Filtering Discomforting Recommendations with Large Language Models

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Presenter: Jiahao Liu

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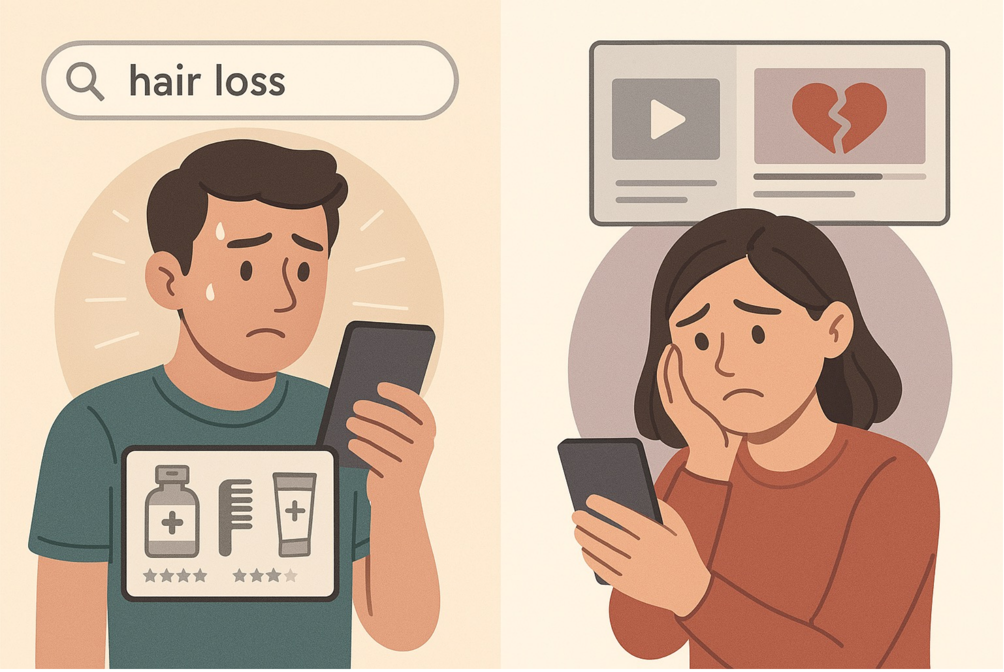
Background

Personalized algorithms can inadvertently expose users to discomforting recommendations

search for sensitive topics (e.g., hair loss) —— potential privacy risks

experience emotional distress (e.g., breakup) —— potential worsening of emotional state



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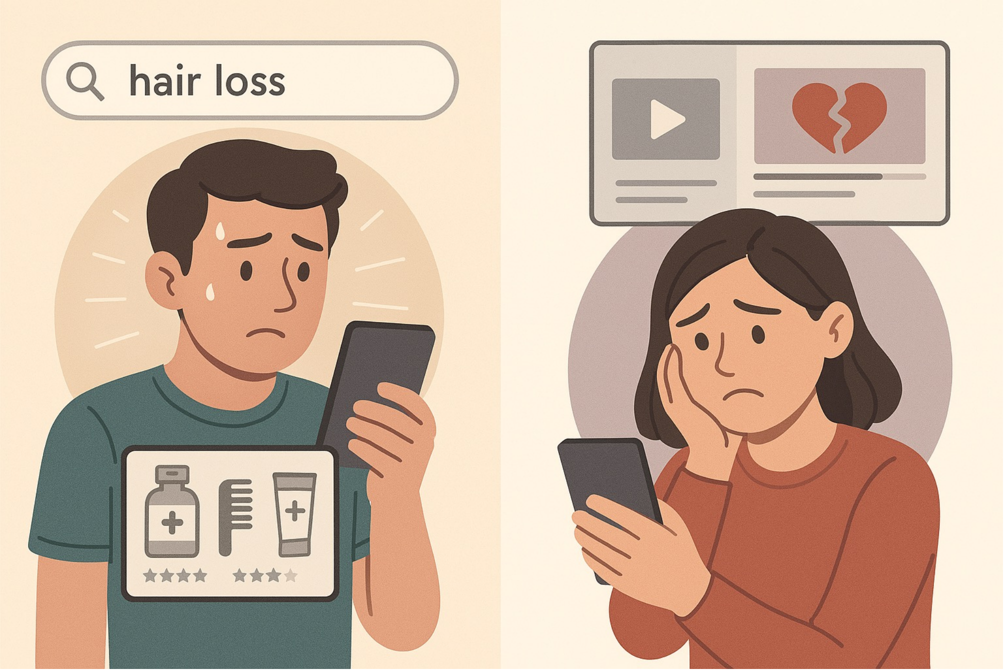

Subjective —— meaning that content one user finds enjoyable may be discomforting to another

