

A Case Study of Smart Home Development

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// This study describes a framework for integrating intelligent orchestration into smart homes. In addition, we used a design science approach to propose and showcase how the framework suggests scenes or rules tailored to smart home users of a Brazilian company. //



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A SMART HOME consists of the integration of numerous connected entities (sensors and devices) that are capable of communicating with each other, and that can be controlled (via hub or smartphone) for ensuring automation for homes.^{1,2} By simplifying everyday

tasks—like turning on the coffee maker or adjusting the air conditioning temperature—smart homes enhance the home experience and deliver security, practicality, and energy savings.²

When it comes to practicality, smart homes offer the convenience

of controlling all devices via a single interface, for example, on a smartphone, regardless of the user's location.³ Regarding security, sensors can notify the homeowner via smartphone or communicate with other devices, such as alarms and door locks.⁴ Smart cameras, for example, can transmit images and sound in real time, allowing users to view and hear everything on their smartphones.

Although home automation is a reality,⁵ the “intelligent” orchestration of scenes is still the result of research and experimentation. Generally, in a smart home, sensors and devices compose trigger-action scenarios to perform tasks. Sensors provide input to the devices (trigger), and devices take autonomous decisions (actions) based on these inputs.² While trigger-action systems are often straightforward and follow a cause-and-effect logic, they are not necessarily “intelligent” in decision-making or learning capabilities.² In this context, decisions about the actions of devices should reside more in artificial intelligence (AI) and less in human interference.⁶

There are studies demonstrating the potential of AI in smart homes. For instance, Qela and Mouftah⁷ developed an expert system to enhance energy management, while Mandal et al.⁸ proposed Helion, a framework that generates natural home automation scenarios. However, these studies do not address the dynamic and personalized nature of user interactions in smart homes. Differently, Chen et al.⁹ and Jeon et al.¹⁰ used data mining and deep learning to capture and analyze patterns or correlations in devices from the users' behavior. Consequently, their approach

allows the smart home to learn behavior autonomously.

Considering that successful applications of AI in smart homes are still rare, given the complexity of integration and costs,¹¹ we conducted our investigation into the Smart Universe Project, a collaboration between “Company A” and researchers from the Applied Artificial Intelligence Lab (LIAA) at the Federal University of Bahia. Company A is a Brazilian technology company founded in the 1980s that develops electronics and information technology solutions, investing in education, research, and innovation. More specifically, we used a design science approach¹² to propose a smart home framework that uses AI to recommend scenes or rules tailored to Company A users.

Our work builds upon Chen et al.⁹ and Jeon et al.¹⁰ concepts by incorporating similar principles of autonomous learning and pattern analysis. Additionally, we extend these approaches by considering additional device statuses, such as light intensity and air conditioner modes. This enhancement allows our framework to offer a more nuanced and responsive smart home experience compared to previous approaches. Moreover, this article contributes with examples of case scenarios performed within Company A smart homes besides presenting a high-level architecture to support the interaction among users, devices, and AI.

Research Methodology

We adopted a design science research methodology, which involves answering questions relevant to human problems by creating innovative artifacts.¹² We designed and developed a set of artifacts for the orchestration of devices and management

strategies (see the “[Smart Home Framework](#)” section).

The design science methodology emphasizes the importance of proper evaluation.¹² Therefore, we used a case study as a method to apply and evaluate the proposed framework in a single real-world context¹³ (see the “[Smart Home Application](#)” section) to investigate: How does the integration of AI into Company A’s smart home ecosystem optimize the user experience?

Context Selection

Our investigation takes place in the Smart Universe Project, a three-year research collaboration with Company A and researchers from LIAA.

The interdisciplinary collaboration brought together 15 researchers from LIAA into four specialized teams: 1) the Recommendation Systems Team, composed of researchers experts in recommendation systems; 2) the Software Engineering Team, composed of researchers with expertise in software architecture and reuse for highly configurable systems; 3) the Internet of Things (IoT) Team, composed of researchers with expertise in hardware, communication protocols, and IoT device modeling; and 4) the DevOps Team, formed by experts on system deployment. Moreover, four senior researchers managed each team in their respective expertise areas, and two other project managers acted as intermediaries in the connection between the research team and 10 industry practitioners from Company A.

Data Collection

The study was built on two primary sources: 1) datasets with device information to simulate users’ behavior and other artifacts generated through the development of the

AI-based smart home application, and 2) notes taken during meetings between researchers and industry practitioners.

