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Techno-economic assessment of building energy efficiency systems using behavioral change: A case study of an edge-based micro-moments solution

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ABSTRACT

Energy efficiency based on behavioral change has attracted increasing interest in recent years, although, solutions in this area lack much needed techno-economic analysis. That is due to the absence of both prospective studies and consumer awareness. To close such gap, this paper proposes the first techno-economic assessment of a behavioral change-based building energy efficiency solution, to the best of the authors' knowledge. From the one hand, the technical assessment is conducted through (i) introducing a novel edge-based energy efficiency solution; (ii) analyzing energy data using machine learning tools and micro-moments, and producing intelligent, personalized, and explainable action recommendations; and (iii) proceeding with a technical evaluation of four application scenarios, i.e., data collection, data analysis and anomaly detection, recommendation generation, and data visualization. On the other hand, economic assessment is performed by examining the marketability potential of the proposed solution via a market and research analysis of behavioral change-based systems for energy efficiency applications. Also, various factors impacting the commercialization of the final product are investigated before providing recommended actions to ensure its potential marketability via conducting a Go/No-Go evaluation. In conclusion, the proposed solution is designed at a low cost and can save up to 28%–68% of the consumed energy, which results in a Go decision to commercialize the technology.

1. Introduction

Recent predictions assume that the urban population is expected to double by 2050, leading to a surge in the overall urban power consumption from approximately 240 EJ to more than 730 EJ (Carréon and Worrell, 2018). Particularly in urban areas, only the building sector consumes more than 35%–40% of the overall energy used in such environments and accounts for roughly for more than 50% of the CO_2 emission (Giraudet, 2020). That elects buildings as the primary power consumer and the principal contributor to gas emissions (Sayed et al., 2021a; Pan and Zhang, 2020). Also, the consumption could be further increased due to some unexpected circumstances. e.g., the COVID-19 pandemic and its impact on energy consumption in households because of isolation practices, which have promoted teleworking and e-learning, and hence has boosted the energy usage in residential buildings (Qarnain et al., 2021; García et al., 2021). Consequently, developing green buildings, including measures to curtail energy usage, has become a current challenge, in which governments, decision-makers, and utility companies invest large sums of money annually to develop innovative solutions to promote energy efficiency (Al-Kababji et al., 2020; Strielkowski et al., 2021). The market of energy efficiency systems is driven by users' and governments' requirements for higher energy efficiency in residential buildings. That could be achieved by incorporating cutting-edge energy-saving technologies, such as the Internet of things (IoT), artificial intelligence (AI) and machine learning (ML), and edge/cloud computing (Barzegar et al., 2020). On the

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Nomenclature

AI	artificial intelligence
B2B	business-to-business
B2C	business-to-consumer
BMC	business model canvas
CAGR	compound annual growth rate
DACR	device active consumption range
DFM	data Fusion Module (DFM)
DOT	device operation time
DSPC	device standby power consumption
DNN	deep neural networks
DRED	Dutch residential energy dataset
DT	decision tree
EBT	ensemble bagging tree
HVAC	heating, ventilation, and air conditioning
ICT	information and communication technologies
IoT	Internet of things
KNN	k-nearest neighbors
KAM	knowledge abstraction module
LDA	linear discriminant analysis
LR	logistic regression
ML	machine learning
MLP	multi-layer perceptron
NB	naive Bayes
NPV	net present value
NGO	non-governmental organizations
PaaS	platform-as-a-service
QUD	Qatar University dataset
QOS	quality of service
PCB	printed circuit board
RF	random forest
ROI	return on investment
SaaS	software-as-a-service
SiD	simulated dataset
SVM	support vector machine

other hand, human-centered solutions focusing on the analysis of consumers' behavior change through big data analytics, anomaly detection techniques, and recommender systems are also receiving increasing attention (Xu et al., 2021b; Alsalemi et al., 2021).

Although the interventions to the buildings can significantly reduce energy consumption, they are costly and are more challenging to apply in old buildings or buildings that are already in use (Soares et al., 2021). That has raised the potential of IoT-based solutions that perform lightweight interventions to the building and promote change by adding sensors or actuators that can be controlled using AI and information and communication technologies (ICT) (Himeur et al., 2021a). In this line, energy providers, policymakers, and end-users have become progressively more aware of the importance of these technologies and behavioral change towards energy saving and reduction of carbon emission in residential (Zhu et al., 2021; Xu et al., 2021a) and office buildings (Rafsanjani et al., 2020). In this context, an increasing number of research works (Iwasaki, 2019; Himeur et al., 2021b) and projects (e.g. MOBISTYLE (Barthelmes et al., 2018)) as well as commercial products. For example, Hive (AlertMe, 2020) provides a wide range of smart products (thermostats, lights, cameras and motion sensors, etc.), which can be controlled through a mobile app or using popular personal assistant services such as Alexa, Google Assistant, and Siri. In a simpler approach, Ecois.me (Ecoisme, 2020) provides a smart sensor that can be attached to the main electrical panel. Hence, it automatically identifies the connected appliances and their consumption. Similarly, Loop (Loop, 2020) provides a monitoring kit, a mobile application, and a recommendation engine for finding the best energy provider per case scenario. Although commercial applications are primarily targeted into monitoring and analytics, research projects capitalize on the potential of change towards a more sustainable behavior, and they address the detection and matching of consumer attitudes with specific recommended actions (Sardianos et al., 2021). For example, the Eco-Home Diagnosis program in Japan (Iwasaki, 2019) studies the behavioral intentions of people to reduce energy consumption and the factors that influence their decisions. Similarly, the EnerGAware project (Casals et al., 2020) evaluates the effect of gamification in reducing domestic energy consumption. The MOBISTYLE project (Barthelmes et al., 2018) combines gamification (e.g. an energy-saving mission) with analytics to motivate users towards energy saving. In contrast, the $(EM)^3$ project (Alsalemi et al., 2019) employs intelligent recommendations and analytics to shape more efficient behaviors gradually. Besides, the Schools4energy framework in Pietrapertosa et al. (2021) attempts to strengthen the educational awareness towards energy consumption using analytical methods, co-creation, and gamification. Generally speaking, the intelligent systems deployed in the building energy sector aim to monitor all the possible aspects of user activity that consume energy, evaluate the impact of all actions and behaviors on the energy-saving potential, and prioritize the recommended actions accordingly (Starke et al., 2020). Moreover, to further maximize the recommendation acceptance rate, they consider the elasticity of users' needs and estimate the probability of positive users' responses to a recommended energy-saving action (Ashouri et al., 2018; Varlamis et al., 2020).

However, the adoption of technology-based energy-saving solutions in real-world applications is still a challenge since individuals are unaware of their power usage and effectiveness. Hence, they are unable to adopt energy-efficient actions. Additionally, the cost of installation and end-users privacy preservation solutions is still an obstacle, especially when cloud data centers are deployed to meet the computing requirements of the solutions. On the other hand, when developing and commercializing any new energy efficiency solution, a techno-economic assessment should be conducted (Das et al., 2021) to evaluate its marketability potential (market assessment). Explicitly, a thorough analysis of the energy-saving market's forces, drivers, barriers, risks, opportunities, and potential competitors must be conducted in addition to the technical evaluation and validation. Put simply, before launching a new solution, performing a market assessment is of utmost importance to estimate the potential customer base. Thus, a properly implemented marketability study aids in (i) understanding how to deploy the new solution with limited resources; and (ii) comprehending how to pursue the best market opportunities while providing the greatest return on investments. By contrast, failing to conduct an accurate marketing assessment may lead to wasting resources, missing on market opportunities, and lowering the return on investments (Akinyele, 2017).

Intending to meet the objectives mentioned above, this paper proposes, to the best of the authors' knowledge, the first techno-economic study that discusses the technical and business potential of a novel edge-based energy efficiency system based on behavioral change. In this regard, the proposed energy-saving solution adopts an efficient AI classifier, a micro-moment analysis concept, and an explainable recommender system to boost energy saving in buildings. This solution is mainly adequate for buildings relying only on electricity for their energy-related needs. However, it can also be used for other kinds of buildings that use gas or different fuel types. That is because our solution is built upon the Home Assistant open-source platform, which is the main engine for collecting and fusing data from any IoT device and delivering personalized recommendations to a smartphone app. In this context, the hardware and software contributions of the proposed solution are explained in detail with a focus on three case scenarios: (i) data collection; (ii) data analysis and anomaly detection of energy consumption; and (iii) explainable recommendation generation. Moreover, we conduct a comprehensive **Go/No-Go** marketability evaluation based on discussing four areas related to the most recent products, patents, research projects, and commercialization strategy considerations. In this line, a market assessment study is performed to evaluate the commercial potential of a new energy-saving product based on behavioral change and micro-moments. We also provide overall recommendations based on a cursory examination of (i) possible competing products, (ii) existing/published patents, (iii) business model, (iv) market barriers, (v) market drivers, and (vi) commercialization considerations.

The main objectives of this article, which are in essence its novel contributions, are summarized below:

- Discussing related work to inform the current research initiatives on the application of ICT to curtail energy demand and realized that implementation in real scenarios is still lagging due to lack of marketability and economic analysis.
- Proposing a novel energy-saving solution based on behavioral change, in which a robust ML classifier and micro-moment analysis are used to detect abnormal energy consumption. Moreover, an explainable recommender system is introduced to recommend contextual and engaging recommendations to end-users and incentivize them to adopt the recommended actions. Whereas the use of explainability in recommender systems is still in its infancy, to the best of the authors' knowledge, there is no commercial energy-saving solution built upon the explainable recommender systems.
- Designing the hardware/software prototype of the proposed solution, which includes two main parts: (a) the smart plug and (b) the mobile app. The former encompasses sensing devices that capture different kinds of data and safely store them in a secure database.
- Conducting the first techno-economic analysis of behavioral change-based energy-saving solutions, where the proposed solution is considered a case study. Specifically, the technical validation is performed with regard to four use case scenarios, including data collection, data analysis and anomaly detection, explainable recommendation generation, and data visualization.
- Assessing the marketability potential of the proposed solution in comparison with existing products.
- Providing recommendations based on a Go/No-Go marketability evaluation of the proposed energy-saving solution.

Fig. 1 presents a graphical illustration of the structure and main contributions of the proposed framework.

The rest of this paper is organized as follows. Section 2 discusses related work that adopt the ICT tools, behavioral change, and recommender systems to promote building energy-saving as well as the marketability of building energy-saving solutions. Section 3 dives deeper into the technical contributions of our paper, in which the $(EM)^3$ framework[1] is introduced. In Section 4, the technical contributions of the proposed solution are evaluated with reference to four use case scenarios. While Section 5 assesses its marketability potential. Finally, Section 6 concludes this work with the next steps for improving the $(EM)^3$ solution and strengthening its marketability potential.

[1] $(EM)^3$: Consumer Engagement Towards Energy Saving Behavior by means of Exploiting Micro-Moments and Mobile Recommendation Systems (http://em3.qu.edu.qa/).

2. Literature review

Various frameworks, patents, and products have been proposed in the literature to promote energy saving in buildings. In this section, we perform a comprehensive investigation of the state-of-the-art by analyzing several energy-saving works from different sources. In addition, because our paper focuses on a techno-economic analysis, we also survey the frameworks highlighting the marketability of various solutions in the energy sector and then derive their pros and cons.

2.1. Energy saving solutions based on behavioral change

Recent advances in green energy efficiency allow modern buildings to save energy by more than 50% compared to ordinary buildings and can even produce energy with energy-producing add-ons (e.g., photovoltaic or wind generators). Such technology can further reduce consumed energy (Aydin et al., 2019a). However, access to this kind of buildings is still minimal, especially in developing countries, because of the high cost of designing green buildings with structural improvements. Therefore, in addition to the structural changes in the buildings and the technological advancement of appliances, the change in user behavior is supported by a large variety of ICT solutions that combines consumption monitoring and recommendations (Jia et al., 2017).

