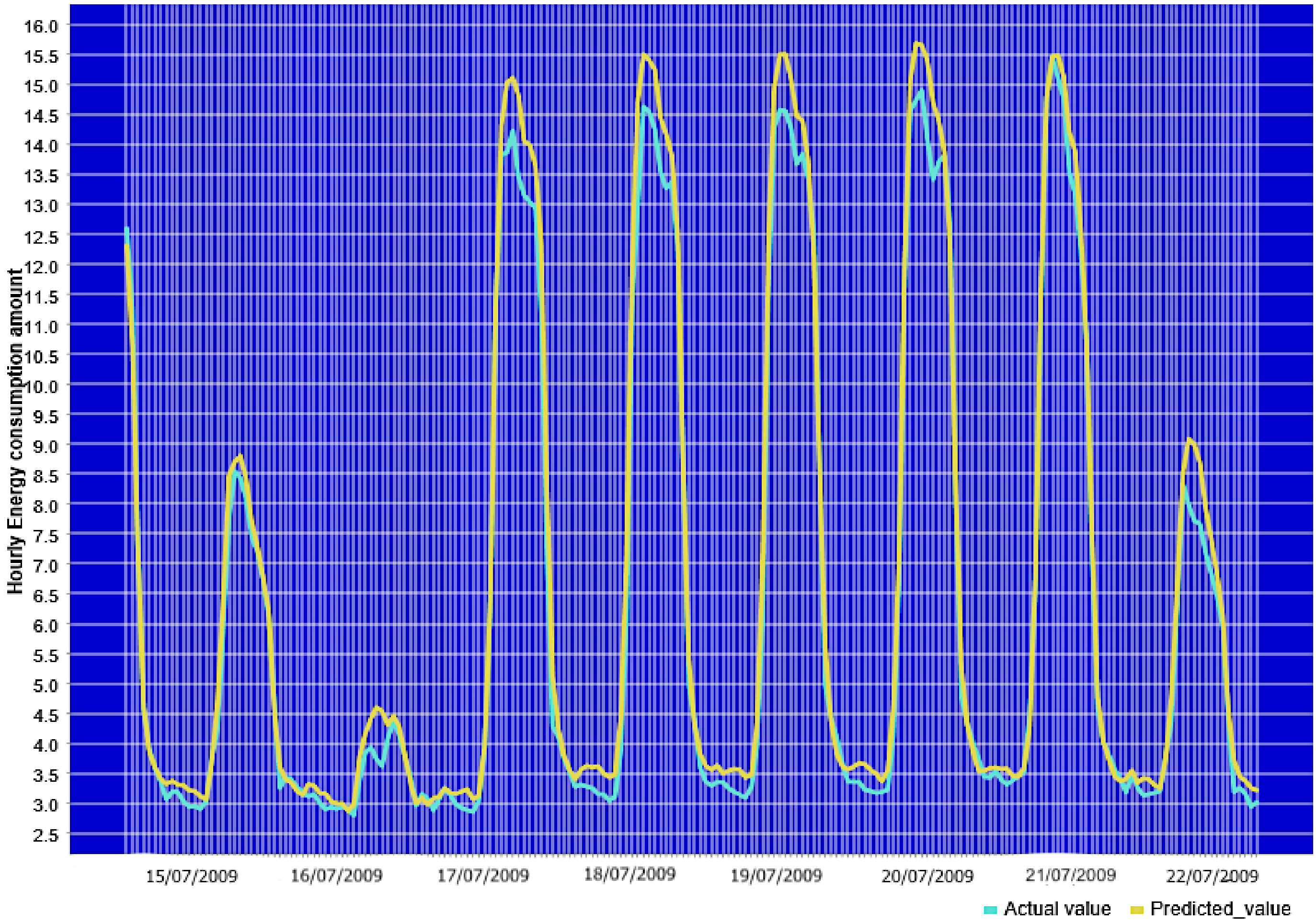

Figure 4. The forecasting model's performance versus the actual energy consumption

