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A Multidimensional Approach to enhance sustainable Building Renovation planning: The RETABIT Project

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Abstract: Building retrofitting is vital for meeting European climate targets and transitioning cities to climate-neutral status. Beyond energy efficiency, true sustainability necessitates a holistic approach, encompassing environmental, social, and economic dimensions. The RETABIT project is creating a geospatial data-driven platform to compute key performance indicators, assisting urban planners in comprehensive assessments. To enhance decision-making, a large language model-based multi-criteria analysis method is proposed, automating processes for city planners and overcoming challenges tied to manual assessments.

Keywords: Building renovation; Multi-Criteria Decision Method; Artificial Intelligence

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1. Introduction

Building renovation plays a pivotal role in fostering decarbonization in the construction sector [1]. The 2012/27/EU Energy Efficiency Directive mandates Member States to establish long-term strategies for mobilizing investments in the renovation of residential and commercial buildings at the national level [2]. Notably, the rehabilitation of buildings plays a pivotal role in accomplishing sustainable development goals. Therefore, it requires a holistic approach that considers environmental, social, and economic dimensions and involves the decisions made by urban planners, construction experts, and society at large.

Collaborative urban planning advocates the integration of all these factors and actors. However, challenges arise precisely from its multidisciplinary nature, as a diversity of objectives need to be aligned to address context complexity, and data uncertainty [3]. These challenges lead to heightened technical knowledge requirements, increased communication needs, and obstacles in information exchange [4]. As a result, the processes of identifying buildings for renovation, developing large-scale rehabilitation programs (district, city, region, country), evaluating alternatives, and monitoring their impact becomes inefficient, time-consuming, and costly [5] [6].

In this paper we introduce a methodology aimed at bridging the gap between conventional urban planning processes and the challenges posed by the multidimensional and dynamic nature of built environments. Through the utilization of advanced geospatial data analytics and the integration of large language models (LLM) with multi-criteria analysis methodologies, the outcomes of this process not only enhance the understanding of the urban landscape but also provide actionable insights for sustainable urban planning.

3. The RETABIT project

RETABIT (www.retabit.es), a research project co-funded by the Spanish Ministry of Science and Innovation, is developing a geospatial data-driven platform for Catalonia aimed at enhancing decision-making processes in urban planning from a multidimensional holistic perspective. This platform integrates data from various sources and at different levels of granularity to compute up to 16 quantitative Key Performance Indicators

(KPI) across multiple dimensions (i.e., environment, social, economic). These indicators enable urban planners to comprehensively assess the built environment while considering its specific socioeconomic and environmental context. For instance, an urban planner can identify economically deprived neighborhoods characterized by non-energy-efficient buildings to devise social planning or renovation grant programs to rehabilitate buildings while at the same time contributing to alleviate energy poverty in these areas.

To help a user of a platform -typically, a team in charge of developing a building rehabilitation program- select and prioritize the selection of indicators, we have developed a multi-criteria analysis method harnessing the capabilities of large language models (MCA-LLM). Figure 1 outlines the implemented process.

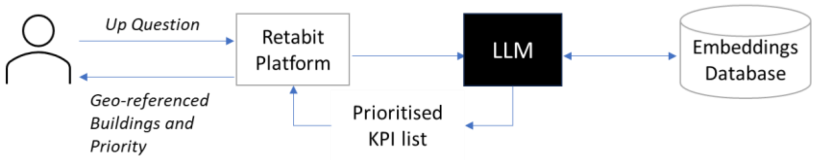

Figure 1. Process representation within the RETABIT platform for addressing a planner's question.

3.1. Multi-criteria analysis based on large language models

The adopted MCA-LLM method produces a prioritized list of KPIs that address queries from members of the planning team. To identify the most suitable KPIs, the user's question undergoes a comparison process with the aid of a Large Language Model (LLM), which generates embeddings for both the question and the KPIs. Embeddings are numerical representations of text input in natural language by the user, subsequently converted into numerical sequences. Their purpose is to enhance a computer's understanding of relationships between conceptual entities. Embeddings map a text to a vector representation, effectively "embedding" it into a high-dimensional space. Each dimension of the embedding captures some aspect of the input, allowing them to capture the meanings and associations present in the text, that is, its semantics.

As embeddings can be seen as vectors of multiple dimensions, they can be compared with a cosine similarity metric. Higher cosine similarity often implies greater semantic similarity between the corresponding texts. A threshold of 0.8 was established to discard non highly similar embeddings. By employing this threshold, only those KPIs most closely related to the question will be selected, as exemplified in Figure 2.

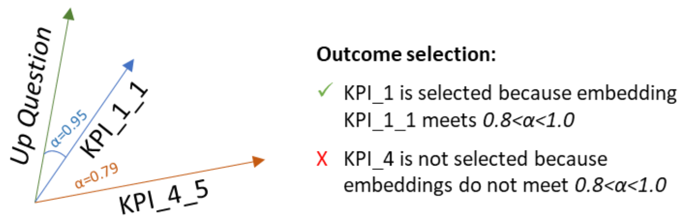

Figure 2. Representation of cosine similarity (α) between KPI_1 (Definition 1) and KPI_4 (Definition 5) embeddings' vectors representation with Urban Planner (Up) Question embeddings vector.

The MCA-LLM methodology involves the use of a set of KPIs (i.e., name, definition, and calculation methodology) selected after an extensive literature review, and a large language model (i.e., OpenAI's GPT) to generate embeddings for the KPI's definitions.

