Recommender systems and reinforcement learning for building control and occupant interaction: A text-mining driven review of scientific literature

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Date：11/05/2024

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1 Introduction

Background | Objectives

Recommendation systems for indoor environment control

- The indoor environment significantly affects human health and well-being [1].
- How to improve indoor environment quality (IEQ) while reducing energy consumption is the major research question of current research [2];
- Smart control systems is a good solution, but the adaption rate of smart building is low because the high initial costs and complexity of implementation [3].
- Remains a need to explore a more feasible, user-friendly, and cost-effective solution.
- Recommendation systems can improve IEQ by giving user suggestion to promote behavioral change [4];
- Central to this strategy is recommendation algorithms that analyze user preferences and environmental data to provide personalized suggestions [5].

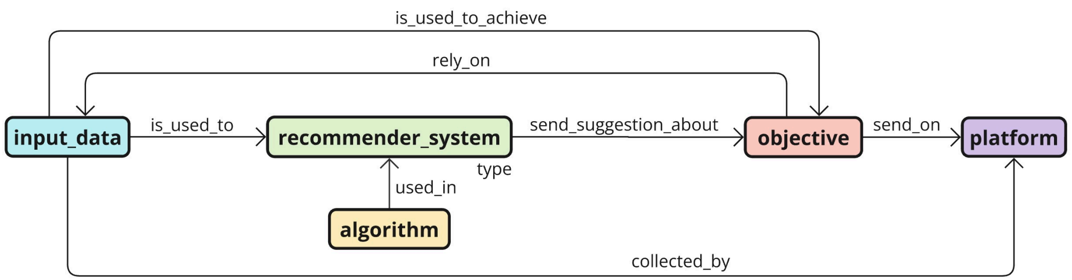
Conventional literature review VS Text mining-based literature review

	Conventional literature review	**Text mining-based literature review**
Method	• Manually searching, reading, and analyzing papers	• Use algorithms to analyze a large number of papers and quickly identify trends.
Comprehensiveness	• Researchers can read papers in detail, but hard to process large amounts of literature; • Typically 80-100 publications.	• Can handle a large number of papers and summarize key points for a broader view; • Typically 1000+ publications.
Subjectivity and Objectivity	• **Subjective:** depends on the researcher's judgment, knowledge, and analysis skills.	• **Objective:** relies on algorithms and data processing, reducing researcher bias.
Depth	• Provides detailed analysis; • Struggling to find the interrelationships among different studies, especially across fields.	• Good at identifying overall trends and common themes in large volumes of literature but lacks detailed critical analysis.
Applicability	• Best for fields where in-depth analysis is needed; • Researchers want to combine multiple theories and offer their own viewpoint.	• Ideal for areas with lots of papers and fast development, • Can quickly get a broad overview and identify research hot spots and trends.

1 Introduction

Background | Objectives

Given the complexity of this field (across computer science, built environment, and mobile health), **this study aims to use data mining methods to analyze current development trends in recommendation systems within the context of the built environment.** Specifically, it utilizes data mining techniques proposed by Dr. Mahmoud [6] to explore the relationships among five distinct categories of keywords.



Def.1: **Input data:** (*input_data*) refers to various types of input data employed in recommendation systems. This includes building and environmental data, such as indoor temperature, humidity, and indoor environmental quality; physiological data, such as heart rate, body temperature, and activity patterns; and user context data, such as user profiles and real-time feedback.

Def.2: **Recommender system:** (*recommende_system*) refers to the types of recommender systems commonly used in the field of the built environment. This encompasses systems like JITAI, context-aware recommender systems for dynamic user environments, and reinforcement learning-based recommender systems that adapt based on user interactions.

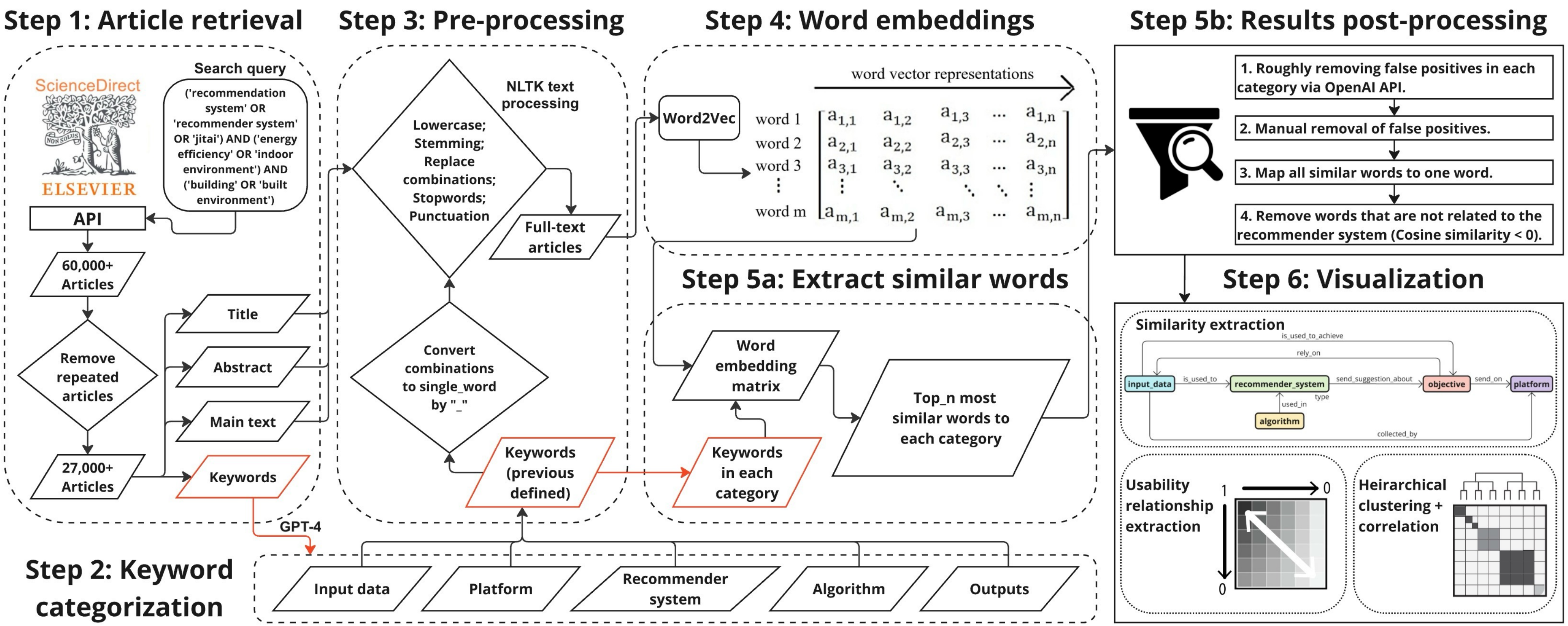
Def.3: **Algorithm:** (*algorithm*) refers to the types of algorithms employed across various recommender systems. Notable examples include NLP, deep learning, and reinforcement learning.