The data collection corresponds to the project development period, from January 2022 until December 2023. As an overview of the project’s workload distribution, some researchers engaged in an average of two weekly meetings, biweekly meetings with senior researchers, and two showcase meetings with Company A per year. The estimated work hours per researcher is 1,416 per year, allocated to developing 10 main activities, further broken down into 42 specific tasks. However, given a non-disclosure agreement, all of the documents and code will remain private.

Data Analysis

First, we analyzed the datasets and other artifacts generated through the development of the AI-based smart home application to describe its architecture. Based on the data our system can handle, we present four case scenarios to optimize energy consumption and comfort (please refer to the “[Smart Home Application](#)” section). Those scenarios showcase the practical applicability of smart homes and offer a holistic view of their outcomes.

In addition, we examined the documents and notes taken in meetings to summarize the challenges and critical insights for AI-based smart home development. The documents describe the investigation of available devices and sensors to derive case scenarios for one or multiple users in the smart home. From this information, we also derived future directions for contributing to the broader landscape of smart home technologies and AI applications.

Smart Home Framework

The concept of a smart home is evolving, from trigger-action systems controlling essential environmental elements to AI-driven ecosystems.¹⁴ In this section, we present our AI-based smart home's architecture and visualization tool that learns from users' behaviors to respond to and anticipate users proactively.

Smart Home Architecture

Figure 1 shows the main components of the smart home, where each color-coded entry represents their respective origins in our collaborative work. The yellow and green boxes highlight the infrastructure provided by Company A and third-party partners. In contrast, the purple boxes represent modules developed by our development team, reflecting our innovative solution tailored for smart homes.

Specifically, Company A integrates prefabricated sensors and devices from a third-party partner that constitute the backbone of smart homes, including motion sensors, presence sensors, light bulbs, switches, door locks, plugs, and robot vacuum cleaners. Our challenge is developing a smart home that integrates those sensors and devices while ensuring efficient end-user control. To overcome this challenge, we sought a solution from a third-party partner, which provides a software as a service (SaaS) cloud architecture to control and manage the devices. On top of that, the third-party partner provides support through application programming interfaces (API) and software development kits (SDK), facilitating the integration and extensibility of our smart home ecosystem.

In addition, the smart home architecture includes the Core and

Smart modules developed by our lab. The Core module is responsible for acquiring data through third-party partner API endpoints and monitoring events. In other words, the Core module works as an orchestrator in our framework, whereas the other modules send and receive data from the Core. The Smart module features an AI based on long short-term memory (LSTM) and multilayer perceptron (MLP).¹⁵ We use the LSTM to process sequential data and capture temporal patterns in user interactions, and the MLP to generate recommendations that operate on the features and outputs generated by the LSTM. In addition, the MLP's performance is evaluated based on user feedback, which helps fine-tune the recommendation process. Users can enable an option to automatically accept or reject recommendations