To capture the relationships between a KPI within a contextual domain, additional descriptions are added, including: (1) KPI definition according to the studied literature, (2) relationships with other KPIs from different domains, and (3) the direction of the KPI (positive and negative). For example, in the case of *KPI1 Energy renovated residential buildings*, a description for a positive direction would be "*Energy renovated have been renovated considering energy efficiency measures*", while a negative one would read "*Non-energy* *renovated have not been renovated considering energy efficiency measures*". And a relation with other KPI would be described as "*Energy renovated have lower demand of energy*".

Additional descriptions of the KPIs were generated following a systematic and iterative approach comprising four steps: (1) identifying questions based on the literature review and in workshops carried out within the project with local stakeholders, (2) proposing additional descriptions to define relationships between KPIs (3) generating embeddings for the additional descriptions, and (4) evaluating the descriptions through retrieving the most similar KPIs for each question based on cosine similarity metric. If the resulting KPIs do not match the expected ones, the descriptions are adapted to continue the process in the third step. In this iterative process, an initial set of thirty-three potential questions was compiled and analyzed. Through the iterative cycle, additional descriptions were added and refined to address each question effectively resulting in 248 descriptions for 16 KPIs.

3.2 Prioritization of buildings based on MCA-LLM method

When users provide a textual description to identify the buildings with specific characteristics, the RETABIT platform generates a priority value for each building in the area of study based on the KPIs identified by the MCA-LLM method. The priority value is an aggregation of KPIs, considering their direction and weight, as described by equation 1,

$$priority = \sum_i (KPI_i * W_i) \quad (1)$$

where KPI_i are the quantitative value of each KPI per building selected by the MCA-LLM, and W_i denotes the weights for each KPI automatically assigned by the MCA-LLM based on their cosine similarity value. To account for the direction of each KPI in the equation, their values are negated $(1 - KPI_i)$, when they possess a negative direction. The calculation of the weights is given by Equation 2,

$$W_i = \frac{\propto_i - Min(\propto)}{Max(\propto) - Min(\propto)} \quad (2)$$

where $\propto_i$ is the cosine similarity for the KPI_i, $Min(\propto)$ is the minimum value of the cosine similarity, which is set in 0.8, and $Max(\propto)$ is the maximum value of the cosine similarity among the selected KPIs to answer the question.

3.3. Validation process

The MCA-LLM methodology has been validated with a survey responded by national and international technicians specializing in social, economic, and environmental urban and building issues. The survey comprised two sections. The initial part lists existing KPIs, encompassing their ID, name, definition, and units. The goal was to promote a comprehensive understanding among technicians, with a provided platform link for KPI visualization. The second part involves four questions aligned with *Spanish Law 11/2022, dated December 29th, focusing on the urban, environmental, and social improvements of neighbourhoods and towns*. The aim of this Law is to create an urban, environmental, and social recovery Fund to confront environmental crisis and avoid social cracks derived from the living conditions in some neighbourhoods and towns. Technicians were tasked with answering these questions using five KPIs from the list and assigning weights to each KPI within a range from most to least important.

4. Results

Regarding the survey results, we examined three main aspects: (1) agreement among respondents in KPI selection, (2) alignment between respondents' choices and MCA-LLM-generated suggestions, and (3) the highest agreement between individual responses and MCA-LLM's selection. These were evaluated separately for both KPI selection and prioritization. The KPI selection results revealed variable perspectives and consensus levels among technicians. While some questions showed strong alignment, others had lower coincidence. This variability extended to MCA-LLM results, aligning with respondents' choices at the same percentages for each question. Notably, the MCA-LLM's suggestions closely mirror the respondent choices, with MCA-LLM higher coinciding individually with specific respondents, even achieving a 100% of coincidence with a respondent for one of the questions. In contrast, the prioritization results demonstrated no consensus or alignment, showing 0% agreement among respondents and between respondents and the MCA-LLM for all questions. Intriguingly, despite this lack of collective agreement, some KPIs had similar priorities between individual responses and MCA-LLM, even though the coincidence remains low.

In summary, while varying perspectives and consensus levels emerged in KPI selection, the prioritization revealed a notable lack of alignment. This disparity emphasizes the complexity of aligning diverse opinions on KPI importance, even when replicated through MCA-LLM. Nonetheless, considering diverse perspectives is crucial in KPI selection, and the findings suggest that MCA-LLM recommendations can closely align with human choices in specific contexts.

5. Conclusion

The MCA-LLM methodology we have developed in RETABIT streamlines information collection and interrelation, offering predefined relationship-based problem-solving. This approach addresses knowledge gaps, providing standardized outputs and adaptable results to meet user requirements. The platform's versatility makes it an agile solution for KPI choices in urban evaluations. However, the validation process revealed the need for further refinement.

Survey results highlighted the need for a more extensive iteration of the finetuning process to enhance the adaptability of KPI selection and weight outcomes. Increasing the sample size of technicians and additional training iterations could help to address this issue. However, survey results also indicate that MCA-LLM KPI selection outcomes align with the choices of most experts, demonstrating its effectiveness for the main goal of the RETABIT platform.

Future research will involve an expanded survey with a larger sample of technicians and a second phase of training iterations based on its results.

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Conflicts of Interest: The authors declare no conflict of interest.

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