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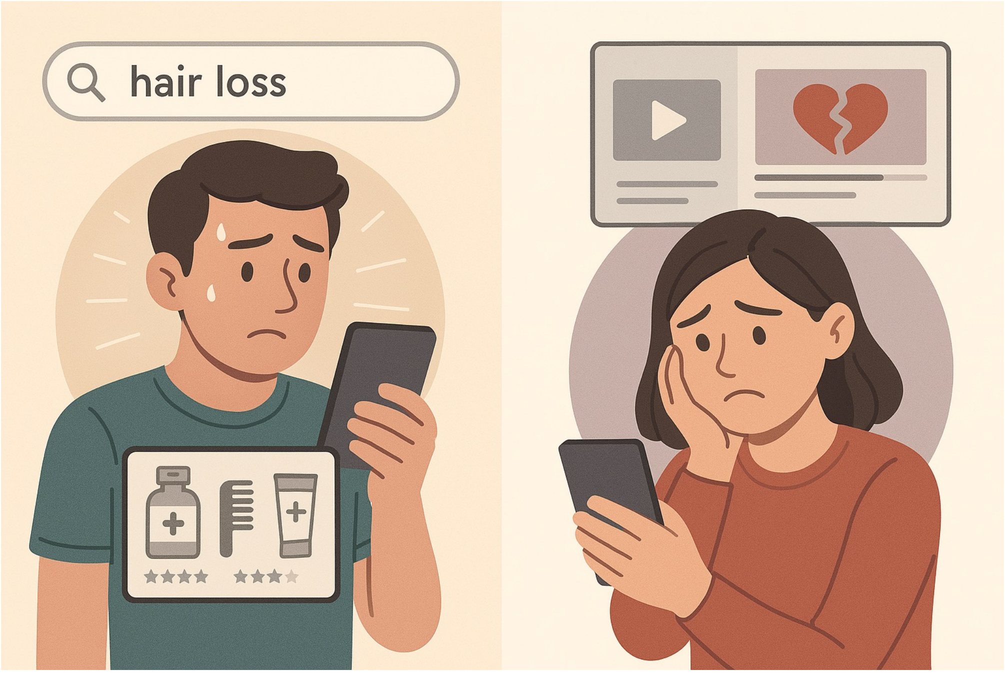
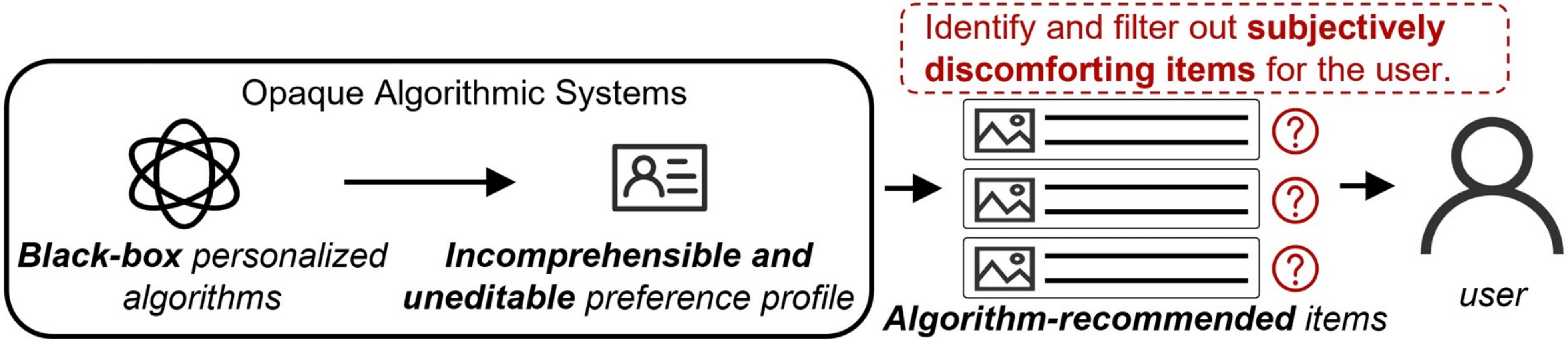


Subjective —— meaning that content one user finds enjoyable may be discomforting to another

We aim to design a tool that helps users filter out discomforting recommendations

Problem Formulation & Challenges

Problem Formulation: Black-box personalized algorithms recommend items to a user based on the inferred preference profile (often implicit in the embeddings), and our objective is to identify and filter out subjectively discomforting items for the user.