Def.4: **Objective:** (*objective*) refers to the goals pursued by recommender systems under the context of the built environment. Examples include promoting energy-saving behavior, altering sedentary behaviors, or providing personalized control recommendations.

Def.5: **Platform:** (*platform*) refers to both the platforms used to collect input data for recommender systems and the platforms on which system outputs are delivered. This encompasses smart wearable devices, as well as traditional computing platforms such as computers and smartphones.

2 Methodology

Overview | Detailed methodology



2 Methodology

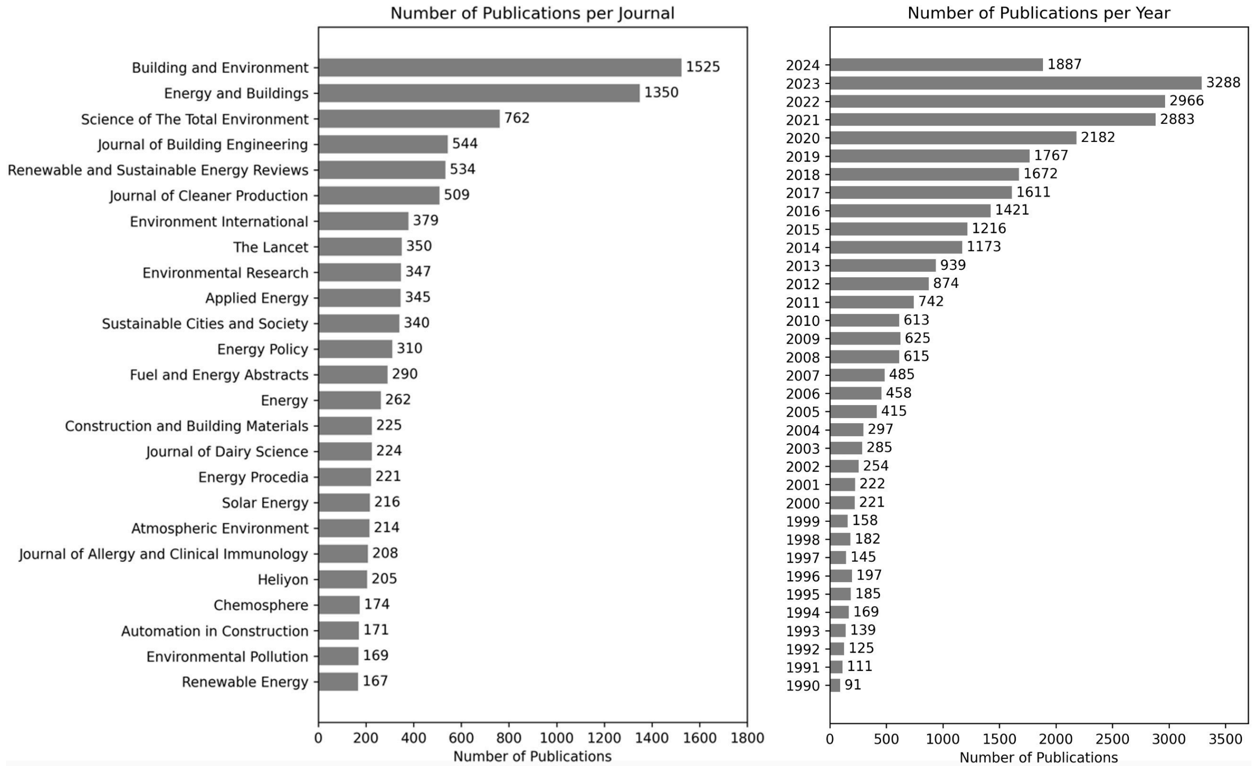
Overview | Detailed methodology

Step 1: Article Retrieval

1. Request Elsevier API Key

2. Search query: ('recommendation system' OR 'recommender system' OR 'jitai') AND ('energy efficiency' OR 'indoor environment') AND **('building' OR 'built environment')**

3. 60000 full-text articles -> remove repeat items -> 27000 full-text articles



Step 2: Keyword Categorization

1. **27000 full-text articles** (Metadata: title, abstract, main text, **keywords**, etc.)

↓ **GPT-4**

Input data, Recommender system, Algorithm, Outputs, Platform
(pre-defined keywords for subsequent similar word extraction processes)

2. The compound keywords are then transformed into single entities by "_".

Compound words: mechanical engineer → mechanical_engineer

The NLP algorithm will tokenize each sentence and trains on word level. Combine compound keywords to prevent the model from breaking down multi-word terms into separate words.

2 Methodology

Step 3: Pre-processing

1. Replace all the **combine words** in the main-text to **single entities** based on **Step 2**.

2. **Lowercase** and **stemming** every words.

Common root of the word: design, designs, designed, Design → design

3. Remove **stopwords**, **punctuations**, and **metadata elements (such as article or image IDs, author information, hyperlinks, and annotations).**

By performing these preprocessing steps, noise can be reduced, and the model's focus on useful information during training can be enhanced.