In this subsection, to be fair in conducting our literature review, we focus on reviewing the existing energy-saving solutions that are commercialized or in the pre-commercialization phase. However, other state-of-the-art research frameworks have been proposed and validated for some use case scenarios, although they are far from being commercialized. For example, the work of Nguyen and Aiello (2013) offers an exciting survey of energy-intelligent buildings based on user activity. The more recent work of Alsalemi et al. Alsalemi et al. (2019) focused on the habitual behavior change and surveyed the more recent works. Moving on, in Petkov et al. (2011), a survey is conducted to provide the main indications to design motivation-specific energy-saving feedback. Accordingly, eco-visualizations have been examined along with norm comparison, temporal self-comparison, one-on-one comparison, and ranking. That mainly helped in exploring the potential of socializing energy-saving feedback. Moreover, the feedback has been embedded in a mobile app named EnergyWiz, allowing consumers to compare their actual consumption with their past performance, neighbors, other EnergyWiz users, and contacts from social networks. Similarly, the authors in Timm and Deal (2016) investigate the crucial role of human behavior in reducing energy consumption by studying the impact of real-time information on affecting building occupant attitudes and behaviors toward energy-saving use. In doing so, different buildings have been outfitted with a central data visualization dashboard of the buildings' real-time power consumption, and a six-week energy behavioral change campaign has been conducted as well. Moving forward, in Iria et al. (2020), a mobile gamification app is proposed for fostering the endorsement of energy-saving behaviors in workspaces. The mobile app encompasses various kinds of dashboards that provide multiple benefits, among them (i) increasing users' awareness using an information dashboard; (ii) engaging users in real-time energy-saving competitions using a gaming dashboard; (iii) promoting peer competitions and comparisons using a leaderboard; and (iv) notifying users with tailor-made messages to reduce power consumption using a dashboard.

Conversely, as mentioned above, there are other energy-saving products or solutions in the commercialization phase, although they have some limitations and drawbacks. Most of them are based on the use of AI tools but without considering the importance of the recommender systems to provide end-users with recommendations and explanations to assist in reducing wasted energy. For instance, WatchWire from EnergyWatch (EnergyWatch, 2020) is a cloud-based data management, auditing, and reporting platform, that calculates energy consumption and CO_2 emissions for commercial buildings. It is used

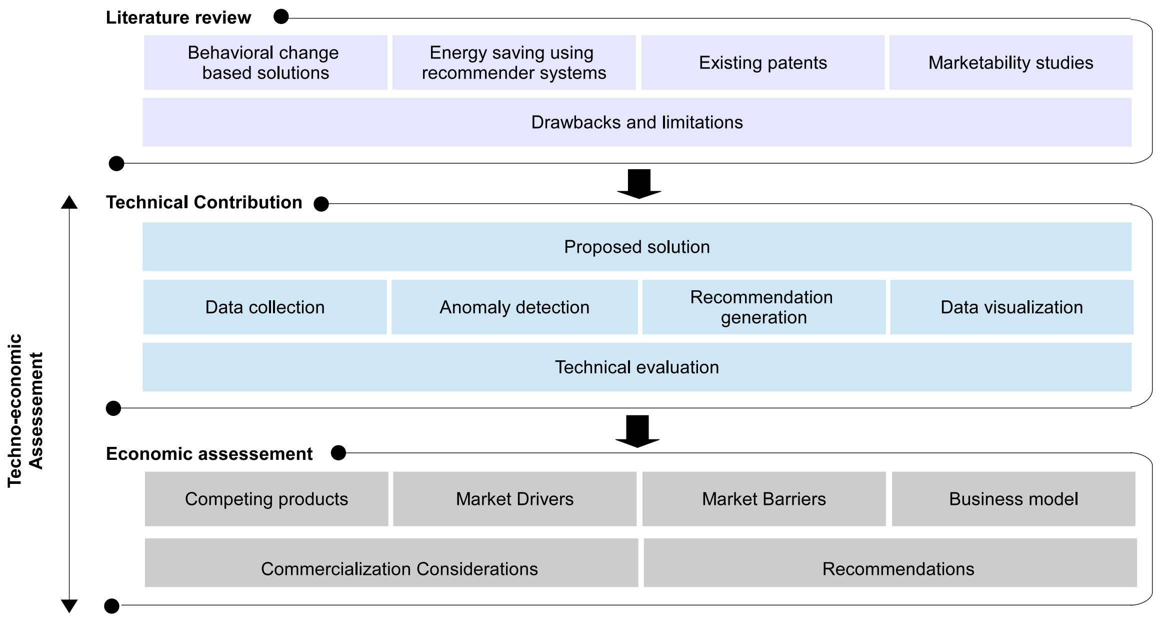

Fig. 1. Graphical illustration of the structure and main contributions of the proposed framework.

to manage the energy efficiency business process, simplify energy reporting, reduce energy expenses and increase energy income. EnergyCAP (Energycap, 2021) is a family of energy management and energy accounting software products used for tracking, managing, processing, reporting, benchmarking, and analyzing utility bills, and providing energy and sustainability information. It is mainly suited for large organizations with comprehensive energy information management needs. Energy Manager from Dude Solutions (Dude, 2021) analyzes utility bills, helps users understand energy consumption, and identifies cost-saving opportunities. The solution is tailored for public and commercial buildings with central utilities. Finally, GreenerU (GreenerU, 2020) provides sustainability solutions for Academic buildings targeting centralized utilities (e.g., HVAC optimization, building automation system, lighting, etc.)

Another group of energy-saving products is mainly addressed for households and smaller private or public buildings. MACH Energy provides a comprehensive suite of energy management software tools (MACH-Energy, 2020)which are primarily targeting public and private buildings. MACH's Initiatives automatically identifies energy-saving opportunities using load profiles of the building and similar buildings in the area and presents facts (e.g., savings in dollars, energy consumption, etc.) that help users prioritize their decisions. Also, SENSE (SENSE, 2020) is developed around a hardware energy monitor installed in the household's electric panel. This module processes millions of current readings per second, identifies device signals, and presents a whole-home consumption view. It also connects with Google Assistant and Alexa to facilitate user interaction. Similarly, the home energy monitor by Neurio (Neurio, 2020) is installed in the household's load panel and provides granular energy data for devices. Table 1 lists the top products, their manufacturer, their relevance to the author's solution, and their application. Moreover, only the SENSE and Home Energy Monitor products have reported the related information in terms of the price. They have been valued at the costs of 300 USD and 200 USD, respectively.

2.2. Energy-saving using recommender systems

With the increasing use of IoT, AI, and big data analytics, recommender systems have found their way into the building energy sector. Typically, while conventional energy-saving solutions considered occupants as immovable objects independent from the energy efficiency problem, solutions based on recommender systems build energy-saving models with human-in-the-loop by encouraging end-users to participate in the optimization process (Himeur et al., 2021a). To that end, using recommender systems to promote efficient and sustainable energy consumption behaviors is receiving significant attention nowadays.

In Wei et al. (2020), energy optimization in a commercial building is formulated as a Markov decision process (MDP), and a deep reinforcement learning (DRL) model is employed for learning energy efficiency recommendations. Following this, DRL is automatically engaged in providing end-users with personalized and engaging energy-saving advice. In Wei et al. (2018), two kinds of energy-saving recommendations are generated using end-users locations and used to promote energy saving in commercial buildings. Accordingly, end-users are recommended for (i) moving from a space to another using "move recommendations"; or (ii) arriving/departing a period-of-time earlier/later using "schedule recommendations". In Sardianos et al. (2020), the authors introduce a goal-based context-aware recommender system, namely REHAB-C, for supporting end-users to transform their energy consumption behaviors in office buildings. Specifically, information related to end-users actions and context is recorded using intelligent sensors, submeters, and actuators before evaluating the proposed energy-saving actions. In this line, after analyzing the data, REHAB-C provides end-users with three kinds of recommendations to trigger an energy-saving action, postpone it or cancel it altogether. Moving on, in Sardianos et al. (2021), aiming at increasing the recommendation acceptance, REHAB-C is augmented with explanations and persuasive facts that are generated for each recommended action. These explanations have been generated for emphasizing either the positive ecological impacts or economic saving prospects. In a similar way, Starke (2019) develop Saving Aid, a recommender system for promoting energy saving in residential buildings by examining the impact of advice solicitation.

Moreover, other frameworks have focused on developing different types of energy-saving recommender systems, such as multi-agent-based (Pinto et al., 2018; Kaur et al., 2019), Rasch-based (Starke et al., 2015, 2017), ML-based (Dahihande et al., 2020; Machorro-Cano et al., 2020), etc. While every type has its pros and cons, it was evident that adding explanations to the recommender framework helps in further increasing the recommendation acceptance rate (Naiseh et al., 2020; Tsolakis et al., 2021). Therefore, there has recently been a move towards developing transparent and explainable recommender

Table 1
Comparison of commercial solutions for energy efficiency based on behavioral change.

Product name	Manufacturer	Relevance	Application
WatchWire	EnergyWatch	Utility budgeting, forecasting algorithm, supply market projections, delivery tariff rates and public service commission rate cases.	Commercial buildings
EnergyCAP	EnergyCAP	Energy management, data presentation troubleshooting, and utility bill accounting workflow.	Work offices, households
Energy Manager	Dude Solutions	Dashboard views, recommending saving actions and reporting	Public & com-commercial buildings
GreenerU	GreenerU	In-depth analysis and understanding of campus energy infrastructure	Academic buildings
Energy Management Software	MACH Energy	Actionable energy data analytics, deep insight into energy usage and costs, tenant billing systems.	Households, public buildings
SENSE	SENSE	Insight into household energy use and home activity through a proprietary iOS, Android, and web apps.	Households
Home Energy Monitor	Neurio	Utility bill accounting workflow, energy reduction tracking, and others	Households

systems (Liu et al., 2020). To that end, we introduce in this framework a micro-moment-based big data analytics and an explainable recommender system, which are components of the overall proposed energy-saving solution. They help in detecting abnormal energy consumption, promoting behavioral change, and boosting energy saving in buildings.

2.3. Existing patents

To extend our literature review on building energy-saving solutions, this section overview existing patents based on behavioral change. Accordingly, Table 2 summaries various competing patents and patent applications. These frameworks indicate the directions of research and development (R&D) and drive the patent literature's state-of-the-art technology. It is worth mentioning that we focus on analyzing existing patents from the standpoint of market competition to highlight their relevance and specific application environment (e.g., domestic applications, office buildings, etc.).

The patent search shows that home energy monitoring is an area of high interest, with novel solutions that improve the current state-of-the-art being actively sought. The absence of any single patent or application that combines the same features, functionality, and approach as our proposed technology is an additional indication of its novelty. In combination, these two factors indicate that the subject technology is of high interest in the market and can provide clear competitive advantages.

2.4. Marketability of energy-saving solutions

To guarantee the success of an ICT-based solution in building the energy efficiency market, it is vital to early assess its marketability potential. The early detection of the market's strengths and weaknesses, needs, and risks will allow introducing and positioning of the product in the market correctly. When designing a sustainable marketable product, it is essential to consider its economic, social, and environmental aspects (Viti et al., 2020). For technology products, e.g., intelligent systems that combine software with hardware, it is also crucial to be technologically advance and at least match the technical features of their main competitors. Monitoring and advisory systems that promote energy efficiency must be offered at lower prices than the competing solutions and should demonstrate higher energy-saving benefits.

