Towards an LLM-based Conversational Assistant for Energy Feedback in Smart Buildings

Laura Canale, Elisa Caracci, Giorgio Ficco, Marco Dell'Isola
Dept. of Civil and Mechanical Engineering
University of Cassino and Southern Lazio
Cassino, Italy
l.canale@unicas.it

Mario Molinara, Francesco Fontanella
Dept. of Electrical and Information Engineering
University of Cassino and Southern Lazio
Cassino, Italy
m.molinara@unicas.it

Biagio Di Pietra, Luca La Notte, Alessandro L. Palma, Alessandra Gugliandolo
Dept. Unit for Energy Efficiency
ENEA
Rome, Italy

***Abstract*—The transition toward sustainable buildings requires not only efficient technologies but also tools that help occupants understand and manage their energy use. Eco-feedback can stimulate energy-efficient behaviour, and conversational agents based on Large Language Models (LLMs) can deliver personalised, actionable feedback in natural language. This paper presents preliminary results of a user-centred survey aimed at defining design criteria for an LLM-based residential energy assistant, conceived as the conversational layer of a web platform for energy and Indoor Environmental Quality (IEQ) monitoring. The survey, administered to 36 university students (Italian and international cohorts), covered energy awareness, indoor comfort, AI-tool habits, and preferences for message framing, channel, frequency and visual format. Economic savings and health/comfort framing emerged as the strongest motivational drivers, generative chatbots are already widely used, and free-form conversation is strongly preferred, supporting an LLM-based design. We also discuss fine-tuned Small Language Models (SLMs) as an energy-efficient implementation option; a larger, more heterogeneous sample is being collected.**

Keywords—eco-feedback; large and small language models; conversational agents; energy efficiency; indoor environmental quality; user-centred design

I. Introduction

Buildings are among the largest contributors to global energy consumption and greenhouse-gas emissions, and a substantial share of their energy use depends on occupant behaviour [1], [2]. Smart meters and IoT sensing have enabled eco-feedback, i.e., making energy and indoor-environment data visible, interpretable and actionable to motivate more efficient behaviour [3]. To turn awareness into lasting change, however, feedback must be personalised, contextually relevant and delivered through accessible, engaging channels and formats [4].

Conversational agents based on Large Language Models (LLMs) are a promising eco-feedback interface, translating complex energy data into natural language and supporting two-way dialogue beyond static dashboards [5], [6]. Recent work shows that LLM- and retrieval-augmented agents can advise on building energy efficiency with near-expert quality [7], [8]. Yet most studies focus on system capabilities rather than user needs, and evidence-based design guidelines for residential conversational eco-feedback remain scarce [9].

This paper addresses that gap with preliminary results of a user-centred survey defining design criteria for an LLM-based residential energy assistant, the conversational layer of a web platform that continuously monitors energy consumption and IEQ parameters and returns personalised, actionable suggestions. Unlike most prior, system-centred work, the study elicits requirements from the user side — from a population already familiar with generative AI — investigating motivational framings, interaction modalities, channels, visual formats, adoption barriers and communication styles.

II. Methodology

The survey comprised 37 items organised in six thematic sections: participant profile (S1); energy awareness and motivations (S2); IEQ experience (S3); AI-tool usage (S4); interaction preferences (S5); and behavioural response and adoption barriers (S6). It combined five-point Likert scales, single- and multiple-choice items, and an open-ended field for example questions to the assistant.

Section S5 rated five message framings grounded in behavioural and persuasive-technology research (Table I): economic savings (A) and health and comfort (B) appeal to intrinsic motivations; social comparison (C) leverages peer benchmarking; predictive advice (D) exploits context such as weather; periodic reports (E) summarise progress.

The questionnaire was distributed in Italian and English through convenience sampling (Google Classroom, mailing lists, LinkedIn). Data collected from 21 May to 5 June 2026 yielded 36 complete responses (17 Italian, 19 international; 92% STEM). The cohorts differed markedly: 94% of Italian respondents lived with their family, without paying bills directly, whereas 68% of international respondents lived in shared flats or residences and paid their own bills — a contrast that helps interpret the divergent preferences below. A replication package with the full questionnaire and the anonymised responses is available from the corresponding author and will be released publicly with the extended study.

Students are the target population because the first prototype will be deployed at the Janula University Residence, a living laboratory being equipped with energy and IEQ monitoring. Given the exploratory sample size (n = 36), the analysis is limited to descriptive statistics.

III. Results

A. *Motivational drivers*

Across both cohorts, economic savings (combined mean 4.36 ± 0.93 on a 1–5 scale) and indoor comfort (4.14 ± 0.96) were the strongest drivers, followed by environmental impact (4.03 ± 0.94); social comparison ranked last (2.94 ± 1.49, wide dispersion; Fig. 1). Economic and health/comfort framings should therefore be prioritised in the assistant's response logic.

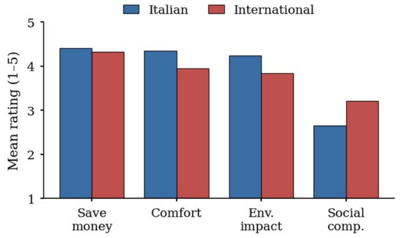

Fig. 1. Motivational drivers by cohort (mean rating, 1–5 scale).

B. AI familiarity and message preferences

Generative AI chatbots were the most frequently used AI category, confirming familiarity with the intended conversational interface. In Table I, the economic-savings message (A) was rated highest, health/comfort (B) second, the social challenge (C) last. Personalised advice via notifications can reduce household consumption [10], supporting predictive framings (D). Free-form conversation was strongly desired (86%), reinforcing a generative design over rule-based or intent-classification systems [11].