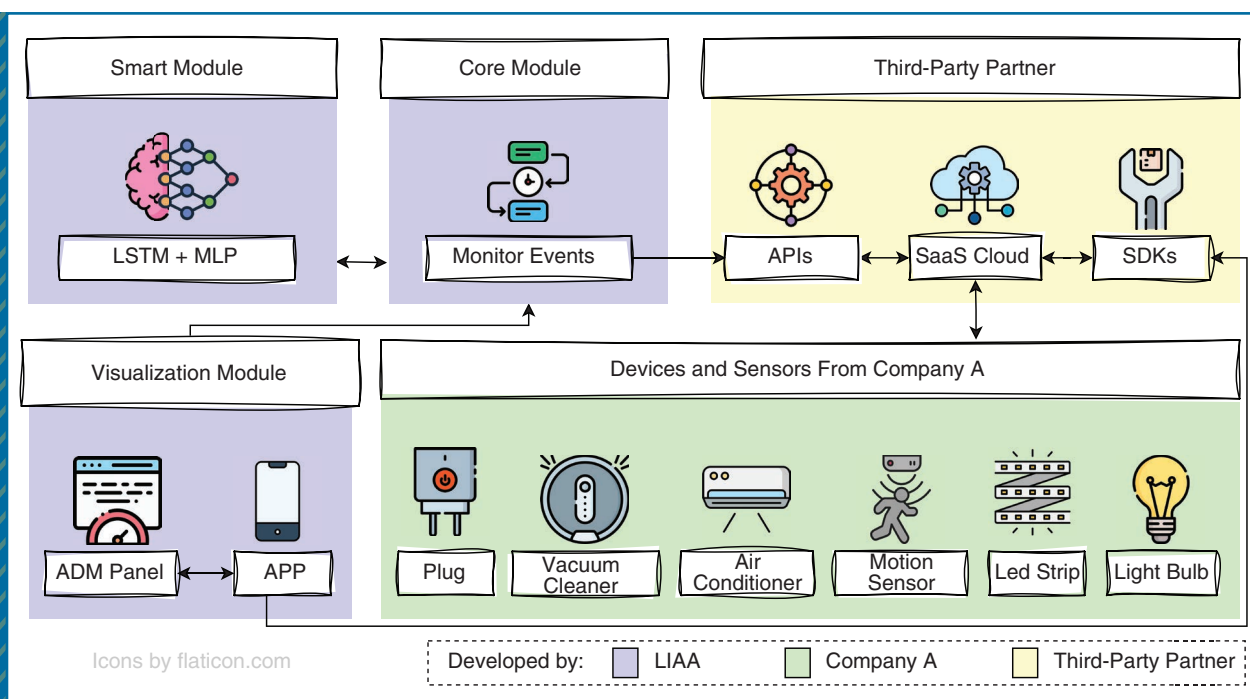


FIGURE 1. A smart home environment and its main components. ADM: administrator; API: application programming interface; LSTM: long short-term memory; MLP: multilayer perception; SaaS: software as a service; SDK: software development kit.

based on a threshold, ranging from 75% to 99%; otherwise, users can also review all recommendations before the system applies them. It is worth noticing that recommendations involving critical actions, such as opening doors, always require manual verification by the user.

All of the recommendations are sent to Core module, which forwards the recommendation message to users through a mobile application. The application uses SDKs from the third-party partner to allow the users to give feedback for recommendations and manipulate devices and houses.

Thus, it is the primary link connecting the devices, house users, and our Core and Smart modules. Through the Visualization module, the system administrator can access an interactive dashboard to visualize the energy consumption and other device-related data from the smart homes.