According to the net present value (NPV) criterion method (Remer and Nieto, 1995; Ameli and Brandt, 2015), the investment on an innovative project must take into account: (i) the free cash flows, (ii) the overall costs (including materials costs, labor, and operating costs, and taxation), and (iii) the time required for production and deployment. These values have to be projected to the present, future, annual, and capitalized worth values to test the feasibility and sustainability of the marketed solution.

Although to the importance of energy efficiency systems for the stakeholders in the buildings sector (e.g., companies, governments, and the end-users), a few frameworks have been proposed in the literature to assess their marketability. These frameworks begin with the identification of the market barriers and drivers. For example, in Alsop et al. (2017), the authors conduct a market assessment that aims at informing governments and utility companies where the best energy investments could be achieved for meeting the objectives of the united nations and improving the living standards of the population in rural regions. Explicitly, different parameters are investigated to identify the associated strengths and weaknesses of a specific region and which products are more appropriate. While, in Aydin et al. (2019b), Aydin et al. focus on studying the relationship between building energy-saving solutions, their aesthetic characteristics, and their marketability.

In Brey et al. (2018), a marketability study is conducted for analyzing the cost related to the primary change of traditional gasoline and diesel fuels by hydrogen fuel for road transport in Spain with reference to two main aspects, which are (i) the investors active in this sector, and (ii) the consumers who will consume the fuel. Moving forward, the authors in Nanduri and Kazemzadeh (2012) present a bi-level and array game-theoretical model for assessing economic impacts and making operational decisions in carbon-constrained restructured energy-based markets. Thus, a reinforcement learning scheme has been used to consider different learning and adaptive factors of the market's participants. While in the early work of Brambley et al. (2005), the authors assess the market for building controls (plant control and maintenance, energy recording and saving) and systems (heating, ventilation and air-conditioning, lighting, security, fire/life safety, and access control). They identify the principal value proposition by (i) enhancing the indoor environment and building an economic activity and (ii) decreasing the building maintenance and operations expenses.

On the other hand, different techno-economic analysis studies have been proposed in the literature to assess the commercialization potential of different energy-based solutions. Among them, photovoltaic- and thermal-based smart building energy systems (Behzadi et al., 2020), hybrid photovoltaic and solar-thermal systems (Herrando and Markides, 2016), solar photovoltaic power-to-heat-to-power storage (Datas et al., 2019) and optimal control of battery storage (Engels et al., 2019). However, to the best of the authors' knowledge, no extensive techno-economical assessment of energy-saving solutions based on behavioral change has been evaluated.

2.5. Limitations and drawbacks

The early work of Heinemeier (1998) introduced eight categories for assessing the marketability of energy-related systems: the system intent, the system value, the action to be taken, the required system reliability, the user notification, the user role, the system cost, and the size of the

Table 2
Description of existing energy efficiency based behavioral change patents.

Patent ID	Relevance	Environment	Assignee
EP2318891A1 (Hoeynck and Andrews, 2010)	Collecting sensor-based occupancy and predicting consumption	Domestic/office buildings	Robert Bosch GmbH
US20140099614A1 (Hu and Zira, 2014)	Analyzing user activity data, identifying anomalous consumption and optimizing energy usage	Households	Lark Technologies Inc
US20140058806A1 (Guenette et al., 2016)	Energy saving using a network-connected, multi-sensing learning thermostat	Households	Google LLC
US20170132722A1 (Nikolopoulos and Staikos, 2017)	Promoting energy saving using real-time social energy behavioral change	Households	-
US6633823B2 (Bartone et al., 2006)	Systems and methods for monitoring and control of energy consumption systems	Households	Michael D. Murphy
US20100286937A1 (Tsypin and Raghu, 2010)	Promoting behavioral change via the estimation of specific energy usage and statistical analysis of collected data	Households	Bizen Green Energy Corp
US9411323B2 (Tappeiner, 2016)	Behavioral energy consumption change and appliances monitoring using IoT devices	Households	LOWFOOT Inc
US9927819B2 (Kolavennu, 2018)	Providing end-users with consumption statistics and controlling of appliances remotely	Households	Honeywell
US20120296799A1 (Playfair and Hammond, 2012)	System, method and computer program for energy use management and reduction	Households	LOWFOOT Inc
US9732979B2 (Fadell et al., 2017)	Optimizing energy consumption of HVAC using behavioral change and a thermostat	Public/domestic buildings	Google LLC
US20110313579A1 (Ling, 2011)	Energy consumption reducing by comparing the temporal habit pattern with current environmental parameters	Households	-

market. These categories influence the methodology for the marketability assessment of any energy-related solution. The analysis of Aydin et al. on the marketability of energy-efficient buildings (Aydin et al., 2019a) identifies the lack of their widespread adoption. It associates it with the market failure and applicability problems of the integrated design approach. It considers it as a significant impediment to the marketability of energy efficiency solutions in buildings. The current lack of an integrated building design that accommodates intelligent energy-saving solutions can be an opportunity for future marketability endeavors.

Another major drawback of existing approaches is that they leave the human factor out of their scope. Although the frameworks mentioned earlier have been proposed to assess energy-saving systems' marketability, a few works have targeted the behavioral change-based energy efficiency issue. Moreover, no one has used the micro-moment paradigm. Even when humans are considered part of the energy-saving ecosystem, existing energy efficiency frameworks (i) provide innovative visualizations of energy consumption in an attempt to gamify the energy efficiency process (Fraternali and Herrera Gonzalez, 2019; Koroleva et al., 2019) but do not help users to perform better with on-time and context-aware recommendations; (ii) target only the energy-consuming HVAC appliances and do not provide a complete solution for households, commercial or office buildings (Wei et al., 2018); and (iii) offer generic recommendations and tips in order to increase awareness but do not consider the actual needs and habits of people (Paredes-Valverde et al., 2020) and do not generate eco-friendly alternatives.

In conclusion, contemporary research approaches have several features that promote behavioral change, such as gamification or visualization to motivate users through competitions or reward. However, these approaches lack automation and mainly rely on user input to achieve energy-saving outcomes. The proposed solution, $(EM)^3$ aligns with future research directions and promotes behavioral change by proactively prompting users to perform energy-saving activities. The latter includes switching the lights off when they exit a room, turning the A/C off when the external weather conditions allow it, or minutes before they leave for work, and so on. That is made possible by analyzing users' profiles and detecting habitual actions that are gradually shaped to promote energy efficiency. Commercial approaches and products such as SENSE or Neurio provide accurate recording of energy consumption but still rely on users' decision to save energy. They do not provide recommendations for energy-saving actions. Also, they do not address these recommendations at the right moment to increase the acceptance of recommendations and the resulting impact. Moreover, the $(EM)^3$ integrates the concept of explainability into the recommender engine, which represents an essential component of the overall solution. That is to increase the recommendation acceptance rate and incentive end-users to adopt recommended actions. Whereas the use of explanations in recommender systems is still in its infancy, no commercial energy-saving solution has already been built using the explainable recommender systems.

The proposed $(EM)^3$ solution overcomes all the aforementioned limitations in one solution by (i) combining sensors and smart-plugs; (ii) taking into account users' habitual actions and focusing on the most promising to behavioral change and the most beneficial ones (in energy-saving); (iii) capitalizing on the interaction with the users who take the final decision for an energy-saving action or can decide to automate this process. In addition, the emphasis is on recommendations' acceptance, so they are persuasive, addressed in the proper context, and aware of user needs and habits. Visualization and comparative analytics add to the effectiveness of the action recommendations and help transform habitual users' behaviors.

3. Micro-moments based energy efficiency solution

Although there are some hardware and software products available for this area, none appears to be based on the "micro-moment" paradigm to monitoring and analyzing human activity within households. Specifically, most of them are based on cloud computing. However, we present an edge-based solution in our case, which makes the subject technology novel in its approach. Beyond its technical foundation, the technology subject also appears to compare favorably with features and functionality. It also appears to be expandable to cover additional parameters such as humidity and temperature.

This section presents a detailed description of the $(EM)^3$ based energy-saving solution, which is developed for inducing conscious energy consumption behavior. That is possible using a micro-moment analysis that helps detect abnormal energy consumption events and

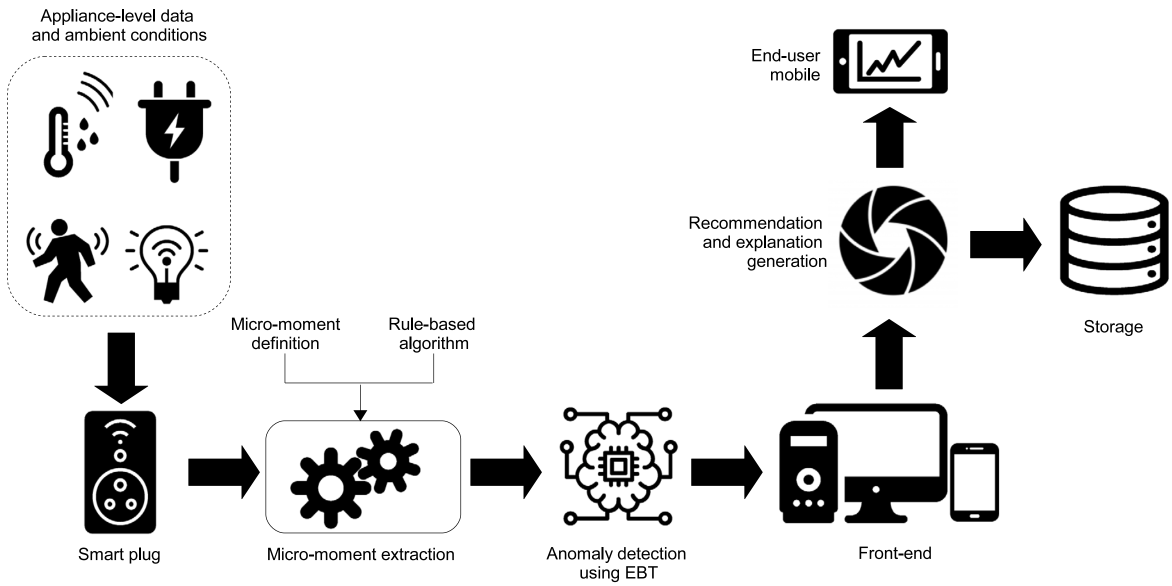

Fig. 2. Flowchart of the (EM)^3 energy-saving solution based on micro-moment behavioral change.

a recommender system to provide end-users with tailored and timely advice (Alsalemi et al., 2020b). Fig. 2 illustrates the (EM)^3 framework, which encompasses a set of components as follows:

1. Data collection: gathers electricity consumption footprints, occupancy patterns, and ambient conditions.
2. Micro-moment analysis: identifies abnormal power consumption behaviors using an ensemble bagging tree (EBT) classifier (Himeur et al., 2020; Sayed et al., 2021b)
3. Recommendation and automation: provides end-users with tailored recommendations for endorsing responsible energy use and possibility for monitoring appliances (Chronis et al., 2020)
4. Statistics and visualization: offers end-users their energy consumption statistics effectively and engagingly through a mobile app and facilitates the visualization of anomalous consumption data.

3.1. Data collection

The (EM)^3 solution includes two main hardware components, a smart plug, and a mobile app. In this context, the smart plug encompasses sensing devices that are used to capture data and safely store them in a secure database (Alsalemi et al., 2020). Accordingly, it records ambient conditions (i.e., indoor temperature and humidity, room luminosity, and occupancy patterns) and power consumption for various domestic devices (e.g., light bulb, computer, TV, etc.). It also provides contextual micro-moment information, including operating an appliance, and adjusting the settings of an appliance, visualizing anomalous consumption of an appliance at a given time (Alsalemi et al., 2020a). Moreover, multiple smart plugs are installed at the building to collect rich micro-moment-based data. On another side, a No-SQL CouchDB server database is utilized for storing data, i.e., end-users micro-moments and occupancy data, user preferences and habits, power-saving recommendations, and its acceptance level.