Step 4: Word embeddings

1. Processed Full-text articles $\xrightarrow{\text{train}}$ **Word2Vec model**

Word2Vec: Python-based tool to create vector representation of words based their sematic meaning.

$$\xrightarrow{\text{word vector representations}}$$

$$\begin{array}{c} \text{word 1} \\ \text{word 2} \\ \text{word 3} \\ \vdots \\ \text{word m} \end{array} \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} & \cdots & a_{1,n} \\ a_{2,1} & a_{2,2} & a_{2,3} & \cdots & a_{2,n} \\ a_{3,1} & a_{3,2} & a_{3,3} & \cdots & a_{3,n} \\ \vdots & \ddots & \ddots & \ddots & \vdots \\ a_{m,1} & a_{m,2} & a_{m,3} & \cdots & a_{m,n} \end{bmatrix}$$

The Principle of Word2Vec：

- Learn the semantic meaning of each word from the position of words in a sentence and their co-occurrence with other words [6];
- Words with similar meaning will be projected into nearby locations in the word vector space.
- The semantic similarity between words is determined by their distances within the vector space: the smaller the distance, the closer the semantic meaning between the words.

2 Methodology

Overview | Detailed methodology

Step 5: Extract similarity

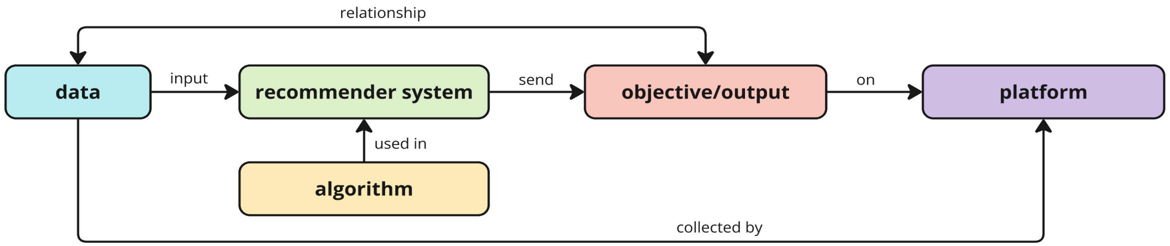
Usage example:

a. "smartphone", "iPhone" --input--> **Trained Word2Vec model** --output--> Similarity: 0.87

b. "smartphone" --input--> **Trained Word2Vec model** --output--> "iPhone", "mobile_phone", etc.

Similarity extraction:

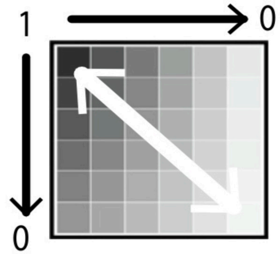
1. Pre-defined keywords ----> Top_100 most similar words to each pre-defined keywords; (Find the miss words in each category, and synonyms to each words)



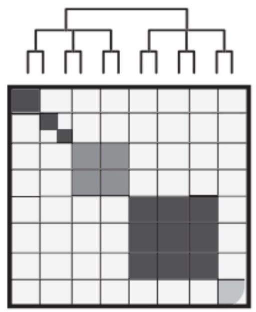
2. Removing false positives in each category via GPT-4;
3. Map all synonyms to one word;
4. Remove words that are not related to the recommender system (Cosine similarity to RS < 0);
5. Extract similarity between keywords.