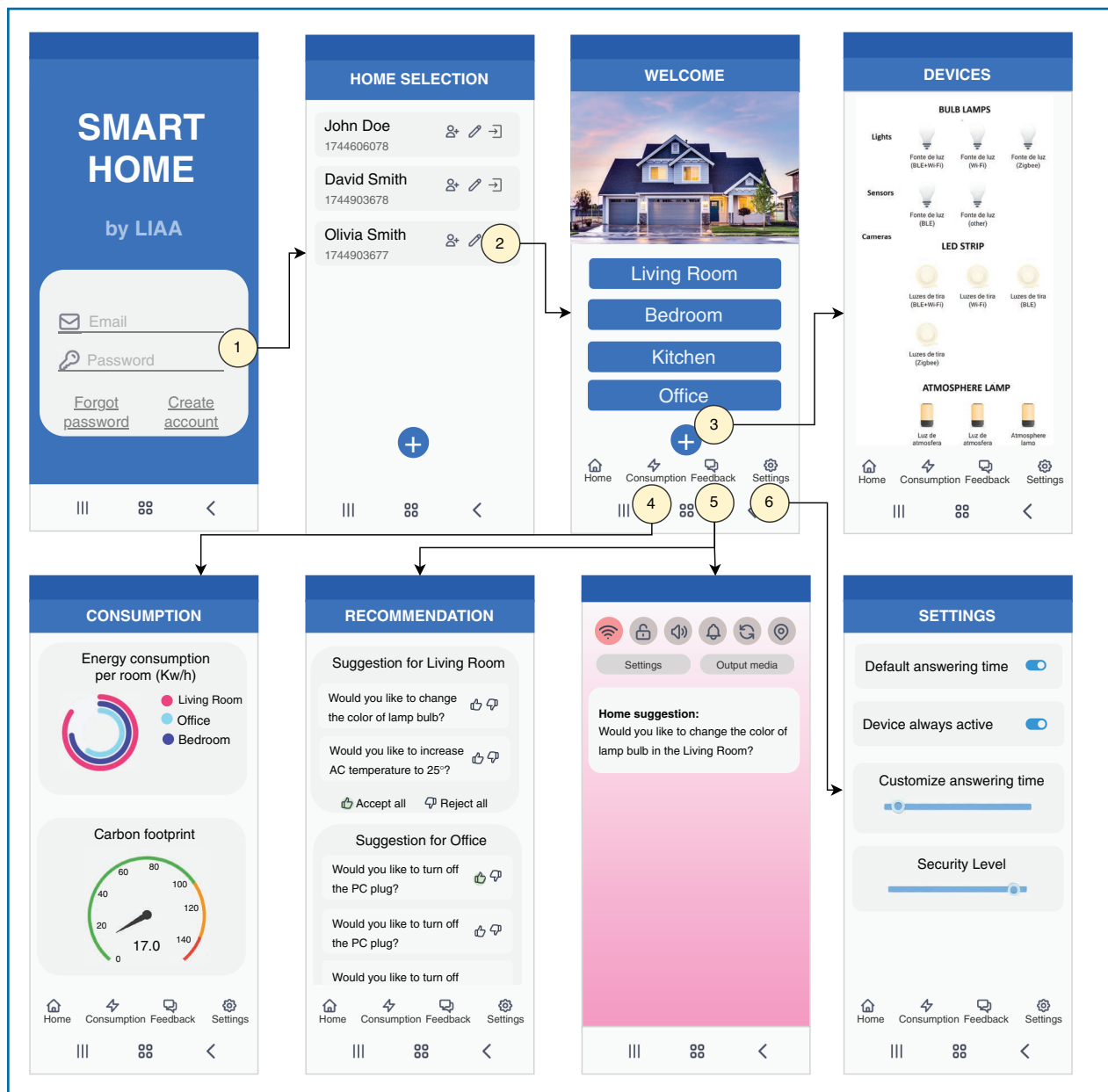


FIGURE 2. Main screens of the mobile application to allow users to interact with the smart home.

Smart Home Visualization Tool

Figure 2 shows the main screens of the mobile application to demonstrate how the users interact with the smart home. Initially, the user creates an account in the application linked with the third-party partner's cloud. Account creation requires the user's name, location, e-mail, and password; the last two are used to log in to the application [(1) in Figure 2].

After logging in, the application shows the Home Selection screen with a list of homes. The application presents three options for each home: 1) invite a member to a home, 2) edit the home information, and 3) enter a home. If the user chooses to enter an existing home [(2) in Figure 2], the application shows the Welcome screen with a list of rooms. For each room, the application shows all of the devices that the user can manage [(3) in Figure 2]. It is worth mentioning that the user can create a new home, room, or device through the floating button at the bottom of the screen.

In addition, the Welcome screen features a navigation bar with buttons to access the Consumption [(4) in

Figure 2], Feedback [(5) in Figure 2], and Settings [(6) in Figure 2] screens. The Consumption screen [(4) in Figure 2], shows charts for 1) Accuracy = (CorrectPredictions)/(TotalPredictions); 2) EnergyConsumption = $\sum_{d \in R} E_d$, where E is the energy usage in kilowatts per hour of a device d in room R ; and 3) (CarbonFootprint = $(\sum_i [P_o(t_i) \cdot T_o(t_i) + P_s(t_i) \cdot T_s(t_i)]) \cdot C$, where $P_o(t_i)$ is the power of the device when it is on at time t_i , $P_s(t_i)$ is the power of the device when it is in standby at time t_i , $T_o(t_i)$ is the time the device was on during interval t_i , $T_s(t_i)$ is the time the device was in standby during interval t_i , and C is the carbon footprint factor.

Meanwhile, if the user selects Feedback [(5) in Figure 2], the application shows a list of recommendations in the last 24 h and their status. To ensure the recommendation is applied at the best moment for the user, the default answering time is set to 10 s. Therefore, the list of recommendations allows users to configure future actions in the home, while the push notification allows the users to accept/reject recommendations.

Last, if the user selects "Settings" [(6) in Figure 2], the application shows the configuration for the answering time and security level. With these two settings, the user can configure the recommendation to be automatically applied if the accuracy level is at least 75% and the time to accept the recommendations.

Smart Home Application

In the first year, the research team implemented a simulation of a smart home environment within a miniature house for experimenting with the smart home architecture.^{1,2} This approach investigated the feasibility and effectiveness of the smart home features, serving as an effective platform for testing and evaluating the main functionalities [Figure 3(a)]. While the simulation did not require extensive physical space, it allowed the management of devices in a smart home without disrupting users' routines. In the second year, the research team scaled up the smart home to a real scenario within an office. The improvement points identified with the simulation were explored in the real scenario, such as grouped recommendations to compose a recommendation scene [Figure 3(a)].