3.1.1. Scalability

In addition to the low-cost property of the (EM)^3 solution, scalability is one of the main advantages of such architecture. In effect, it provides both embedded and external plug-and-play connectivity. Because every device is managed independently or in combination with other appliances based on the end-users preferences and habits, the (EM)^3 solution could seamlessly scale to more scalable case scenarios with other appliances and monitoring options needed. Moreover, the requirements essential to implement the solution are resource-efficient thanks to its reliance on low-cost yet high accuracy sensors and open-source software and hardware building blocks. Also, it does not depend on the number of observed appliances, and hence it is virtually effortless to expand this application in larger spaces.

3.1.2. Privacy preservation

When speaking of the marketability of energy efficiency frameworks, it necessitates a deeper look into the incumbent issues surrounding data management strategies, particularly ones concerned with end-user privacy. The growth of cloud computing has allowed unique access to data through possibly secure Internet servers. Many cloud providers have real-time (or nearly real-time) data transactions. They can also include a bundle of additional helpful functionality for end-users to improve the collection and analysis of data. As a result, in the grand scheme, cloud computing is on the rise to become the default data storage choice, especially for energy-efficient systems.

On the other hand, privacy and cyber security problems emerge, particularly in cloud-based solutions. Questions as to whether the data is fully secure on a third-party server can become severe. Also, even though the data is stored on a cloud server operated by the data owner, concerns regarding the device's reliability can come to light. For instance, how well is the device secured against cyber attacks? Hence, this survey is of critical significance when working with comprehensive energy profiles that can be used in harmful ways.

In this context, that is one of the main reasons behind focusing on local data storage disconnected from the Internet and available only to end-users in the "intranet" of the building (e.g., a house, an education building, a workspace, etc.). Security is virtually assured in terms of data protection and external threats (except when physical interference occurs or where the intranet is hacked). All in all, a local storage solution may be deemed plausible if no external internet link is needed.

However, a device disconnected from the Internet will quickly become redundant due to the continuous change in end-user behaviors, behavior patterns, and subsequent analyzes of those changes. If the data quality does not alter, the retraining of ML algorithms with new external data is appropriate. Inevitably, a hybrid model would emerge, providing a balance between local storage and cloud processing. Critical data may be stored on-site on a private cloud server. Open datasets, device algorithms, and user interfaces can be maintained on a cloud platform on the Internet.

Table 3
Micro-moment classes definition and description for anomaly detection.

Label	Class	Micro-Moment Description
0	Good consumption	<95% of appliance's maximum active power consumption rate
1	Turn on	Switch on an appliance
2	Turn off	Switch off an appliance
3	Excessive consumption	>95% of appliance's maximum active power consumption rate
4	Consumption while outside	Appliance consumption if on while occupants are not present

3.2. Data analysis and anomaly detection

To define normal or abnormal consumption, a micro-moment analysis is conducted on the collected time-series power consumption data. Therefore, the micro-moment classes are identified to describe power consumption observations of each appliance, they have been drawn using the occupancy profile analysis (O) and power consumption (p) of every domestic appliance with regard to device operation time (DOT), device standby power consumption ($DSPC$) and device active consumption range ($DACR$). In doing so, the micro-moment classes are defined as "class 0: good usage" refers to the case when power consumption is less than 95% of the maximum active consumption rate; "class 1: turn on the appliance" refers to the micro-moment when the end-user turns an appliance on, "class 2: turn off the appliance" represents the micro-moment of switching off an appliance. These two classes are fundamental as they describe the intent-driven moments of decision-making, i.e., starting a consumption or stopping it; "class 3: excessive consumption" is an abnormal consumption that is related to the case of having an excessive consumption, either by exceeding 95% of the maximum active consumption rate or exceeding the DOT; and "class 4: consumption while outside" refers to the case of consuming energy while the end-user is absent. That is considered abnormal consumption for an ensemble of device categories, including the air conditioner (A/C), television, light lamp, desktop/laptop, and fan. Accordingly, for these kinds of appliances, the presence of the end-user during their operation is a must to not consider their energy consumption as abnormal. Table 3 summarizes the micro-moment classes defined and detected in this framework to analyze end-users power consumption behavior.

The last two categories result in losing a considerable amount of energy. Therefore, it is of essential to detect this kind of anomalous consumption and correct end-users' behaviors. That is achieved via promoting end-users with personalized advice via the (EM)^3 mobile app, which notifies them to take energy-saving actions when an anomalous consumption behavior is detected.

The adopted strategy for clustering the energy observations into the micro-moment classes (M^{2}C) over time can be described as follows:

- **Step 1. Micro-moments definition:** energy consumption observations p of each electrical device and occupancy patterns O gleaned at a sampling rate t are firstly gathered and saved into a database backend. Following, the aforementioned appliance operation criteria, i.e., $DACR$, DOT and $DSPC$ are defined to be used later for classifying each energy pattern into a specific micro-moment class. Table 4 illustrates a typical example of various device operation specifications, which have been employed in the rule-based algorithm for extracting energy consumption micro-moments.
- **Step 2. Rule-based micro-moment extraction:** a rule-based algorithm is introduced for extracting the micro-moment classes of the energy usage observations $p(t)$, as it is described Algorithm 1.
- **Step 3. Anomaly detection using EBT:** in this stage, each power consumption observation of a specific micro-moment group is classified using the labels generated in the previous step. To that end, the EBT classifier is deployed, which is a low-cost yet powerful classification model. It is mainly suitable for edge-based applications due to its low computational complexity, although it did not receive its merit in the literature and practical frameworks. Indeed, its importance comes from the fact that it could attain excellent classification performance using an aggregation of different weak classifiers.
The concept of EBT is straightforward and based on the bagging idea, which is also named bootstrap aggregation. The latter is based on fitting diverse independent training models and then averaging their prediction outputs. That helps in obtaining a new model with better performance and lower variance. Unfortunately, fitting completely independent models is almost impossible in practice since it requires a massive amount of data. To that end, the approximate property of bootstrap ensembles (i.e., independence and representativity) is used for fitting models, which are almost independent.
Accordingly, different bootstrap sets are firstly created while everyone is acting as another (almost) independent dataset derived from the true distribution. Following, a weak classifier is fitted for every set before aggregating all of them by average their outputs. That results in a new ensemble model with better classification

Algorithm 1: Proposed rule-based algorithm for extracting power consumption micro-moment features.

Result: M^{2}C: the vector of micro-moment features
Read $p, O, DACR, DOT,$, $DSPC$ and O_T: operation time;
Initialization: M^{2}C = ∅ **while** $t \leq l$ *(*with l is the length of the power signal*)* **do**
  Rule 1: Non-excessive usage
  if $p(t) \geq min(DACR)$ **and** $p(t) \leq 95\% \times \max(DACR)$
    M^{2}C(t) = 0 (Good usage);
  Rule 2: Switching on a device
  if $p(t) \geq \min(DACR)$ **and** $p(t-1) \leq \max(DSPC)$
    M^{2}C(t) = 1 (Turn on device);
  Rule 3: Switching off a device
  if $p(t) \leq \max\ (DSPC)$ **and** $p(t-1) \geq \min\ (DACR)$
    M^{2}C(t) = 2 (Turn off device);
  Rule 4: Consumption exceeds 95% of DACR or DOT
  if $p(t) \geq 95\% \times \max(DACR)$ **or** $O_T(t) \geq DOT$
    M^{2}C(t) = 3 (Excessive consumption);
  Rule 5: Consumption without presence of the end-user
  if $O(t) = 0$ **and** $p(t) \leq 0.95 \times\ DSPC$
    M^{2}C(t) = 4 (consumption while outside);
end

Table 4
Power consumption specifications for different home appliances.

Appliance	DOT	DACR (watts)	DSPC (watts)
Air conditioner	15 h 30 min	1000	4
Microwave	1h	1200	7
Oven	3h	2400	6
Dishwasher	1h 45 min	1800	3
Laptop	12 h 42 min	100	20
Washing machine	1h	500	6
Light	8 h	60	0
Television	12 h 42 min	65	6
Refrigerator	17 h 30 min	180	0
Desktop	12 h 42 min	250	12

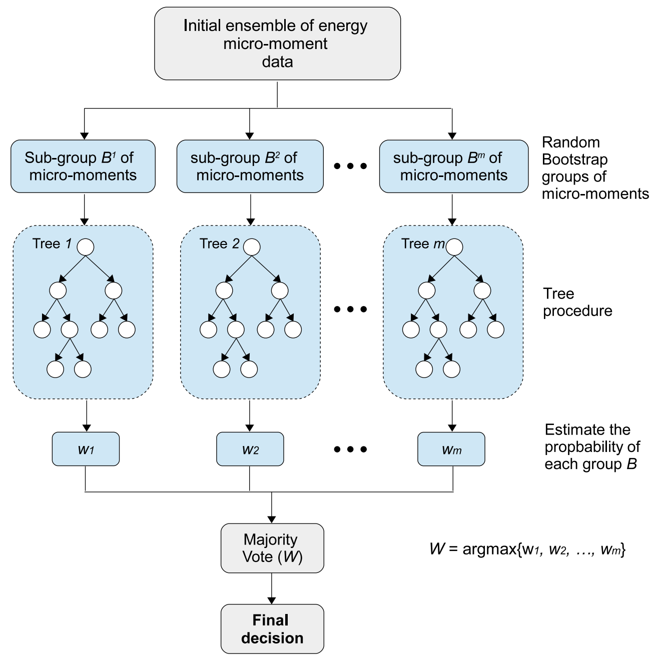

Fig. 3. A simple explanation of the EBT classifier used to classify energy micro-moments and detect anomalies.

accuracy and minor variance than its components. Put differently, because bootstrap sets are roughly independent and identically distributed (i.i.d.). Hence the same can be said for learned base classifiers. Typically, when we average the prediction outputs of weak classifiers, we reduce its variance, which is the concept of i.i.d., i.e., the variables are randomly averaged.

In this context, energy micro-moment patterns extracted using the rule-based algorithm are divided into m bootstrap groups (each one includes S samples):

$$\left\{B^1,\ B^2,\ldots,\ B^m\right\} = \{b_1^1,\ b_2^1,\ldots,\ b_S^1\},\ \{b_1^2,\ b_2^2,\ \cdots,\ b_S^2\},\ldots,\{b_1^m,\ b_2^m,\ldots,\ b_S^m\} \tag{1}$$

where every weak classifier is trained on a specific group via a tree procedure, and therefore an ensemble of probabilities $w_1, w_2, \ldots, w_m$ is produced. Moving on, a majority vote is conducted for estimating the final probability W, as follows:

$$W = \arg\max(w_1, w_2, \ldots, w_m) \tag{2}$$

Therefore, W refers to the probability of the ensemble model with a lower variance. Lastly, the final classification decision is then produced using the predicted probability. Fig. 3 presents the block diagram of the EBT classification adopted in this framework.

3.3. Explainable recommendation generation

The (EM)^3 ecosystem integrates a recommendation system based on combining data from various sensors, smart meters, actuators and then arranging a software application, which helps in endorsing energy-saving via the generation of intelligent, tailored, and explainable recommendations. The (EM)^3 framework is the first energy-saving solution that assists the end-users with explanations for supporting their decision-making, increasing their trust, and improving the acceptance of recommendations. The overall architecture of the (EM)^3 recommendation system is depicted in Fig. 4, which also shows the interactions between the sensor, actuator, software, and knowledge storage components. The energy-saving framework implemented in (EM)^3 is based on using the anomaly detection feedback and a series of scenarios that enable detecting extraneous device use and properly combining multi-modal data in order to reduce wasted energy. Precisely, (EM)^3 forecasts the micro-moments corresponding to a user action and pro-actively generates personalized advice that can further decrease energy consumption. Moreover, appliances working without the user's presence are automatically detected, and the user is notified to turn them off.

