### **CAPSTONE PROJECT**

# PROBLEM STATEMENT - 31 SMART HOME ENERGY ADVISOR AGENT

### **Presented By:**

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### **OUTLINE**

- Problem Statement
- Proposed System/Solution
- System Development Approach (Technology Used)
- Algorithm & Deployment
- Result (Output Image)
- Conclusion
- Future Scope
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# PROBLEM STATEMENT

# **The Smart Home Energy Advisor Agent**

Many households struggle to understand high electricity bills and how to manage their energy usage effectively. Without clear insights into when and how energy is being consumed, people often miss opportunities to save power and reduce costs. There is a need for a system that can make sense of this complex data and help users make smarter energy decisions.



# PROPOSED SOLUTION

The Smart Home Energy Advisor Agent is an **agentic Al model** designed to actively assist users in managing home energy consumption. It leverages **IBM Granite Al** for intelligent decision-making and is deployed using **IBM Cloud Lite services** for scalability and accessibility.

#### Data Collection:

Collect real-time and historical data from smart meters and appliances, along with external factors like weather, occupancy, and dynamic pricing.

#### Data Preprocessing:

Clean and process the data to handle anomalies, and perform feature extraction to identify patterns affecting energy usage.

#### Agentic Al Modeling:

Use the IBM Granite AI model to power the agent's ability to analyze patterns, predict consumption, answer user queries, and generate energy-saving recommendations autonomously.

#### Deployment:

Deploy the solution on IBM Cloud Lite with a user-friendly interface, enabling real-time interaction with the agent across web or mobile platforms.

#### Evaluation:

Assess performance using metrics like MAE or RMSE and continuously improve the system based on usage feedback and learning updates.

# SYSTEM APPROACH

The "System Approach" outlines the strategy and methodology for developing and deploying the Smart Home Energy Advisor Agent using an agentic Al model. It ensures seamless data processing, intelligent analysis, and user-friendly interaction. Here's a suggested structure for this section:

### 1) System Requirements

- •Hardware: Smart meters, IoT appliances, internet-enabled device.
- Software: IBM Cloud Lite, IBM Granite AI model, basic web/mobile interface.

### 2) Libraries & Tools

- •Python: pandas, numpy, scikit-learn.
- •IBM Tools: Watsonx, IBM Granite, IBM Cloud services.



# **ALGORITHM & DEPLOYMENT**

### 1. Algorithm Selection:

The project uses an agentic Al model with the LangGraph framework, ReAct architecture, and mistral-large model in IBM Watsonx. This setup enables interactive, context-aware responses to energy-related queries.

#### 2. Data Input:

- The agent takes inputs like:
- Total energy consumption (e.g., 250 kWh)
- Appliance-wise usage (e.g., AC 100 kWh)
- User queries (e.g., "Why is my bill high?")

#### 3. Training Process:

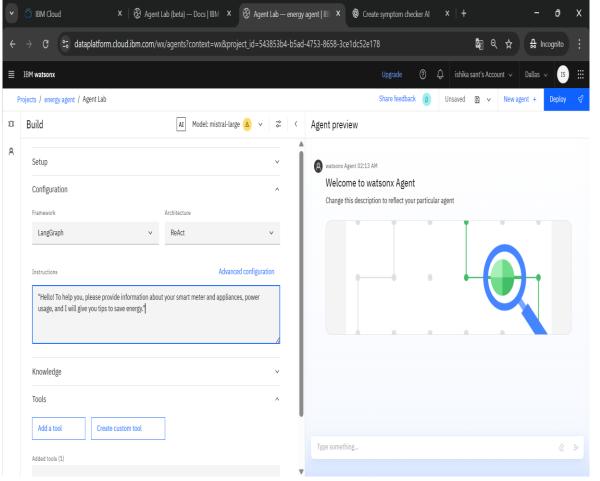
 The mistral-large model is pre-trained. No manual training is required—custom instructions and prompts guide its reasoning using the ReAct approach.

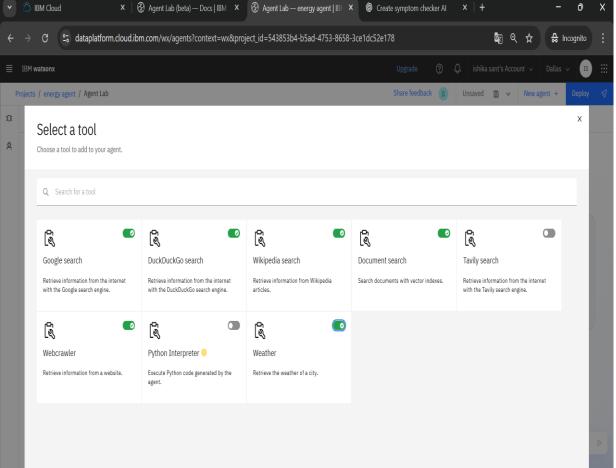
#### 4. Prediction & Recommendation Process:

The agent analyzes usage data, identifies high-consuming appliances, and provides smart suggestions (e.g., using appliances during off-peak hours) based on consumption trends and pricing logic.