Figure 4 shows a floor plan as the foundation for implementing a smart home. In particular, Figure 4 presents four scenarios for enhancing the living environment concerning the user's comfort (scenarios #1 and #2) and energy efficiency (scenarios #3 and #4). Smart sensors strategically placed throughout the home continuously collect data on occupancy and device usage to learn the user's routine. In the beginning, the motion sensors trigger the activation of other devices. After a while, the AI learns the user's behavior

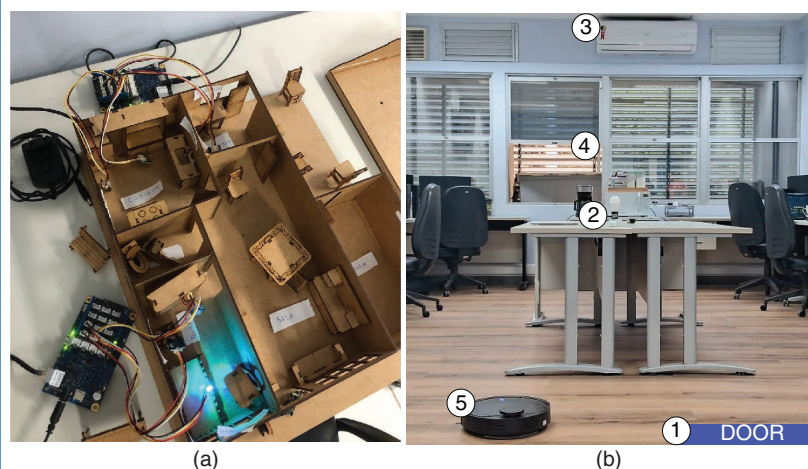


FIGURE 3. (a) and (b) Photographs taken from the AI-based smart home simulation and real-world application.

(for example, time or sequence of activities) and suggests scenarios for the users.

For example, the Cooking Ambiance scenario illustrates how a smart kitchen could streamline tasks, providing automated assistance during and after cooking sessions, particularly in scenarios with time constraints to cleaning up after

a cooking session. Differently, the Workday Routine scenario mitigates the difficulties in starting and ending the workday introduced by the absence of a structured routine during remote work. The Adaptive Acclimatization and Unoccupied Rooms scenarios address energy-saving concerns in different granularity levels.

Limitations And Challenges

The smart home framework primarily uses devices provided by Company A, which introduces two main limitations. First, as Company A expands its device portfolio, incorporating new device attributes into the framework may require minimal but additional effort. Second, the framework