The aggregation of multi-modal data is deployed at the first stage to extract information about the user's status, the building and the outdoor environment, and their relations. For example, using the input from the smart-plug and the inside and outside temperature and humidity sensors, it is possible to detect a case of unnecessary air conditioning usage and recommend actions that can stop it or help avoid it. The knowledge abstraction module (KAM) of (EM)^3 allows efficient handling of the large amount of data generated from the sensors and smart meters. It also generates aggregated user statistics that depict recent user habits, recent indoor and outdoor conditions patterns, and advantage knowledge. The latter concerns the combination of conditions and user actions, e.g., room occupancy probability at any given time, the preferred indoor light level thresholds for each user, etc.

Real-time room occupancy, appliance consumption, and environment-related data, along with knowledge about user habits from the Knowledge base, are fused into the data fusion module (DFM), which detects moments for triggering energy-saving actions. Instead of directly applying such automation, (EM)^3 builds on the habit loop theory of behavioral change and uses these moments for building a better energy-saving profile. The platform issues actionable recommendations to the users in real-time and asks for user feedback before performing the recommended actions. These special moments are denoted as the energy micro-moments, and information about user preferences and habits is stored in the system's knowledge base.

3.4. Data visualization using the (EM)^3 mobile app

The (EM)^3 architecture uses the (EM)^3 mobile app, which aims to boost energy saving by providing end-users with innovative visualizations of their consumption footprints in real-time. The (EM)^3 mobile app has been built upon the Home-Assistant open-source platform,[2] which enables to provide end-users with recommendations and gathers user feedback (i.e., accept, reject, or ignore). Fig. 5 portrays the essential screens of the (EM)^3 mobile app. Accordingly, it demonstrates the mobile app's functionalities where the end-users can receive notifications regarding their energy consumption with areas of improvement. Moreover, the (EM)^3 mobile app helps end-users visualize their consumption footprints and the surrounding environmental data.

4. Technical validation

4.1. Scenario I: Data collection

In terms of the hardware implementation, the smart plug encompasses a printed circuit board (PCB), a 3D-printed casing, a plug, and a socket extension, as illustrated in Fig. 6(a). The core of the smart plug is the PCB. The board, as in Fig. 6(b), features a self-powered mechanism through the line of the appliance, eliminating the need for a separate power source to operate it, an occupancy sensor, a luminosity sensor, a temperature and humidity sensor. Also, a relay is included to enable remote appliance operation. In addition, invasive energy monitoring is employed due to the direct connection with the appliance. It is worth noting that the system consumes an average of 45–60 mA, which is used in the analysis and recommendation generation processes. The PCB is conceived to accommodate two micro-controllers categories, which could offer the best compromise between the cost and computing performance. Therefore, it could support both the Arduino MKR-1010

[2] https://www.home-assistant.io/.

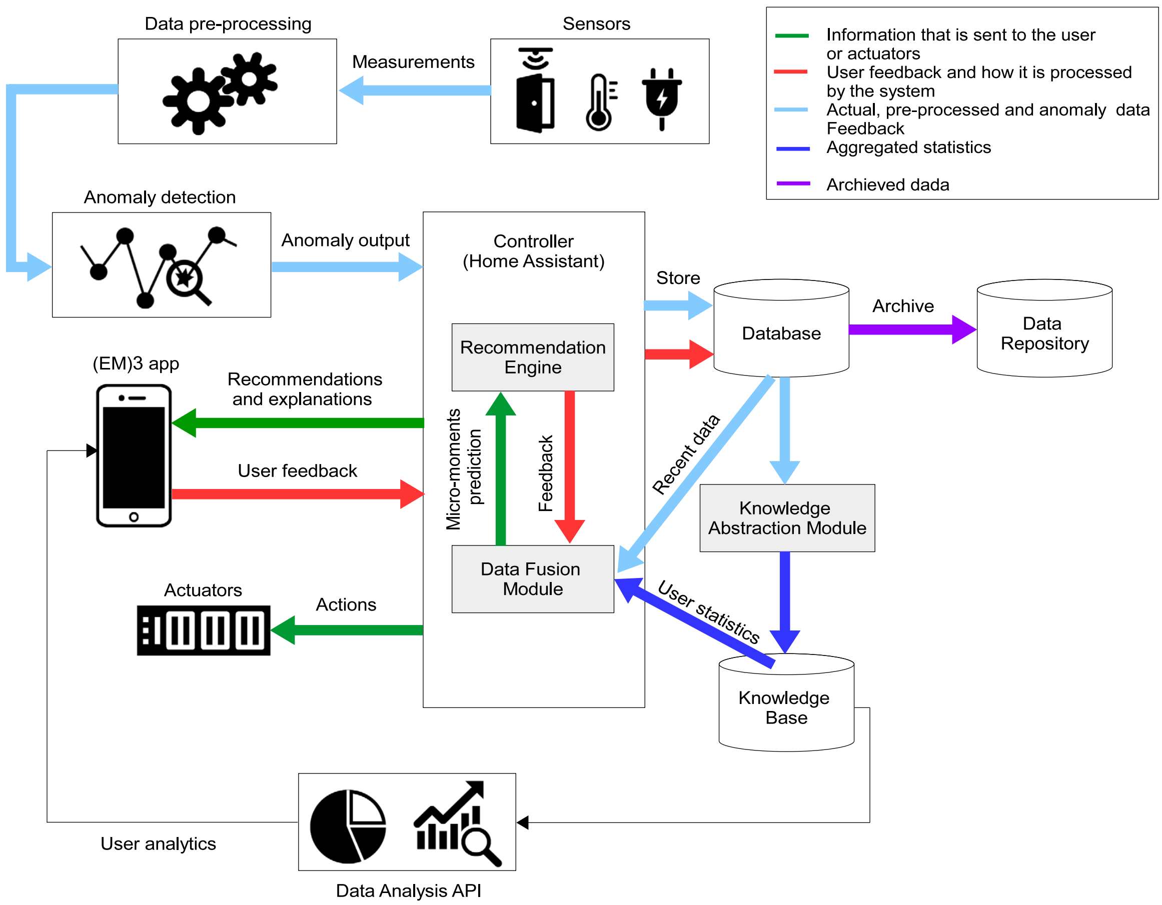

Fig. 4. The core architecture of the (EM)^3 system and the explainable recommendation extensions.

Table 5
Performance of the (EM)^3 Smart plug per micro-controller.

User board name	Processing speed (s)	Communication latency (s)	Cost (US $)
ESP-WROOM-32	0.16	3.19	10
Arduino MKR 1010	1.05	2.25	33.90

and the ESP32 micro-controllers. Specifically, this enables additional testing in terms of performance and wireless capabilities. To provide the reader with more details, we have computed and compared the performance, communication latency, and costs in Table 5. Regarding the cost of the (EM)^3 smart plug, the latter could be built with a cost ranging between 20 USD–40 USD depending on the used micro-controller. That is considered highly cost-effective compared to its capability to improve the adoption of residential power consumption monitoring technology. Further cost reduction can be performed when mass-producing the components, allowing for scalable deployments.

4.2. Scenario II: Anomaly detection

4.2.1. Anomaly detection performance

To validate the (EM)^3 solution for the anomaly detection, we proceed with the tests on (i) real-world data collected via QUD and DRED datasets and (ii) simulated dataset (SiD) that is produced to fit the end-users daily consumption in a typical building. Moreover, the empirical evaluation is conducted in comparison with various ML classifiers, i.e., logistic regression (LR), linear discriminant analysis (LDA), support vector machine (SVM), naive Bayes (NB) decision trees (DT), random forest (RF), multi-layer perceptron (MLP), k-nearest neighbors (KNN) and deep neural networks (DNN). Fig. 7 illustrates the obtained results with reference to (a) accuracy and (b) F1 score. It has been seen that the proposed EBT classifier outperforms the other classifiers under the three datasets. Accordingly, using EBT, more than 1.2%, 1.3%, and 2.7% accuracy improvement have been obtained compared to DNN (which is ranked in the second position) under QUD, DRED, and SiD, respectively. On the other hand, more than 1.8%, 1.85%, and 3.3% F1 score improvements have been achieved compared to DNN under QUD, DRED, and SiD, respectively.

4.2.2. Electricity saving rate

To assess the energy-saving potential of the (EM)^3 solution, we first measure the number and percentile of detected anomalous events under the three datasets considered in this framework. Table 6 summarizes the number and percentage of patterns detected in each class, including those referring to abnormal usage (i.e., class 3: excessive energy consumption and class 4: consumption while outside). Specifically, it has been seen that abnormal usage (class 3 + class 4) states 67.49%, 68.67%, and 28.66% under QUD, DRED, and SiD, respectively. Therefore, it is evident that massive anomalous behaviors have been detected in both QUD and DRED, which means that by following the recommendations generated by the (EM)^3, a large amount of energy could be saved (more than 68% of consumed energy). On the other side, moderate anomalous energy usage has been identified under SiD, which has attained 28.66% of total used energy. Consequently, more than 28% of electricity could be saved in the case of SiD.

A real-world experiment was conducted by three users from the research team at Qatar University energy lab (QUEL), which includes different cubicles that in turn incorporate many appliances used by each user. Thus, the system was installed in QUEL, as a proof-of-concept. Fig. 8 portrays the overview of the test-bed used to validate the energy-saving solution based on the recommendation system. The

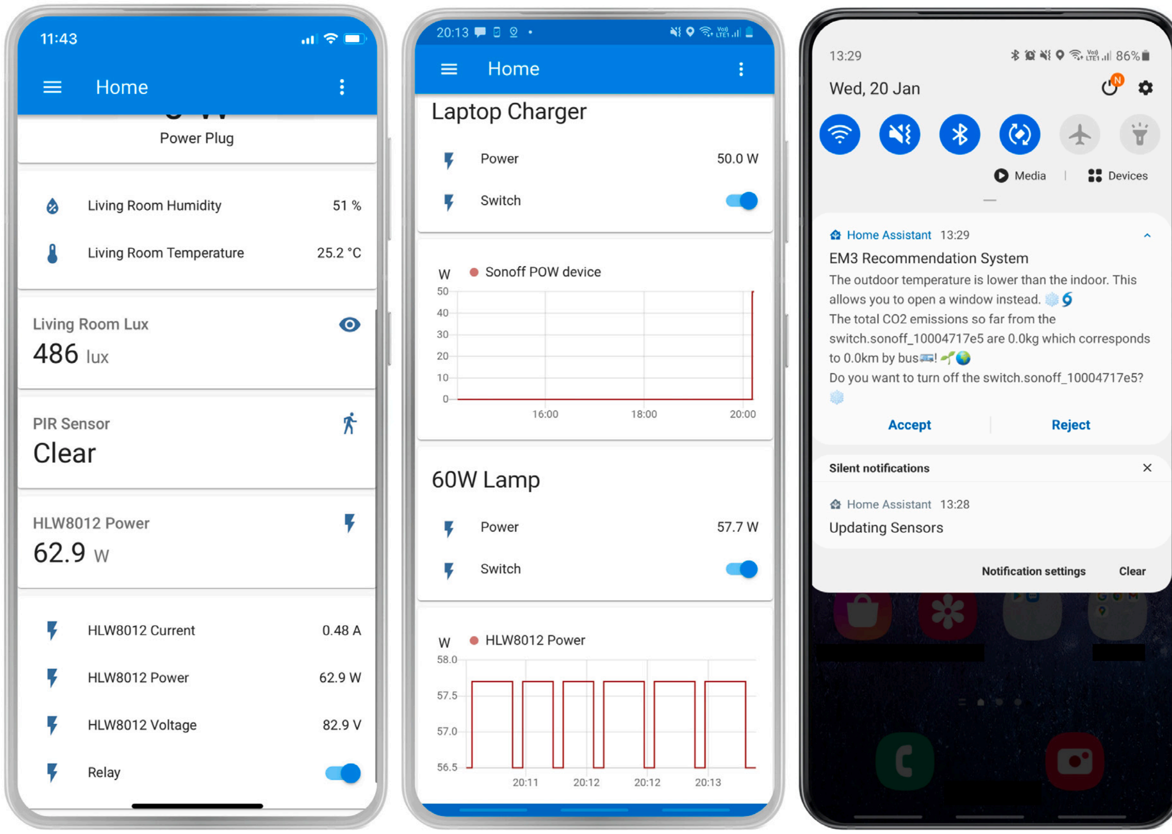

Fig. 5. $(EM)^3$ mobile app built upon the Home-Assistant platform, denoting, the (left) environmental data, (middle) power consumption visualization with appliance control, and (right) generated recommendations.