Step 6: Visualization

Usability relationship extraction

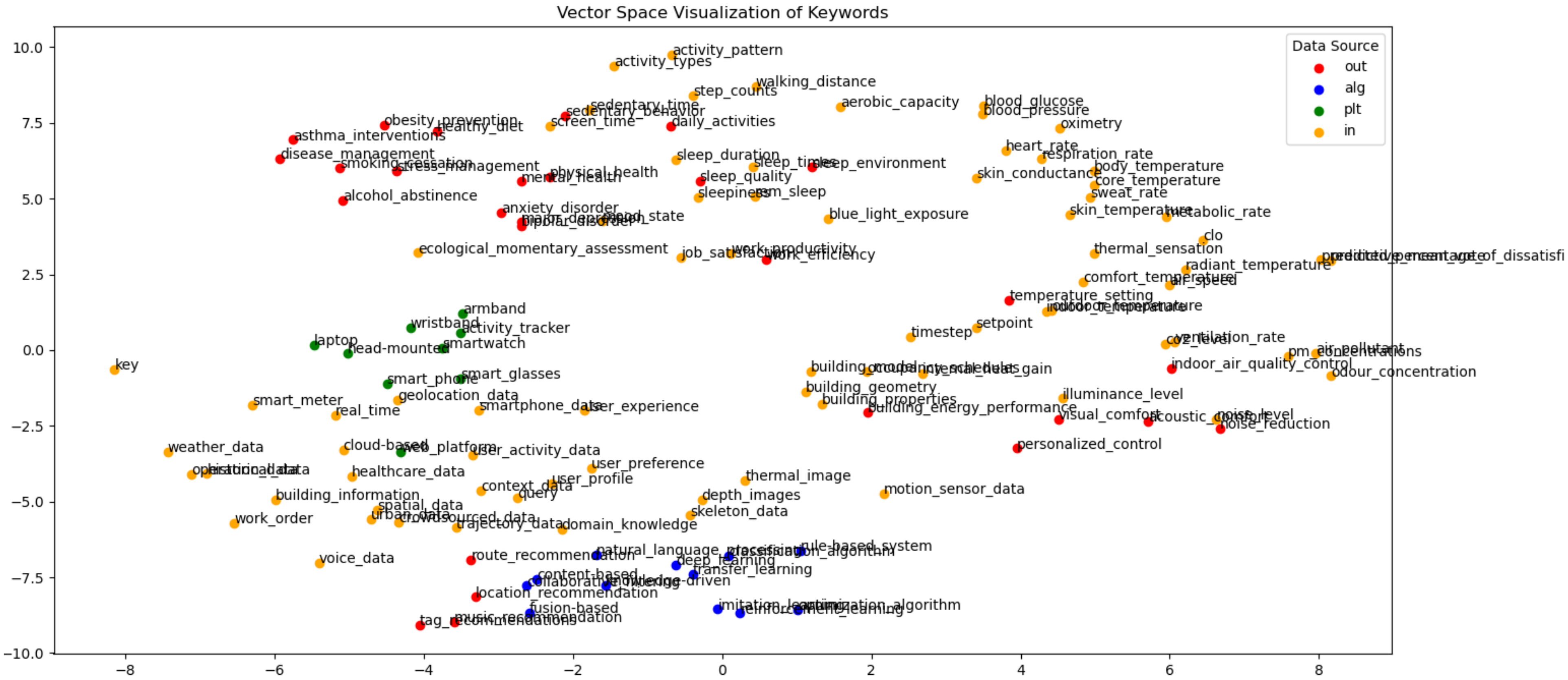


Heirarchical clustering + correlation



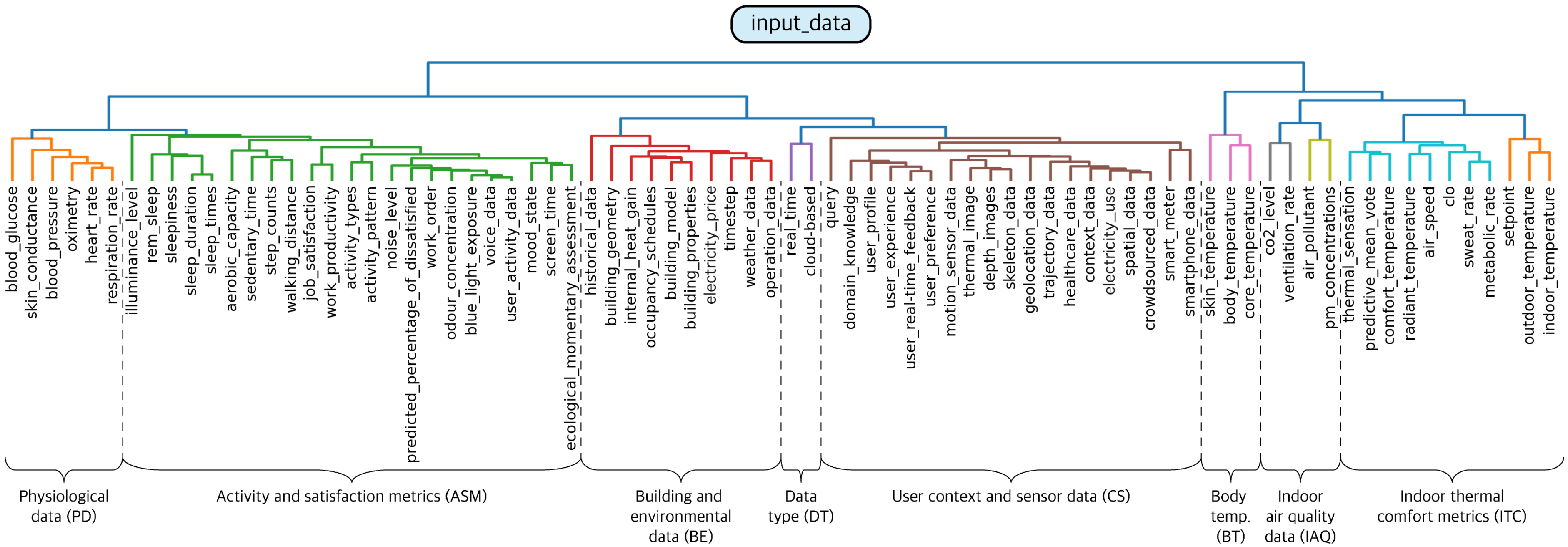
Results and Discussion

Vector representation | Keywords clustering | Result interpretation | Similarity heatmap

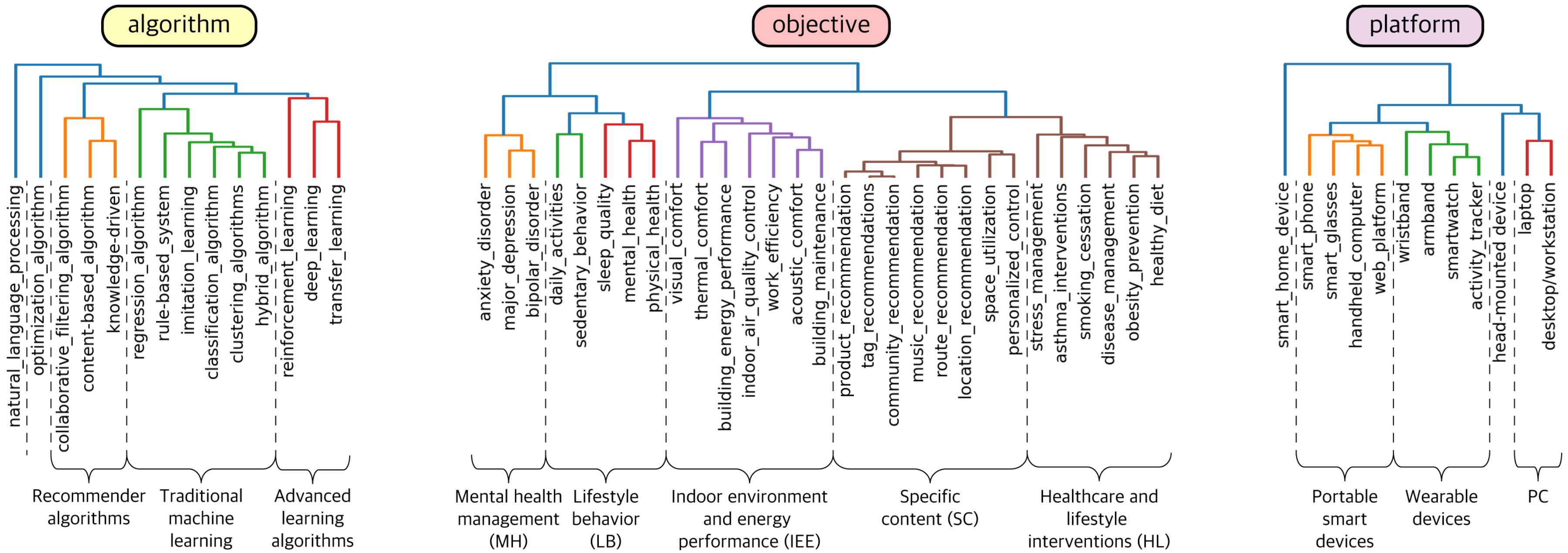


3 Results and Discussion

Vector representation | **Keywords clustering** | Result interpretation | Similarity heatmap