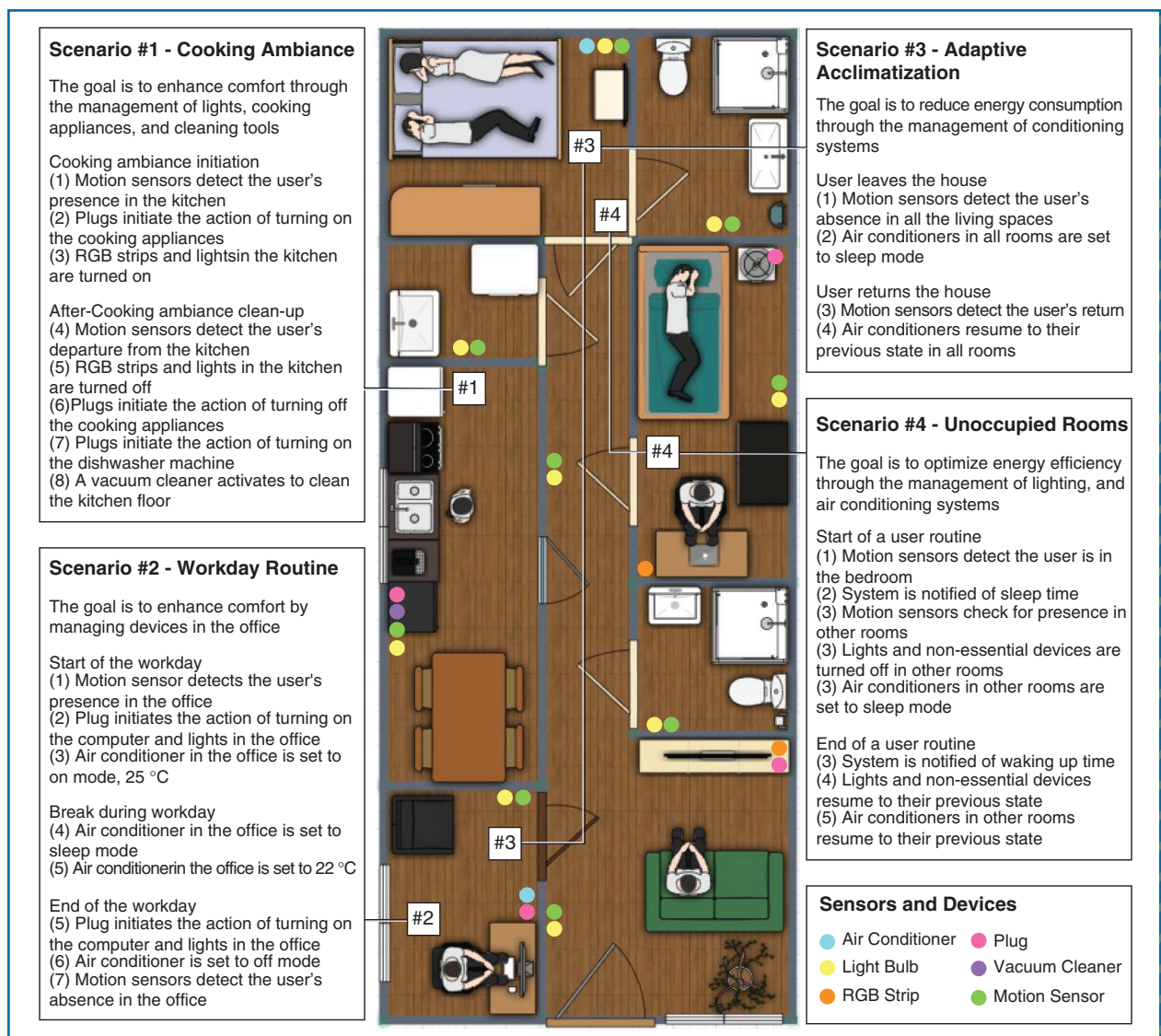


FIGURE 4. Floor plan of Company A smart home, including four scenarios with a number of sensors and devices for enhancing the living environment with respect to comfort and energy management.

may not fully address interactions with devices from other platforms, limiting its generalizability to diverse smart home environments.

In addition, the evaluation of our smart home system's performance was

highlighted the significance of further investment opportunities.

Some initiatives we aim to approach in future work include implementing a: 1) Smart Home Living Lab to create a research space that brings

Smart sensors strategically placed throughout the home continuously collect data on occupancy and device usage to learn the user's routine.

performed in simulated and real-world scenarios. The system relies on devices to not be compromised and to report correct states. If the devices do not work properly, it could skew the AI's performance. Therefore, we still have to evaluate whether the performance holds beyond those specific settings. For example, we could test for the system's scalability and applicability across diverse home sizes and with a broad spectrum of user behaviors.

The evolution of smart homes has introduced a new era of convenience, security, and efficiency. While trigger-action scenarios have streamlined everyday tasks, the true potential lies in integrating AI for intelligent decision making.

Our study showcases the practical implementation of AI in recommending tailored scenes for smart home users. Company A's feedback on the smart home development was positive, underscoring its success in administrative execution and implemented case scenarios. This achievement

together cutting-edge technologies to encourage innovative findings, and 2) Intelligent Classroom to transform the educational process into a natural and dynamic environment. It would also include improvements in the framework to handle interactions with devices from different platforms. Additionally, we plan to conduct a more thorough evaluation of the framework, including quantitative data on improvements in user experience, energy savings, and security. We also plan to compare the proposed system with existing smart home solutions to highlight its advantages and understand whether their features could complement each other. ☞

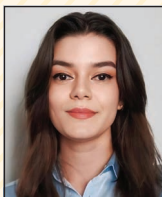
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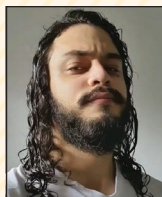
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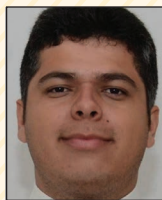
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