Fig. 6. Anatomy and PCB of the implemented smart plug.

data collected is then saved to the QUD repository. In this regard, based on the time-series data collected during the experiment, normal and abnormal patterns were identified, and their percentiles were calculated with regard to the overall number of observations (as explained in Table 6). Typically, excessive consumption represented an abnormal percentile of 8.42%, while consumption while outside attained an abnormal percentile of 59.07%. Therefore, the overall abnormal percentile was 67.49%. Also, the average monthly energy consumption has been recorded for two consecutive months before using the $(EM)^3$ and then compared with the result obtained during another month after adopting the $(EM)^3$ to inform the behavioral change and energy-saving rate. Accordingly, it has been seen that up to 68.03% of energy consumption has been saved by using the proposed solution, which represents a slight difference compared to the previously calculated rate using the percentile of abnormal patterns. This saving rate has been reached because of the generated explainable recommendations that helped the end-users correct their abnormal energy consumption habits.

Similarly, the abnormal consumption percentiles that can be corrected using $(EM)^3$ for the case of DRED and SiD have also been estimated, where they have reached 68.66% and 28.66%, respectively. By consequence, based on the three scenarios considered in this framework, it is clear that the $(EM)^3$ can have a saving rate of 28%–68% when end-users are provided with appropriate and explainable recommendations.

Overall, the amount of energy that can be saved using the $(EM)^3$ solution depends mainly on the end-users abnormal energy usage behaviors. For this framework, it is worth noting that 28%–68% of the total energy consumption has been detected as abnormal. Thus, the same quantity could be saved if personalized and explainable recommendations are produced to assist end-users in optimizing their energy consumption.

Table 6
Number of anomalous energy patterns along with the anomaly detection rate (percentile) obtained using the $(EM)^3$ solution for each dataset.

Micro-moment description	Class label	# micro-moment patterns					
		QUD		DRED		SiD	
		# patterns	Percentile (%)	# patterns	Percentile (%)	# patterns	Percentile (%)
Good usage	0	12114	25.81	45482	32.75	59,425	56.53
Turn on a device	1	1568	3.34	3315	1.99	7780	7.4
Turn off a device	2	1569	3.34	3316	1.99	7779	7.4
Excessive consumption	3	3954	8.42	35044	21.06	6343	6.03
Consumption while outside	4	27725	59.07	79196	47.6	23,793	22.63
Total		46930		166353		105,120	

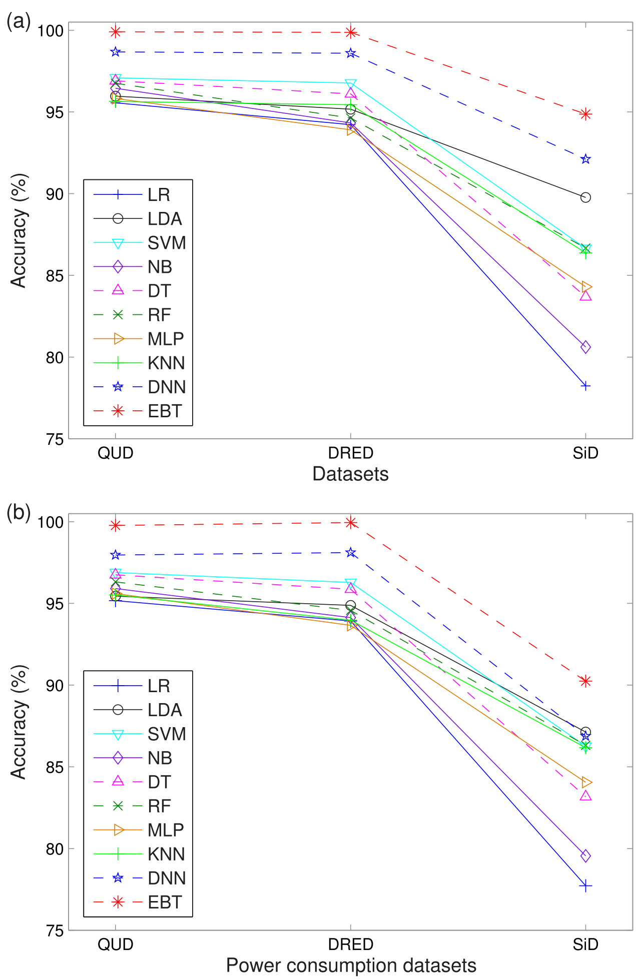

Fig. 7. Anomaly detection performance of the $(EM)^3$ solution in terms of: (a) the accuracy, and (b) F1 score achieved under QUD, DRED and SiD datasets.

4.3. Scenario III: Recommendation generation

Based on the different types of energy efficiency recommendation systems and the latest demand towards explainable AI solutions, it is evident that the dimensions of *Explainability* and *Persuasion* are almost missing in the energy efficiency recommenders. Interpretable models focused on straightforward processes for determining the recommended items make it simpler to produce proper straightforward justifications to explain why the model recommended each specific item (Zhang et al., 2014). However, few contributions in the energy conservation research area include a basis for providing explainable recommendations.

In the recommendation generation scenario, the $(EM)^3$ solution builds on the ecosystem depicted in Fig. 4, in order to detect user habits and provide explainable recommendations. Based on the ***micro-moments based recommendation*** strategy, the system discerns the moments of the daily end-user routine, which are usually tied with an energy-related action (e.g., user exits a room) or status (e.g., the user is asleep), or an external condition (e.g., room temperature is low). The approach combines sensors, smart meters, and actuators and predicts the right micro-moment to issue a recommendation. In addition to the recommendation, the user is informed of the conditions that triggered it before receiving a fact related to the expected savings from accepting the recommendation. An example of this use is to learn when the user switches the heating unit on or off in terms of time and environmental conditions, such as temperature and humidity (indoor and outdoor), and associate this information with the respective personalized micro-moments. When the conditions are met for a user, the system generates the right energy-saving action at the right moment, which can be very helpful in reducing energy footprint (Sardianos et al., 2019).

The probability of approving a recommendation raises when the ***recommendation*** has a function, and the purpose is explicitly justified by the (Zhang et al., 2020) customer. In the case of energy conservation, the fundamental goal is to prevent inefficient usage of appliances. The other goal that further decreases electricity consumption could be to limit the use of high energy-consuming machines. In addition to the intent of the recommendation, a variety of considerations that remind the recipient of the advantages of the intervention can help enhance the approval of the recommendation. ***persuasive fact*** improves the advice and allows users create a more energy-efficient profile.

Accordingly, the $(EM)^3$ solution includes built-in several recommendation scenarios to evaluate the performance of the recommendation engine. In the "unnecessary device usage" scenario, the system developed for it can discern the following criteria: (a) the end-user's **presence** in a given room, (b) the **context** — which refers to the indoor and outdoor ambience i.e., temperature, humidity, luminosity, and (c) the consumption **habits** with respect to used domestic appliances . To increase the probability of a recommendation getting accepted, the system explains the recommendation's rationale to the user (***reasoning***) and the benefits from its acceptance (***persuasion***).

The ***reasoning*** element of the explanatory advice focuses on presenting the reason(s) for the recommendation, which, in our case, is strongly related to the unnecessary usage of computers. As a consequence, the explanation for the shutting off of a cooling or heating system could be due to the actual atmosphere factors (e.g., temperature and humidity or merely "apparent temperature") being identical to those inside and the device is still operating. While all of these energy-saving steps can be effectively applied using sensors and automation, the usage of guidelines brings humans into the loop. It allows them to determine how to meet energy saving targets (Alsalemi et al., 2020b).

The ***persuasion facts*** serve as an extension to the critical explanatory nature of the suggestion, which attempts to convince people to follow the recommendation by pointing out the advantages to the customer by following the suggested action. The **Eco** (a.k.a. ecological) category of facts is directed at consumers who prefer the environmental aspects of their energy use. Such examples are meant to improve persuasiveness and serve as a motivation element for consumers involved in positive ecological behavior but who require a catalyst to inspire

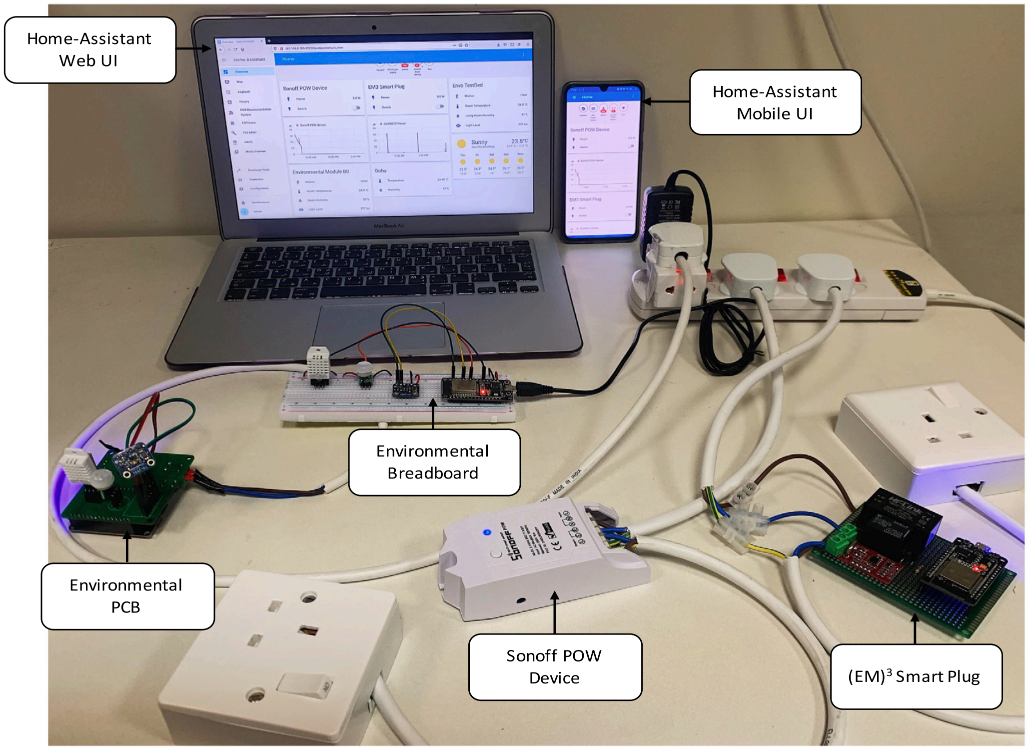

Fig. 8. Overview of the test-bed used to evaluate the (EM)^3 solution.