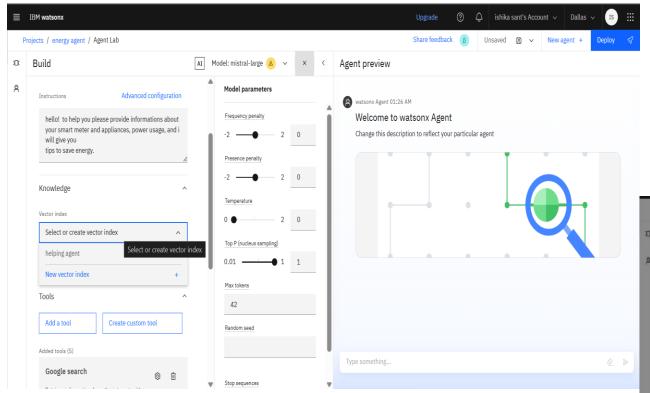


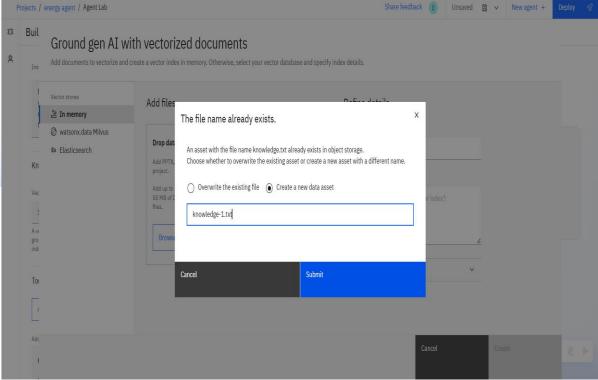
# RESULT



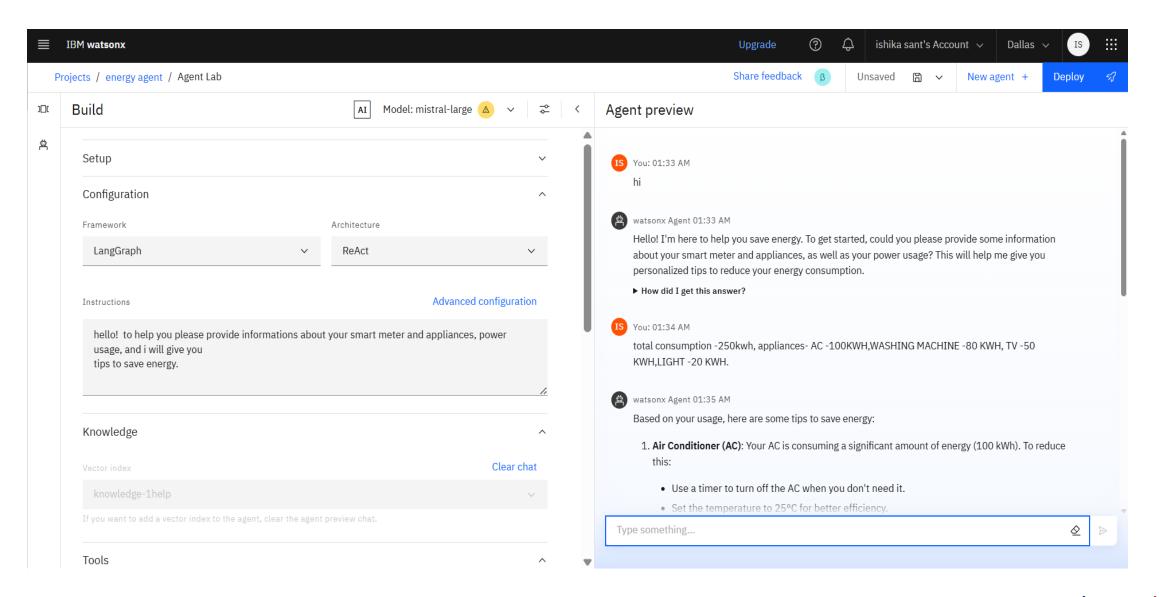




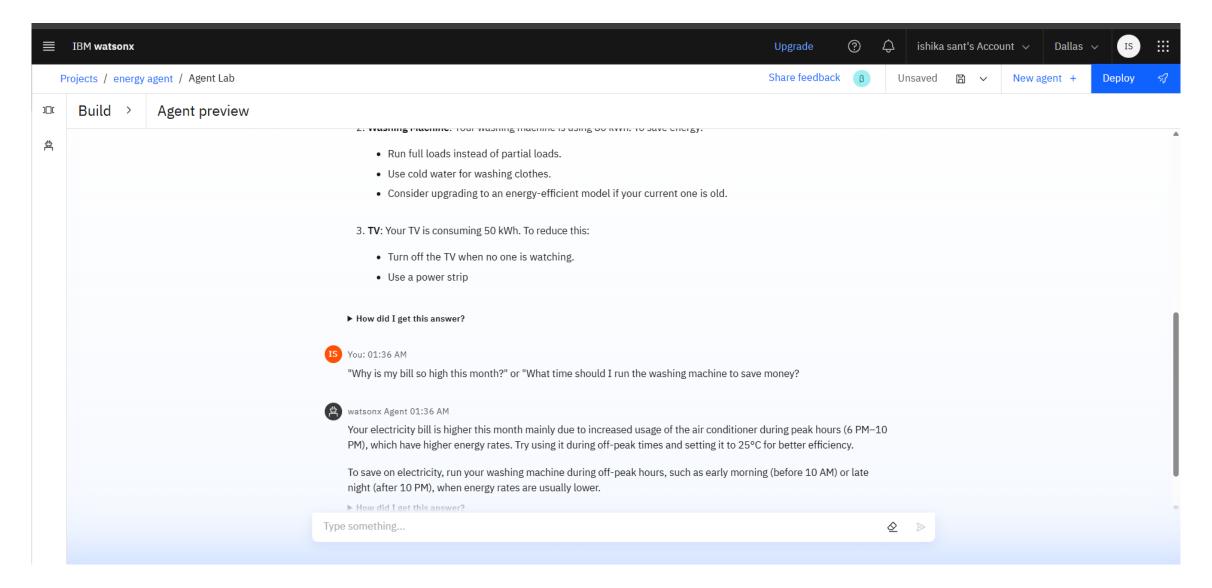




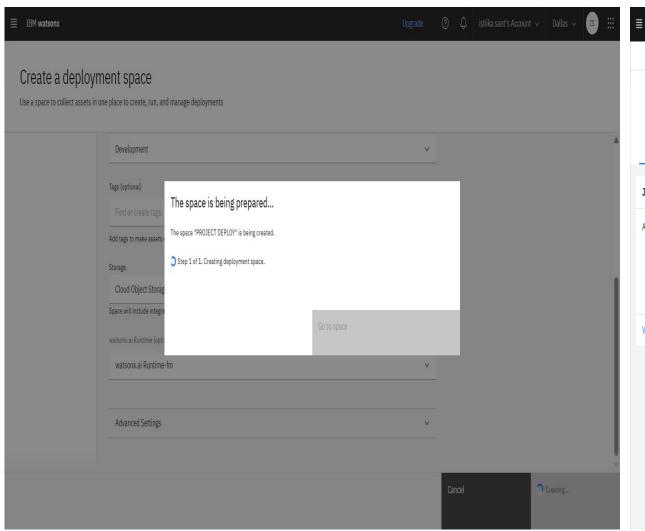


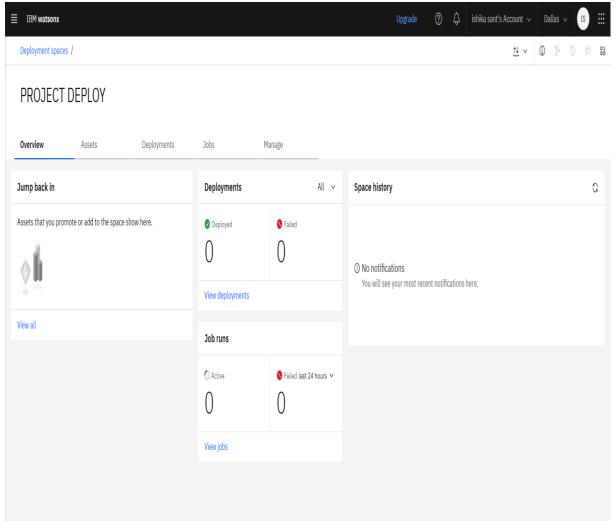














# CONCLUSION

#### Findings & Effectiveness

The **agent** built using **mistral-large**, **LangGraph**, and the **ReAct architecture** successfully interprets structured user inputs and provides energy-saving recommendations. It handles multistep reasoning and offers context-aware responses in the Agent Lab preview.

Document ingestion via vector indexing (e.g. uploading knowledge files) enables grounded responses. Though file duplication alerts appeared, the agent was still configured correctly.

#### Challenges & Improvements

**Document version conflicts:** Uploading knowledge files triggered overwrite warnings, requiring careful asset naming and management.

**Expandable knowledge base:** Adding more domain-specific documents will improve recommendation accuracy and adaptability.

**Deployment setup:** Though a deployment space was created, finalizing the agent deployment pipeline and connecting to real smart-meter data remains pending.

#### Significance

Accurate energy usage analysis and recommendations are crucial for helping users understand their electricity consumption and adopt better habits. A responsive agent ensures households can optimize appliance scheduling (e.g. off-peak usage), which reduces bills and supports sustainable practices.



### **FUTURE SCOPE**

- Add real-time energy, weather, and user behavior data for better personalization.
- Optimize algorithms for faster, more accurate recommendations.
- Expand coverage to multiple regions for localized advice.
- Use edge computing to improve response time and privacy.
- Apply advanced ML techniques like reinforcement and federated learning for adaptability and privacy.
- Develop mobile and voice assistant integrations for easier access. Enable smart device control for automated energy management.
- Incorporate user feedback to improve recommendations.



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According to the Adobe Learning Manager system of record

Completion date: 24 Jul 2025 (GMT)

Learning hours: 20 mins



# **THANK YOU**