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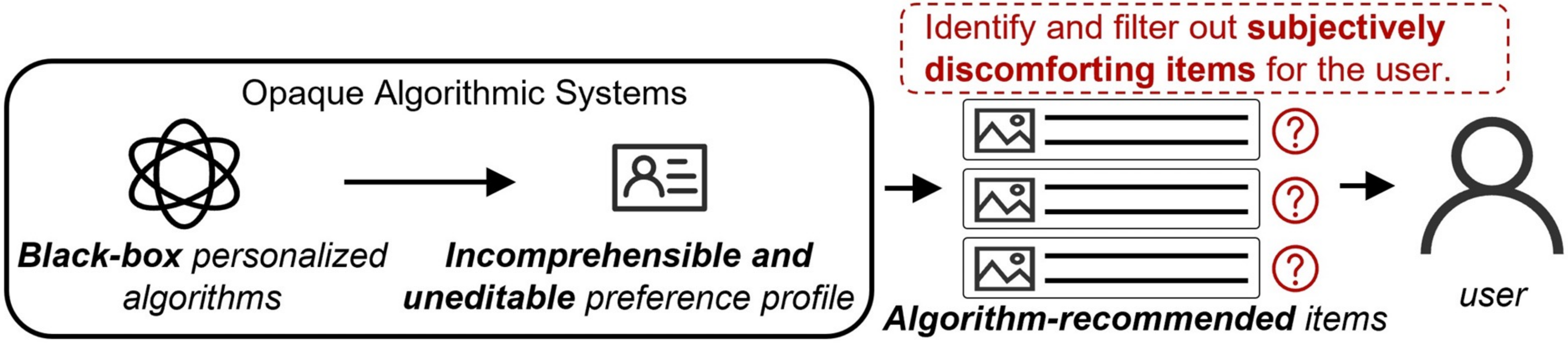


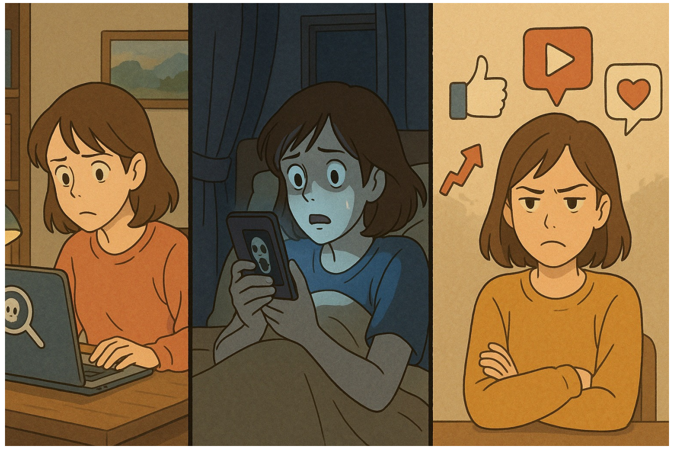
Challenge: the preference profile is both incomprehensible and uneditable

Formative Study

Methods: Conducted semi-structured interviews with 15 participants.

Finding 1: Users may encounter discomforting recommendations for three reasons.

- **User Behavior Deviation** (Curiosity-driven search behavior and clickbait-induced clicks may fail to reflect a user's true long-term interests, leading inaccurate user preference modeling: "*Out of curiosity, I once searched for adult products, and now they keep showing up in my recommendations—so embarrassing.*")
- **Algorithmic Modeling Bias** (Personalized algorithms cannot fully capture the nuanced interests and contexts of users: "*Getting horror content at night is awful, even if I watch it during the day.*")
- **Conflicting Interests** (Platforms may promote content designed to boost user engagement, even if it may cause discomfort. Seven participants mentioned scenarios where this was the case.)



Formative Study

Finding 2: Platforms' "Not Interested" button faces three major limitations.

- Lack of **Personalization** —— only preset options can be selected
- Lack of **Flexibility** —— the duration of the block cannot be set
- Lack of **Transparency** —— the effect cannot be known

Zhihu

Weibo

Bilibili

Xiaohongshu

Formative Study

Methods: Conducted participatory design with 15 participants.