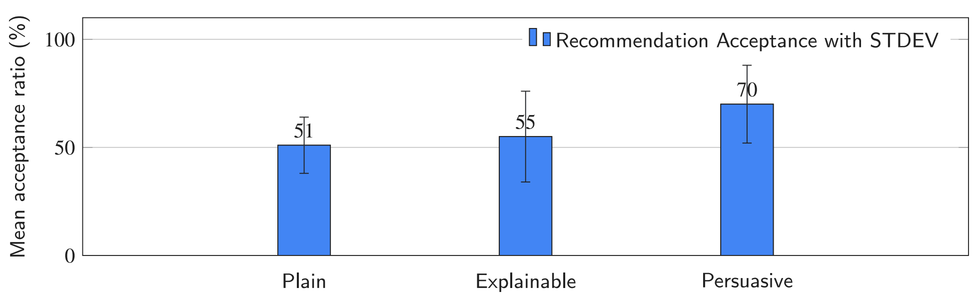

Fig. 9. Average recommendation acceptance ratio and standard deviation for plain recommendations, explainable recommendations, persuasive recommendations cases.

them. The **Econ** (a.k.a. economic) form of advice targets people who value their financial savings over the world. It is an alternative to the Eco form of advice for consumers who are mainly worried about the financial aspects related to energy usage (electricity or gas).

Fig. 9 illustrates the evaluation of the energy-saving recommendations, only 16.5% of the issued recommendations have been ignored. When comparing plain recommendations with their explainable and persuasive versions, we identified that the persuasive insights boost the average acceptance rate from 51% to 55%. On the other side, using the explainable and persuasive recommendations, the performance is 19% higher than using only plain recommendation messages, reaching an acceptance ratio of 70%.

5. Economic potential analysis

After analyzing the technical contributions of the (EM)^3 solution, it is of utmost importance to investigate its economic potential on the profitability of the energy-saving-based behavioral change on the building's energy consumption. In this way, from an economic point of view, the motivation behind the use of energy efficiency based on behavioral change solutions is discussed. Moreover, the economic analysis helps in designing the business model of the (EM)^3 solution, addressing various market failures, and by contrast exploiting market drivers that help in commercializing this solution.

The economic analysis can be performed with reference to the following points:

- **Technology's maturity level:** according to the setup information of the energy-saving based on behavioral change and micro-moments, the subject technology appears to be in the early stages of development, with crucial components yet to be defined and developed to the working prototype stage.
- **Intellectual property:** following a thorough investigation of the literature, no patent application has been filed for such technology, nor have its technical details been publicly disclosed. Therefore the subject technology may be covered under Trade Secret.
- **Possible competing products:** we found no commercially available systems that utilize the micro-moment concept to analyze human behavior within the home/building and make suggestions based on that data. Also, we did not find any system that clearly provides a more robust feature set. Therefore, the functionality and approach of the subject technology appear novel and may have commercial applications.

- **Possible competing patents:** our brief review of recent patenting indicates a high level of activity involved in developing technologies related to home energy monitoring and management. However, we did not find any single patent or application that evidently combines the same features, functionality, and approach as the subject technology, particularly the use of micro-moments.
- **Possible competing R&D:** recent publicly disclosed R&D appears to indicate a moderate to light level of interest in home energy monitoring, with perhaps 10 to 20 (or so) recent projects which could represent likely competition in the near future. For instance, one energy monitoring system based on detecting and classifying human activities within the home claims an 18% reduction in energy consumption. We found no single project based on micro-moments, nor did we find any project that offers a feature set that compares favorably with the subject technology.
- **Examples of Potential Targets:** a list of potential targets has been described previously in this paper, including SENSE, EnergyWatch, EnergyCAP, MACH Energy, Dude Solutions, among others.

5.1. Business model

In general, the "business model" refers to estimating the economic potential and commercialization prospective of a given solution (Osterwalder et al., 2010). That is achieved by discussing the services to be provided, their identified target market (market drivers and barriers), their competing alternatives, and their anticipated expenses. Therefore, a business model is of relevant importance for deciding whether to proceed with commercialization or not.

A proper business model for the (EM)[3] solution elaborates on its potential to create and deliver value to the potential stakeholders (e.g., prosumers, energy network operators, aggregators, etc.) and how they can get remunerated for their engagement. Typically, the business model is created using the business model canvas (BMC),[3] which is a strategic management template offering a visual representation with components illustrating the value proposition of a new solution, key partners, costs, customers, etc. That assists researchers in aligning their activities following the potential trade-offs. Based on the main sections of the BMC methodology (Kristensen and Ucler, 2016), we describe in this section the various aspects of our business model. Typically, three models have been identified as a good fit for the solution: software-as-a-service (SaaS), platform-as-a-service (PaaS), royalty, and licensing. The business model outlined below will consider a dynamic combination of all the above.

The **Value Proposition** of our solution comprises several benefits for the users. The envisioned solutions and products will ensure technological innovation, prosumer–consumer empowerment, energy savings without compromising comfort levels, a balanced mix of all the required actors of the market value-chain, up-to-date service (software) delivery, as well as cost and time effective solution acquisition over the forecast period (i.e., 2021–2030).

The network of **Key Partners** comprises the following stakeholders: (i) the (EM)[3] consortium members, (ii) commercial ICT infrastructure providers, (iii) (EM)[3] partners, (iv) energy retailers, (v) energy network operators, (vi) local authorities, and (vii) housing associations.

The **Key Activities**, which will ensure that the envisioned solution will provide and deliver its anticipated value proposition. The Key Activities defined here help ensure that the proposed business model can work effectively and efficiently. Primary activities include the following: (i) market R&D, (ii) evaluation of customer needs, (iii) assignment of resources, and (iv) marketing.

The identification of **Market & Customer Segments** is vital in order to get a better picture of the types of groups we are aiming the proposed solutions to be part of. To define customer segments for the envisioned solutions, the groups of individuals need to be determined based on their needs, behaviors, and other traits they share. The identified actors and stakeholders benefiting from the solutions comprise, among others: (i) private/public building owners, (ii) residential consumers, (iii) regional and national companies in the utility and IT, sector in regards to energy solutions for buildings, (iv) energy utility companies, aggregators, energy network operators, local service/technology providers, and (v) environmental associations and non-governmental organizations (NGOs).

Moreover, the envisioned product aims to address a diversified market. The customers we aim to provide these solutions to all have different requirements and needs related to energy efficiency and data visualization. The defined customer segments have few overlaps. However, we see value in investing in all of these diverse segments, including:: (i) evidence-based results on the costs and benefits of ICT-enabled energy efficiency techniques, (ii) clear and real-time guidance, (iii) exploiting micro-moments to create recommendation systems, (iv) data transparency, (v) usable interface design, (vi) ICT Resources escalation, (vii) behavioral engineering, (viii) adaptive incentivization, and (ix) support for exploiting the solution.

The effective distribution of the solution also depends on identifying the Distribution Channels, Customer Relationships, and Revenue streams.

The **Distribution Channels** can be used to present and promote the solution to the potential customers. It is essential to create as many channels and activities as contextually suitable to spread the message effectively. The main promotional channels comprise: (i) pilot demos, (ii) public consultation & standardization, (iii) publications, info days, dissemination activities, (iv) tech partners & their resources, (v) website of the project and the application, (vi) social media marketing and influence groups, and (vii) email campaign tools.

Various promotional activities can be considered for promoting the developed solution (Osterwalder et al., 2010): (i) develop a pitch deck to promote the solution to potential sponsors and/or investors; (ii) set up Google Alerts: Detect where people are talking about the problem the app solves. Also, track where people are talking about the app directly by setting up a branded keyword alert; (iii) promoting through social media channels (e.g., Twitter, LinkedIn, Instagram, Facebook, etc.) (iv) app localization according to market surveys of different focus groups; (v) A/B testing: run pilots of different app versions to different focus groups; (vi) search engine optimization; (vii) in-campus promotion: directly target audiences with physical means, i.e., billboards, posters in academic and corporate premises; (viii) promo video to be used in traditional media and digital (viral) channels; (ix) appeal to app review sites to feature the solution; (x) respond to all reviews: provide personalized communication to existing and potential users; (xi) apply for awards; (xii) write press releases; and (xiii) write email newsletters.

The **Customer Relations** define the types of relationships that will be established with the specific customer segments through an array of different channels. In the case of the solutions provided, the partners aim to engage with the users through channels, such as: (i) building precompetitive applications — proof of impact and return on investment (ROI), (ii) context-aware triggering, (iii) cultural appropriation and localization, and (iv) energy solution for policy development.

The strategic ways in which the project and its partners seek to be paid for the developed solution and their services are depicted in the **Revenue Streams & Pricing Models** section of the BMC. Questions that must be answered include: (i) what value the customers are really willing to pay, (ii) for what do they currently pay, (iii) how they currently are paying, (iv) how they would prefer to pay, and (v) how much each Revenue Stream will contribute to overall revenues. The main identified revenue streams comprise: (i) smart Energy Dashboard subscription, (ii) mobile App revenues (Freemium), (iii) customization and professional services, (iv) consulting, and (v) white label platform offering (PaaS).

[3] https://www.strategyzer.com/canvas/business-model-canvas.

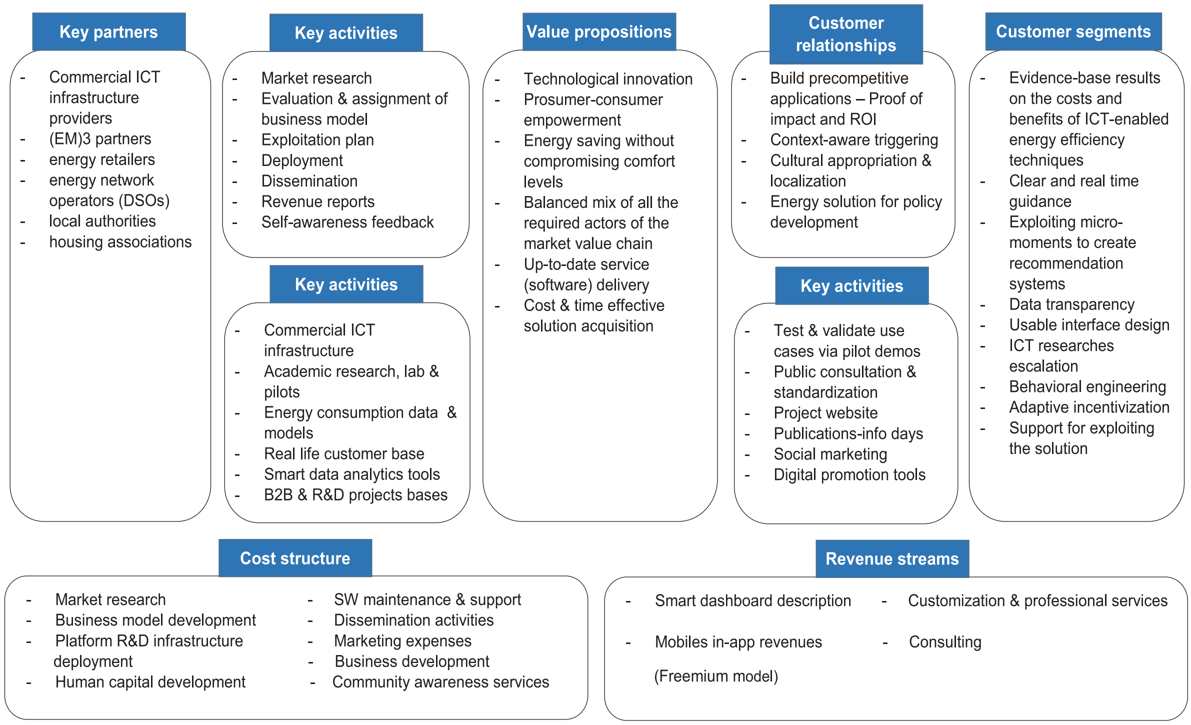

Fig. 10. BMC describing the key sections for the SaaS approach .