Employing XAI in influencing citizens behaviors

XAI aims to provide a suite of ML techniques that produce more explainable models and enable human users to understand and appropriately trust these models. It describes the AI model's impact, outcomes, and biases. By explaining this to users, XAI will allow users to trust the model's generated results, increasing their knowledge of the system's workings and goals and resulting in a smooth behavioral change experience. Although an ML model can provide precise forecasts, it is deficient in two crucial stages: understanding and explaining. The explaining phase is critical when an ML model is implemented and utilized in practical applications. It can expose human-readable explanations to end-users, describing how the predictions are derived. Explanations can be categorized into various types; however, two primary categories are data explainability and model explainability. Whereas the understanding phase deals with training and quality control of an AI model. Especially in DL, with the inclusion of several neural network layers, it is difficult for designers to explain the algorithmic outcomes.(13) Thus, the design of an explainable DL model will provide the necessary insights. Various XAI frameworks and toolkits exist, such as Arize AI, Artificial Intelligence Fairness 360 (AIF360), AI Explainability 360 (AIX360), InterpretML, Amazon SageMaker, and Fairlearn. AIX360(14), which is an open-source Python toolkit developed by IBM, provides different explanations based on users' types by forming questions centered on users' concerns and providing their answers. For example, in our scenario, such questions and answers presented below can be provided.

Q1) Why am I a member of this cluster?

A1) Based on your energy consumption history, you had a behavior similarity with other members grouped in this cluster. You have an average of 15 kW, you are a daily user (a high daily usage of electricity and a reduced electricity usage at night), and you have increased activity during weekends.

Q2) Why was I dropped from my previous cluster, which was better ranked?

A2) In the past month, your energy consumption (170 kW) has increased significantly above the threshold of your past group and your mean seasonal value (90 kW). Therefore, considering your consumption behavior, you have been added to a new cluster.

Security threats and challenges

The IoB's innovation has opened up new research opportunities, along with security and privacy challenges to address. The security of an IoB system must be considered in light of the features of each of its constituent parts (data storage, AI models, IoT infrastructure, and online platforms), and identifying the threats and challenges of every component or layer of the IoB framework is essential. As seen in our study, an IoB framework is in a way based on IoT, meaning that an IoB's system security also heavily depends on the IoT devices and network security. Thus, IoB's development should also encourage further IoT security implications. An IoB system should also protect the identity of IoT devices and enable dynamic trust in the IoT network to allow IoT gadgets to join and leave the network when required. People's activity in an IoB ecosystem is recorded by a variety of channels, including software platforms, IoT devices, and so on. Therefore, data type, extent, and scope should be thoroughly examined. The operations manipulating behavioral data in IoB involve the aggregation, transfer, control, and sharing of data.[15] presented a method to ensure security and privacy in behavioral data operations. In operations related to data aggregation, the classic aggregator-oblivious encryption framework[16] can be used, allowing an untrusted data aggregator to learn desired statistics over the data reported by multiple nodes without leaking each node's privacy. When transferring data, there is the Data Transfer Project (DTP),[17] which creates an open-source, service-to-service data portability platform, allowing individuals to move their data across the web between online service providers according to their will. Thus, protecting their personal data security and privacy. Controlling data can be achieved with two approaches: a centralized data control policy and a decentralized one. MyData project,[18] aims to provide human-centered management that combines industry needs for data with digital human rights. With this approach, individuals can easily have control over their personal data. Thus, they can facilely know where their data goes, specify who can use it, and alter their decisions at any time. On the other hand, the Solid project[19] aims to create a decentralized system in which individual persons are the only owners of their data and have full control over it. It is composed of a solid hosting provider, applications, and pods and supports storing linked data, meaning that different applications can utilize the same data. An individual can decide what data to share and which persons or applications may access his data, and he can revoke access to it whenever he wants.