Results and Discussion



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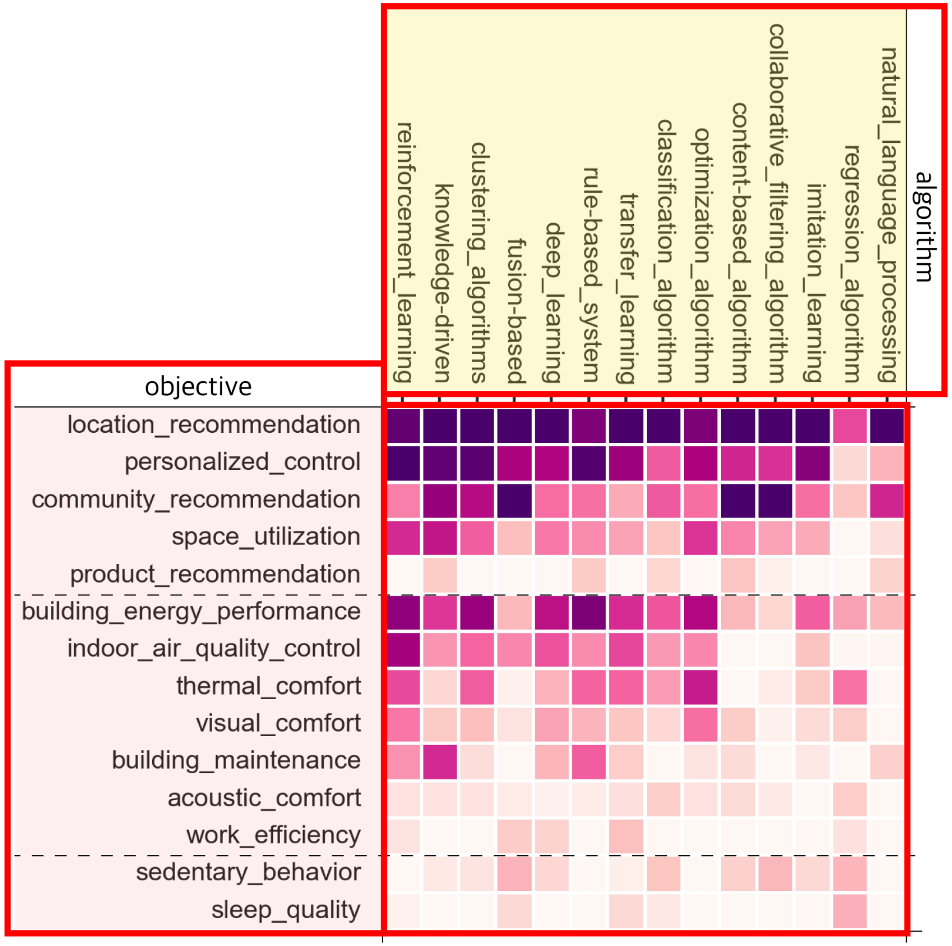
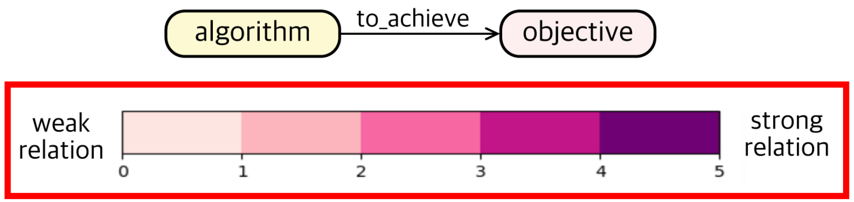


Y-axis: all the algorithms used in recommendation system extract from literature.
X-axis: all the objectives of recommendation system extract from literature.

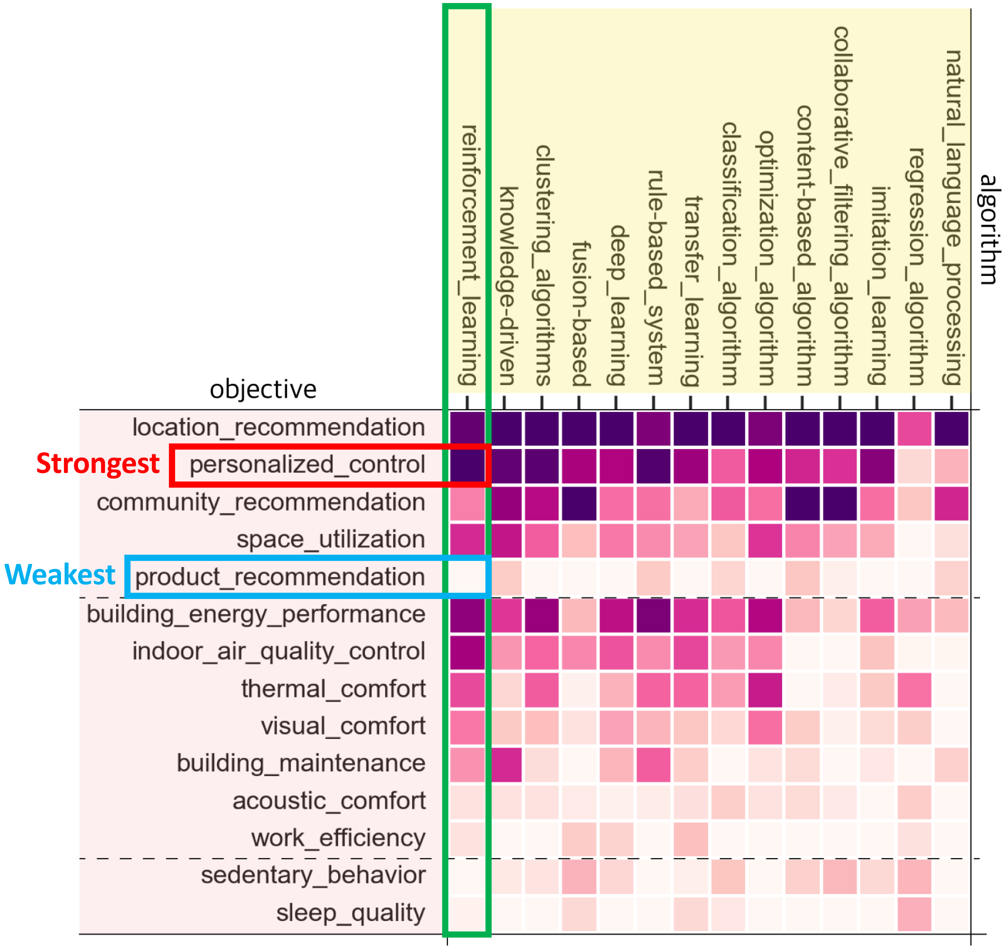
The color palette indicates the relationship between two keywords:

- The darker the color, the stronger the relationship;
- The lighter the color, the weaker the relationship.