TABLE I. PERCEIVED USEFULNESS OF MESSAGE TYPES (1–5 SCALE)

Message framing	ITA	Int'l	Comb.
A — Economic savings	4.82±0.39	4.53±0.84	4.67±0.68
B — Health & comfort	4.47±0.51	4.53±0.84	4.50±0.70
C — Social challenge	3.24±1.20	3.68±1.25	3.47±1.23
D — Predictive advice	4.18±0.88	4.05±0.97	4.11±0.92
E — Periodic report	3.94±1.09	3.84±1.12	3.89±1.09

C. Interaction design and adoption barriers

A dedicated smartphone app was the preferred channel (69%), with at most one message per day or event-triggered alerts. Visual preferences diverged — text with highlighted figures for Italians, emojis and icons for internationals — suggesting configurable presentation layers. Deterrents diverged too: generic/obvious messages for Italians; notification overload and complexity for internationals.

Behavioural intentions were encouraging: shown a high-consumption alert, 65% of respondents would feel motivated to take concrete action, smaller groups being uncertain or put off (Fig. 2). Open-ended prompts clustered into temporal-comparison, root-cause, improvement and appliance-level queries, confirming free-form, data-driven dialogue as a core requirement.

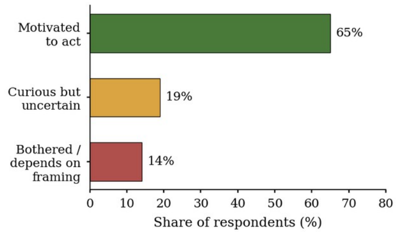

Fig. 2. Reaction to a high-consumption alert (combined sample).

IV. CONCLUSIONS

This user-centred study provides evidence-based criteria for an LLM-based residential energy assistant: economic and health/comfort framings are the strongest behavioural levers; AI familiarity is no longer an adoption barrier; free-form conversation is strongly preferred over rule-based interaction; and a smartphone app with low-frequency, event-driven and configurable messaging is the preferred interaction model.

These criteria constrain the interaction more than the scale of the model implementing it. Since large-scale LLM inference carries a non-negligible energy cost [12], a Small Language Model (SLM) fine-tuned on the residential-energy domain promises comparable reliability at a fraction of that cost, enabling on-premise or on-device deployment with privacy benefits [13] — a coherent choice for an assistant aimed at saving energy. The prototype will therefore benchmark fine-tuned SLMs against larger LLMs on the elicited query types.

The main limitation remains the small, STEM-dominated convenience sample (n = 36): data collection now targets a larger, more heterogeneous population (non-STEM profiles, wider age ranges, household types), a prerequisite for generalising these criteria in a follow-up full paper. Future work will address co-design and longitudinal testing within the Janula living laboratory, evaluating usability and behavioural impact.

ACKNOWLEDGMENT

This work stems from a collaboration between the University of Cassino and Southern Lazio and ENEA on residential energy monitoring.

REFERENCES

[1] P. C. Stern, “New environmental theories: toward a coherent theory of environmentally significant behavior,” J. Soc. Issues, vol. 56, no. 3, pp. 407–424, 2000.

[2] L. Canale, B. Peulicke Slott, S. Finsdóttir, L. R. Kildemoes, and R. K. Andersen, “Do in-home displays affect end-user consumptions? A mixed method analysis of electricity, heating and water use in Danish apartments,” Energy Build., vol. 246, p. 111094, 2021.

[3] M. L. Chalal, B. Medjdoub, N. Bezai, R. Bull, and M. Zune, “Visualisation in energy eco-feedback systems: a systematic review of good practice,” Renew. Sustain. Energy Rev., vol. 162, p. 112447, 2022.

[4] D. Wemyss, F. Cellina, M. Grieder, and F. Schlüter, “Looking beyond the hype: conditions affecting the promise of behaviour change apps as social innovations for low-carbon transitions,” Environ. Innov. Soc. Transit., vol. 47, p. 100702, 2023.

[5] M. Sanguinetti and M. Atzori, “Conversational agents for energy awareness and efficiency: a survey,” Electronics, vol. 13, no. 2, p. 401, 2024.

[6] U. Gnewuch, S. Morana, C. Heckmann, and A. Maedche, “Designing conversational agents for energy feedback,” in Proc. DESRIST, 2018, pp. 18–33.

[7] S. Ghani, A. Håkansson, O. Pasichnyi, and H. Shahrokni, “Conversational agents for building energy efficiency: advising housing cooperatives on reducing energy consumption,” IOP Conf. Ser. Earth Environ. Sci., vol. 1546, p. 012027, 2025.

[8] T. He and F. Jazizadeh, “LLM-based building energy management assistants,” in Computing in Civil Engineering 2024. Reston, VA: ASCE, 2025, pp. 1058–1068.

[9] L. Canale, E. Caracci, G. Ficco, G. Puglisi, and M. Dell'Isola, “Designing feedback systems for buildings: features and user preferences for energy consumption and indoor environmental quality,” Energy Res. Soc. Sci., vol. 129, p. 104382, 2025.

[10] H. B. Kim et al., “Field experiment of smartphone-based energy efficiency services for households: impact of advice through push notifications,” Energy Build., vol. 223, p. 110151, 2020.

[11] M. Giudici, P. Crovari, and F. Garzotto, “Persuasive conversational agents for environmental sustainability: a survey,” ACM Comput. Surv., vol. 58, 2026.

[12] A. S. Luccioni, Y. Jernite, and E. Strubell, “Power hungry processing: watts driving the cost of AI deployment?” in Proc. ACM FAccT, 2024, pp. 85–99.

[13] P. Belcak et al., “Small language models are the future of agentic AI,” arXiv:2506.02153, 2025.