DISCUSSION

The proposed IoB framework, with its DL-based model, XAI integration, and reflection loop, has exceptional opportunities to influence, alter, and optimize citizens' energy consumption behaviors. The high performance of the proposed prediction model, as indicated by an R^2 value of 0,986 and a mean absolute error equal to 0,359, underscores the potential of this framework to capture intricate temporal patterns within the time-series data and accurately predict future consumption. Notably, the LSTM-based model demonstrated remarkable efficiency in dealing with the inherent complexities of smart meter data, which exhibit significant weekly seasonality due to repetitive consumption behaviors over the course of each week. By successfully capturing and following this seasonality, the model is able to forecast consumption patterns with high accuracy. Through visual inspection of the time-series graph, which plot real consumption values against the predicted ones, it is evident that the model not only predicts well but also closely mimics the actual consumption data. The predictive curve shows similar trends and fluctuations to the real data points, highlighting the model's ability to generalize well across different time frames without overfitting. This performance suggests that the LSTM-based model effectively learns the underlying structure of the energy data and adapts to both long-term trends and short-term variations. The model's robustness, combined with its capacity to handle dynamic, time-dependent patterns, makes it a promising tool for optimizing energy consumption and guiding users towards more sustainable practices. Moreover, the interpretability afforded by XAI enhances transparency, ensuring that citizens can comprehend and trust the system's decisions and recommendations, fostering a collaborative approach towards sustainable energy practices.

To further enhance the IoB framework's robustness and address emerging challenges, recognizing the sensitivity of behavioral data, future research directions will prioritize integrating privacy and security mechanisms across all components and layers of the IoB system. Our model should integrate technologies that add more control over security and data privacy. It should add a privacy-preserving component and address security and privacy concerns arising from data transmission to its storage.[20] This will ensure that individual privacy is safeguarded and citizens have confidence in the confidentiality and integrity of their behavioral information, resulting in further user acceptance. Moreover, extending the IoB framework to accommodate a

https://doi.org/10.56294/dm2024.441

multi-modal approach and incorporating additional data sources such as various smart home devices, weather patterns, and social factors will enrich the understanding of energy consumption behaviors. The synergy of diverse data streams will refine predictions and interventions, making the system more adaptive to dynamic user contexts and further improving users' QoE. Additionally, exploring strategies to enhance user engagement and feedback mechanisms will be pivotal for sustained behavioral change. For example, gamification elements can represent avenues to reinforce positive energy practices.

CONCLUSION

The IoB aims to thoroughly understand, analyze, and influence human behavior through the behavioral data generated by connected devices and online. It transcends IoT's technicalities by delving into individuals' motivations, preferences, and decision-making processes, thus unlocking a deeper understanding of user needs and facilitating more personalized and context-aware interventions. The IoB's potential is not limited to a single domain. Still, it extends its transformative impact across sectors, and the energy sector stands out prominently among the domains where the IoB's potential is poised to revolutionize societal practices. It is then in this perspective that our research falls. In this work, we proposed an IoB framework applied to an energy consumption scenario to heighten citizens' common responsibility and awareness regarding home energy consumption in smart cities and thus reduce energy waste. The proposed ecosystem includes leveraging smart meter data, clustering citizens based on similar consumption patterns and behaviors using K-Means, predicting their next energy consumption, and influencing their behaviors through a continuous personal reflection loop. Our proposed LSTM-based prediction model achieved high-performance results, an R^2 value equal to 0,986, and a mean squared error equal to 0,242. Furthermore, to foster trust, XAI principles are also integrated into our framework to ensure citizens comprehend and trust the IoB model's outcomes.

REFERENCES

1. Moustati I, Gherabi N, Massari H El, Saadi M. From The Internet of Things (IoT) to The Internet of Behaviors (IoB) for Data Analysis. In: 2023 7th IEEE Congress on Information Science and Technology (CiSt). IEEE; 2023. p. 634–9.

2. Moghaddam MT, Muccini H, Dugdale J, Kjagaard MB. Designing Internet of Behaviors Systems. In: 2022 IEEE 19th International Conference on Software Architecture (ICSA). IEEE; 2022. p. 124–34.

3. Moustati I, Gherabi N, Saadi M. Leveraging the internet of behaviours and digital nudges for enhancing customers financial decision-making. International Journal of Computer Applications in Technology. 2024;1(1).