3 Results and Discussion

Vector representation | Keywords clustering | **Result interpretation** | Similarity heatmap

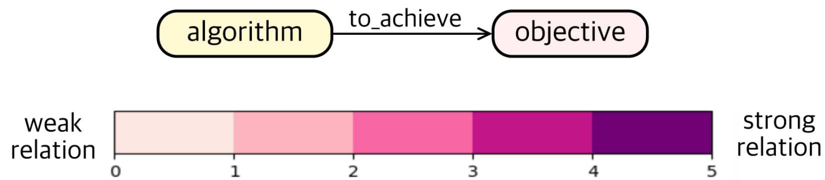


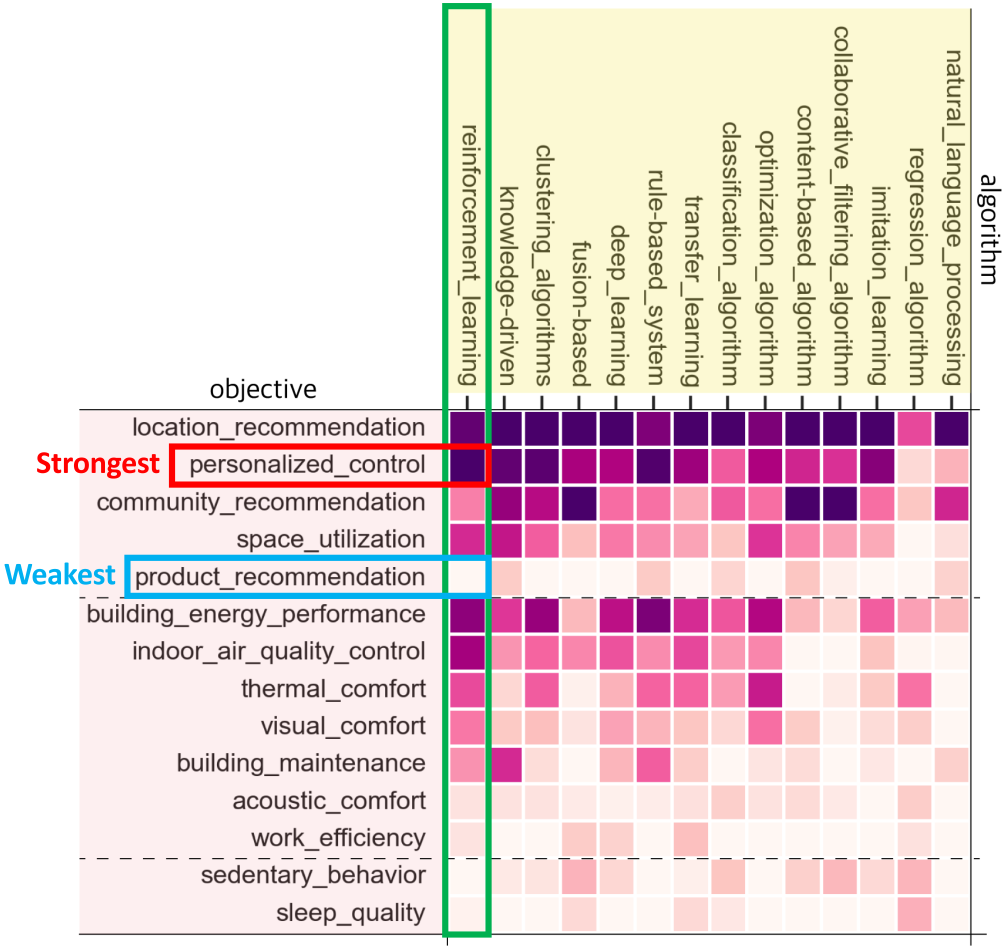
Example:

- **Reinforcement learning (RL)** has the strongest relationship with **personalized control (dark purple)**;
- **Reinforcement learning** has the weakest relationship with **product recommendation (white)**.

The relationship between the words here can be interpreted as how often these two keywords appear together in the literature, therefore:

- Many studies use **RL** to generate **personalized control recommendations**;
- Few studies use **RL** to generate **product recommendation suggestions**.





Example:

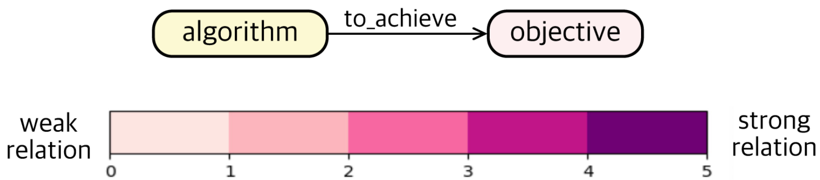
- **Reinforcement learning (RL)** has the strongest relationship with **personalized control (dark purple)**;
- **Reinforcement learning** has the weakest relationship with **product recommendation (white)**.

Strong correlation between **personalized control** and **RL** implies that:

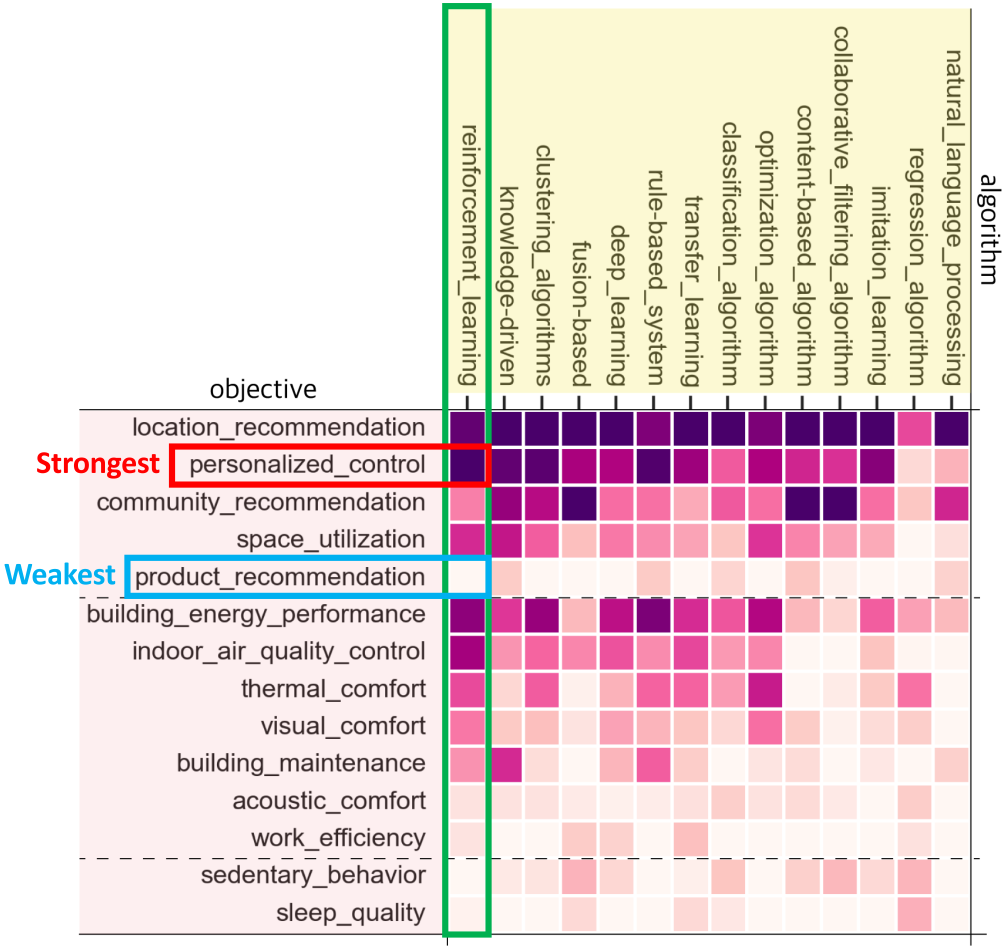
- This is the most mainstream research direction;
- The field is probably well-established.

Weak correlation between **product recommendation** and **RL** implies that:

- There is currently less relevant research;
- This is an emerging research area.

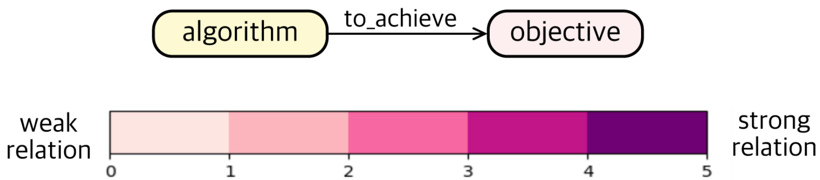


Results and Discussion



Further literature searches can be performed based on the results, i.e:

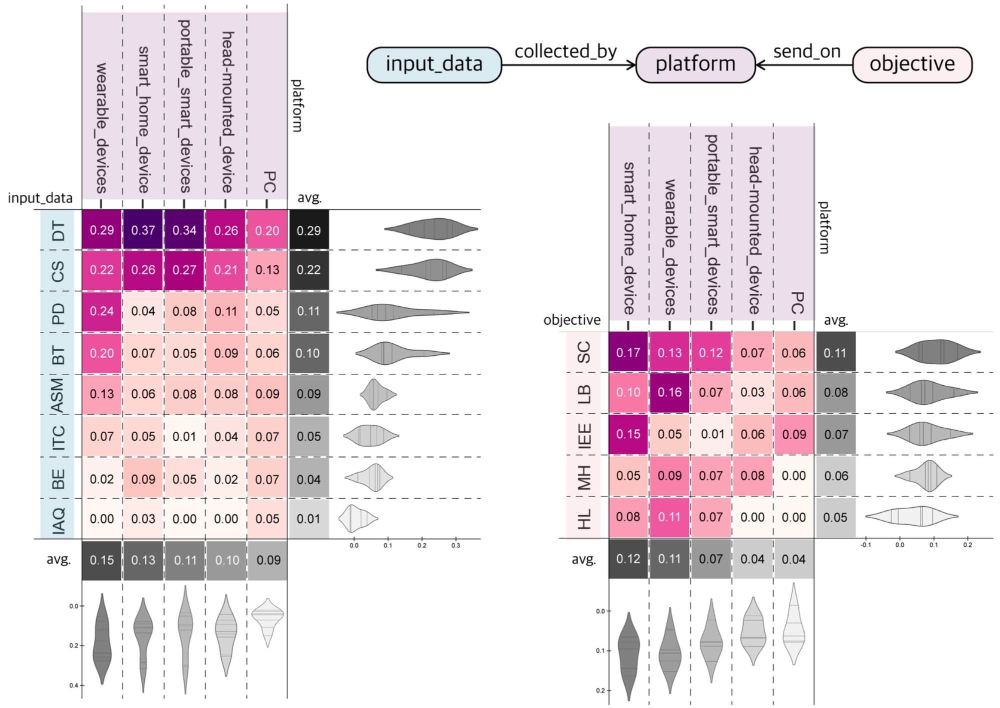
- What are the advantages of these most commonly used algorithms?
- What are the current research status of these well-developed applications?
- Is there any future opportunities for these low relevance applications?