The **Key Resources** section defines the necessary resources and skills which help to make this business model and value propositions work. It also emphasizes which distribution channels and customer relationships need to be analyzed to realize the proposed revenue streams. In order to interact with the digital world, the envisioned solutions will need to rely on a sound commercial ICT infrastructure. Furthermore, to effectively spread the message, it is critical to engage in academic research, "labs & pilots". Indeed, when wanting to increase energy efficiency, for any scenario, valid energy consumption "data & models" are necessary; these will rely on a real-life customer base and be created with intelligent data analytics tools. For a well-suited business model to be established, the channels through which customers will be reached need to be discussed and explored. These will mainly encompass business-to-business (B2B), business-to-consumer (B2C), and R&D pathways.

Finally, the **Cost Structure** section involves an estimate of the most substantial costs inherent in the business model. Additionally, it evaluates which Key Resources and which Key Activities are most expensive. Throughout the duration of the project, the main costs are identified as: (i) market research, (ii) dissemination activities, (iii) business model development, (iv) manufacturing, (v) deployment, (vi) human capital development, (vii) platform R&D infrastructure, (viii) community awareness services, and (ix) marketing expenses. Once developed, the solution will mainly include the costs related to handling customer requests and retaining the audience and costs corresponding to human resources required for the further development and maintenance of the assets.

The developed assets will be mainly distributed through three methods: (i) SaaS, ii) PaaS, and (iii) royalty and licensing payments. As mentioned above, for developing the business model prototype, the BMC was used as guidance. To get a more compact view of the identified sections, the partners have combined them into a comprehensive illustration. Fig. 10 identifies the critical sections for the SaaS approach.

5.2. Market barriers

Various market barriers in state-of-the-art hinder the overall adoption of energy efficiency-based behavioral change solutions. In our case, we have identified a set of possible market barriers that could be outlined as follows:

1. High installation costs accompanied by system complexity are envisaged to raise difficulties to the market's growth over the reference period.
2. A number of prominent players are already active in the home energy monitoring market. This includes global companies such as Honeywell International,[4] General Electric,[5] Comcast Cable (Xfinity)[6], Panasonic,[7] and others. These may comprise a formidable challenge to new entrants hoping to gain market share.
3. Lack of consumer awareness concerning home energy management systems (HEMS), behavioral change and the advantages/profits they offer may impede the marketability of the proposed solution.

5.3. Market drivers

On the other hand, we have determined an ensemble of possible market drivers, which are defined as the forces that push individuals to purchase the (EM)^3 product and pay for the proposed services. They could be summarized as follows:

1. The widespread use of smart meters, rising investments related to the smart grid technologies, and growing attention to reducing energy cost by the efficient deployment of power resources are envisaged to driving the market for the hardware segment over the forecast period, with the fastest growth in the Asia-Pacific region (Hossein Motlagh et al., 2020).

[4] https://www.honeywell.com/us/en.
[5] https://www.ge.com/.
[6] https://www.xfinity.com/.
[7] https://www.panasonic.com/global/home.html.

2. Environmental concerns and increasing energy cost have combined to drive interest in making more efficient energy use at home. The necessity for conserving and optimizing energy usage is considered a key market driver.
3. It is anticipated that North America will dominate the energy monitoring market during the forecast period. Such region concentrates on improving and changing their aging infrastructures, enhancing grid reliability, and allowing more intelligent electrical networks, which could boost the demand for energy monitoring systems. Furthermore, the U.S. and Canadian electric utilities are intended for investing USD 880 billion and USD 100 billion, respectively, in electrical and energy networks over the upcoming years 2020–2030 (Andoni et al., 2019). These investments would incorporate different sectors, such as smart grid, digitization, energy monitoring, energy management, and blockchain.
4. Increasing connectivity and widespread endorsement of mobile phones is also expected to positively impact energy market growth.
5. The rising consciousness among energy end-users regarding durable energy usage stimulates demand for energy-efficient devices and HEMS. End-users understand that those systems could not only reduce energy expenses, but they are also playing a significant role in making the existing energy resources more sustainable.
6. Demand for HEMS and monitoring devices has assumed greater importance over the last few years due to the use of variable pricing approaches provided by service providers. Advantageous regulatory policies/initiatives in the U.S. related to energy conservation are intended to incite regional HEMS market growth.
7. Other significant factors driving the HEMS market include the rising Internet penetration across both developed and developing economies, the increasing role of IoT and big data analysis in energy management, booming market for intelligent buildings, etc.
8. The technological development and propagation, together with the reduced sensor and display costs, improved device-level data processing potential, and roll-out of smart utility meters, offer new paths for energy management market growth.

5.4. Commercialization strategy considerations

We believe that the development, commercialization, and eventual market introduction should proceed for the subject technology. One of the first steps could be to seek intellectual property protection in the form of a patent, particularly the part related to its utilization of micro-moments to track and analyze user behavior and activities. However, if protection can be obtained, this may make the subject technology more attractive to potential licensees. It could also make it more difficult to “reverse engineer” products based on micro-moments. When the subject technology is nearing commercial introduction, a campaign to educate the market should be carefully prepared and undertaken. We feel that users could likely make purchasing decisions based on features, functionality, and value rather than the novelty of the fundamental technological approach. Therefore, the performance advantages of the subject technology need to be identified and emphasized. As noted above, one challenge facing the home energy monitoring market is the lack of awareness and understanding among potential customers. This challenge needs to be carefully addressed, with users provided a clear understanding of the subject technology’s benefits over currently available options.

Moving forward, the key findings regarding the commercial potential for the proposed technology could be summarized as follows:

- Likely markets and basis for feasibility: the home energy monitoring, which refers to a multi-billion dollar (and growing) global market opportunity, and several positive factors appear to be driving future growth.
- Indicator(s) suggesting how ample the market opportunity might be: the global HEMS market was worth US$ 1.6 Billion in 2018. Looking forward, the market value is projected at US$ 4.4 Billion by 2024, exhibiting a CAGR of around 17% during 2019–2024.
- Product opportunities: the market niche of energy monitoring and management technologies can likely be adapted seamlessly into the building energy monitoring market for facilities, such as office and municipal buildings, retail stores, sports facilities, and factories.

5.5. Recommendations

We summarize the final decisions following the technical-economic analysis of the $(EM)^3$ solution conducted in this framework by generating a set of Go/No-Go recommendations. Specifically, we have evaluated the potential of the $(EM)^3$ solution based on the following aspect; product, patent, research project, and commercialization considerations. For each area, we have provided one of four scores from (highest to lowest) as below and then an overall score which can be no better than their lowest score of one area. As summarized above, we find several strong positive drivers for this market and challenges that do not present insurmountable obstacles. We can predict that this market is favorable for introducing a novel and superior home energy monitoring and management product.

In this regard, given the technical contributions of the $(EM)^3$ solution, our commercialization strategy considerations, and all the market drivers and impediments, a set of relevant findings have been derived as follows: (i) we conclude a decision “Go” for the subject technology, from different aspects, such as patenting the proposed idea after making more hardware and software improvements and overcoming the drawbacks listed above, developing the final product, and then going forward with its commercialization. That is because we have noticed that a more transparent economic advantage would be obtained in comparison to existing solutions in terms of cost-effectiveness and feature-set (e.g., providing explanations to increase the end-users trust in the generated recommendations); (ii) the combination of anomaly detection based on AI, explainable recommender systems, and data visualization can lead to significant energy saving levels, which can attain 68% of the total energy consumption as the case of the $(EM)^3$ platform; and (iii) the percentage of energy-saving is mainly related to the abnormal energy consumption behavior of end-users, which can vary from a building to another.

6. Conclusion

Developing energy-saving-based behavioral change in the building sector along with adopting efficient ICT-based systems are the immediate and critical solutions to reduce wasted energy in buildings, especially in unexpected global circumstances. The first part of this article discussed the current research initiatives on applying technology to curtail energy consumption and realized that implementation in real-life scenarios is yet lagging due to the lack of marketability and economic studies. Intending to bridge the gap between the potential and currently accomplished energy saving solutions in buildings, this work covered the energy efficiency solutions landscape, from research contributions to patents and commercial products. The second part of this study discussed the key techno-economic findings of this analysis, in which a novel solution was introduced along with a techno-economic assessment. Typically, the solution includes different technical contributions concerning data collection, data analysis and anomaly detection, explainable recommendation generation, and visualization using a mobile app. It also performed a technical validation of the proposed $(EM)^3$ solution in various scenarios that verified the low cost of the $(EM)^3$ platform, the accuracy of its embedded prediction and detection models, and the acceptance ratio of the recommendation it generates in an actual setup. Together, such characteristics appoint the $(EM)^3$ solution a promising candidate for supporting energy-efficient behaviors and promoting clean, green, and sustainable environment.

The economic analysis of the proposed solution examined various aspects that affect the potential of the solution, including the maturity of the employed technology, the handling of intellectual property, the competitors, and the possible adopters. A comprehensive business model that follows the BMC methodology and records possible barriers, drivers, and enablers allowed us to decide on the commercialization of the proposed technology. Accordingly, recommendations for commercializing the solution were drawn after evaluating its marketability potential using a Go/No-Go evaluation.

Nevertheless, the current implementation has some limitations: the physical size of the plug is a drawback, which is considered bulky compared to other existing solutions. Also, the current sensing can be enhanced by using more accurate monitor chips. In addition, in terms of cyber-security, the current implementation lacks the defense mechanisms against cyber-attacks. Moving on, regarding the energy consumption of the heating systems, the $(EM)^3$ solution is mainly adapted to the buildings where heating is provided by electricity. However, it can also deal with other kinds of buildings that use gas or different fuel types as it is built upon the Home Assistant platform. The latter is the main engine for collecting and fusing data from any IoT device and delivering personalized recommendations to the $(EM)^3$ smartphone app.

To that end, it is part of our future work to investigate the use of cutting-edge cyber security and decentralized exchange, such as blockchain. That will reinforce the security on the edge devices and address users' privacy concerns and other security issues in some scenarios, e.g., when sending data to cloud data centers for further complex processing. In addition to its security and privacy preservation salient features, blockchain has other relevant characteristics that can improve the quality of service (QoS) of the $(EM)^3$ solution, i.e., its resilience, adaptability, fault tolerance, and trust features. On the another side, as most of the old buildings are only collecting the overall energy consumption, without any insights about the individual consumption of appliances, an integration with an energy disaggregation module is to be carried out into the $(EM)^3$ platform. Such integration help recognize individual appliances and equipment responsible for any energy consumption in real-world scenarios.

Finally, it is worth noting that the proposed framework is considered a relevant reference for the energy research community and other researchers from the related topics, especially those developing energy-saving solutions and seeking to assess the their techno-economic potential as well as devise business models for improving the marketability of their final products and maximizing their impact.

CRediT authorship contribution statement

Yassine Himeur: Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Abdullah Alsalemi:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Faycal Bensaali:** Funding acquisition, Writing – review & editing, Project administration, Supervision. **Abbes Amira:** Funding acquisition, Writing – review & editing, Project administration, Supervision. **Iraklis Varlamis:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **George Bravos:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **Christos Sardianos:** Conceptualization, Formal analysis, Methodology, Writing – review & editing. **George Dimitrakopoulos:** Funding acquisition, Writing – review & editing, Project administration, Supervision.

Declaration of competing interest

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

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