4. Lai CF, Chen SY, Wei YF, Chen MY, Lai SY. IoB-Enhanced Deep Learning for Non-specific Thermal Respiratory Rate Monitoring. In: 2023 IEEE International Conference on Networking, Sensing and Control (ICNSC). IEEE; 2023. p. 1–6.

5. Embarak OH. Internet of Behaviour (IoB)-based AI models for personalized smart education systems. Procedia Comput Sci. 2022;203:103–10.

6. Srimaharaj W, Chaisricharoen R. Internet of Behavior and Brain Response Identification for Cognitive Performance Analysis. In: 2022 Asia-Pacific Signal and Information Processing Association Annual Summit and Conference (APSIPA ASC). IEEE; 2022. p. 1308–11.

7. Zhang G, Poslad S, Rui X, Yu G, Fan Y, Song X, et al. Using an Internet of Behaviours to Study How Air Pollution Can Affect People's Activities of Daily Living: A Case Study of Beijing, China. Sensors. 2021 Aug 18;21(16):5569.

8. Elayan H, Aloqaily M, Karray F, Guizani M. Internet of Behavior and Explainable AI Systems for Influencing IoT Behavior. IEEE Netw. 2023 Jan;37(1):62–8.

9. Mezair T, Djenouri Y, Belhadi A, Srivastava G, Lin JCW. Towards an Advanced Deep Learning for the Internet of Behaviors: Application to Connected Vehicles. ACM Trans Sens Netw. 2023 May 31;19(2):1–18.

10. Abri KAS Al, Mastouri M, Bouyahia Z, Haddad H, Yasar AUH, Shakshuki E. On the Interest of Extending Internet of Behaviors to Internet of Habits: A Preliminary Exploration. Procedia Comput Sci. 2023;224:122–30.

11. Bangui H, Cioroaica E, Ge M, Buhnova B. Deep-Learning based Trust Management with Self-Adaptation in

the Internet of Behavior. In: Proceedings of the 38th ACM/SIGAPP Symposium on Applied Computing. New York, NY, USA: ACM; 2023. p. 874–81.

12. Commission for Energy Regulation (CER). (2012). CER Smart Metering Project - Electricity Customer Behaviour Trial, 2009-2010 [dataset]. 1st Edition. Irish Social Science Data Archive. . 2012.

13. Angelov P, Soares E. Towards explainable deep neural networks (xDNN). Neural Networks. 2020 Oct;130:185–94.

14. https://www.ibm.com/blogs/research/2019/08/ai-explainability-360/ [Internet]. Ai explainability 360.

15. Zhao Q, Li G, Cai J, Zhou MC, Feng L. A Tutorial on Internet of Behaviors: Concept, Architecture, Technology, Applications, and Challenges. IEEE Communications Surveys and Tutorials. 2023;

16. Elaine S, Hubert C, Eleanor R, Richard C. Privacy-preserving aggregation of time-series data. In: Network and Distributed System Security Symposium. 2011.

17. D. Team. https://datatransferproject.dev/dtp-overview.pdf,2018.dtp-overview.pdf.

18. M. G. Organisation. mydata-white-paper-english-2020.pdf [Internet]. 2020. Available from: https://mydata.org/wp- content/uploads/2020/08/mydata-white-paper-english-2020.pdf

19. S. Team. https://solidproject.org/. 2021. Home·solid.

20. Lin JCW, Srivastava G, Zhang Y, Djenouri Y, Aloqaily M. Privacy-Preserving Multiobjective Sanitization Model in 6G IoT Environments. IEEE Internet Things J. 2021 Apr 1;8(7):5340–9.

FINANCING
The authors did not receive financing for the development of this research.

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

AUTHORSHIP CONTRIBUTION
Conceptualization: Imane Moustati.
Data curation: Imane Moustati.
Formal analysis: Imane Moustati.
Research: Imane Moustati.
Methodology: Imane Moustati.
Project management: Noreddine Gherabi.
Software: Imane Moustati.
Supervision: Noreddine Gherabi and Mostafa Saadi.
Validation: Noreddine Gherabi.
Display: Imane Moustati.
Drafting - original draft: Imane Moustati.
Writing - proofreading and editing: Noreddine Gherabi and Mostafa Saadi.