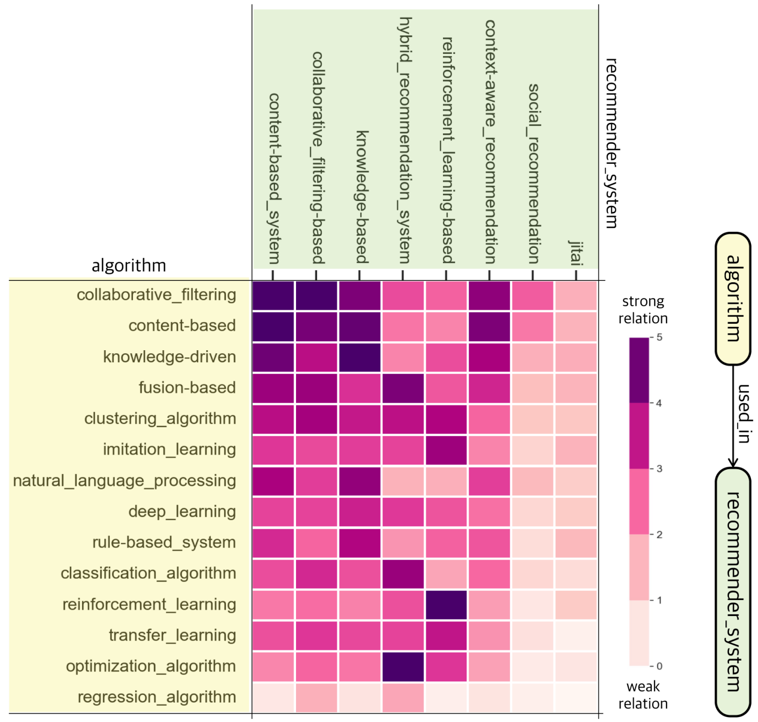
- For recommender systems with different objectives, what data do they typically need as inputs.

3 Results and Discussion

Vector representation | Keywords clustering | Result interpretation | **Similarity heatmap**

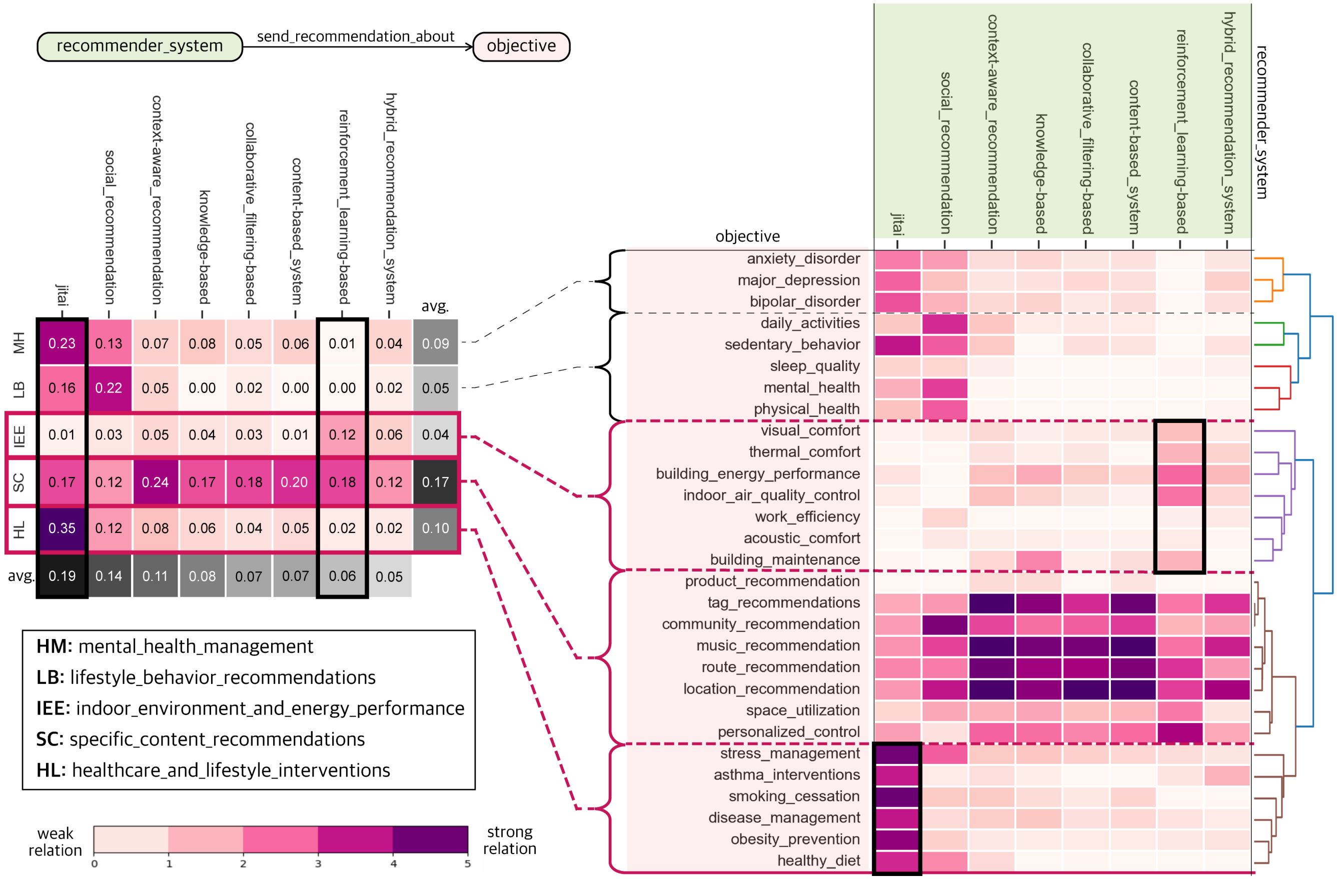


- For different types of input data what equipment is usually used to collect;
- For different types of intervention information what equipment is usually used to deliver the message.



- For different types of recommender systems what are the most commonly used algorithms.

3 Results and Discussion



- Typical objectives for which different types of recommender systems are used (cluster level and keywords level).

4 Conclusion

Summary | Limitation and Future Work

Conclusion:

This study employs text mining techniques to perform a comprehensive review of the literature in the context of built environment and recommendation systems. Text mining can handle large volumes of literature, making it great for quickly getting an overview of a field or identifying trends.

Text mining techniques can also be applied beyond literature reviews. For example, in the medical field, some studies have used text mining to determine effective treatments for different types of cancer [7].

4 Conclusion

Summary | Limitation and Future Work

Limitation:

1. This approach only focuses on quantitative analysis;
2. It is difficult to capture nuances in the literature, cannot provide a deep understanding of the literature;
3. The effectiveness of text mining depends on the quality of the algorithms and models used.

Future directions:

1. Integrating transformer-based pertrained models (such as BERT and LLM, which could improve the comprehension of complex academic texts;
2. Fine-tuning these models on specific academic datasets could significantly improve the precision with which key information is extracted, potentially transforming the landscape of automated literature reviews.

Reference

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