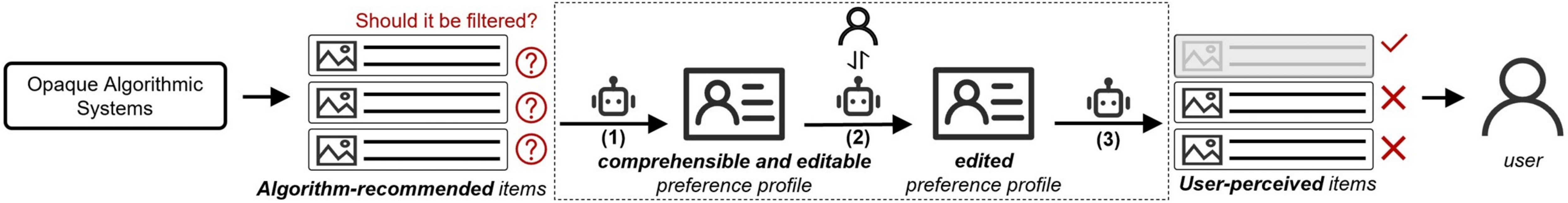
Design Goals

- **Support Conversational Configuration** (Participants prefer expressing filtering needs in natural language as it is unrestricted and personalized. Participants also find conversation-based interaction more natural, addressing the issue of "lack of personalization".)
- **Provide Preference Explanations** (While participants struggle to articulate filtering needs proactively, all agree that understanding platform recommendations and personal behaviors aids expression. Reviewing and correcting recommendations enhances clarity and accuracy.)
- **Provide Feedback Channels** (All participants emphasize the need for transparency and contestability. Knowing what content is filtered and why builds trust, while enabling corrections refines filtering needs, addressing "lack of transparency.")
- **Operate in a Plug-and-play Manner** (The tool should work independently of specific algorithms and directly affect outputs. Key factors: (1) Filtering needs are dynamic; (2) It should be user-managed across platforms; (3) Users prioritize mitigating discomfort over algorithm understanding. This approach enhances flexibility.)

DiscomfortFilter

Large language models provide promising solutions for achieving these design goals ……

The workflow of DiscomfortFilter:



(1) Construct a comprehensible and editable preference profile based on user click behavior

(2) Assists the user in expressing filtering needs, and then masks the discomforting preferences

(3) Filters out discomforting recommendations based on the edited preference profile

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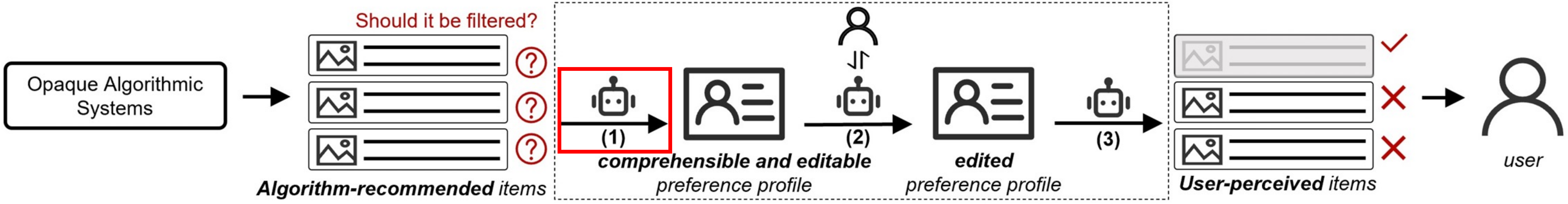

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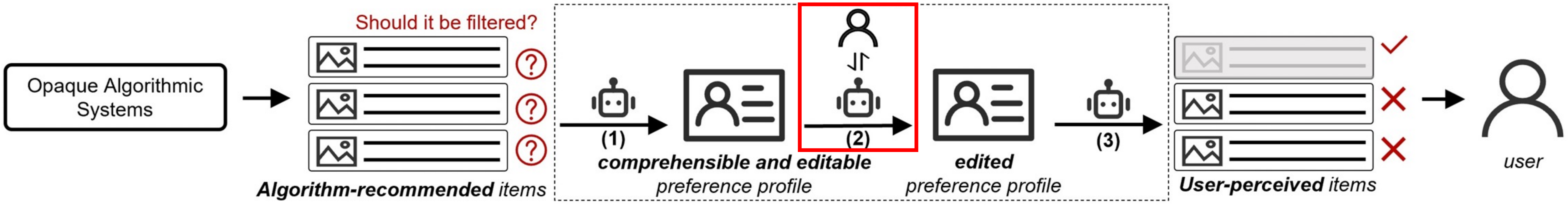

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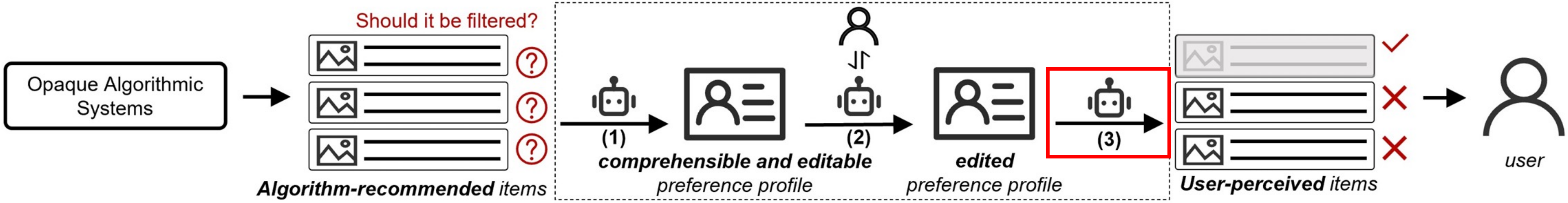

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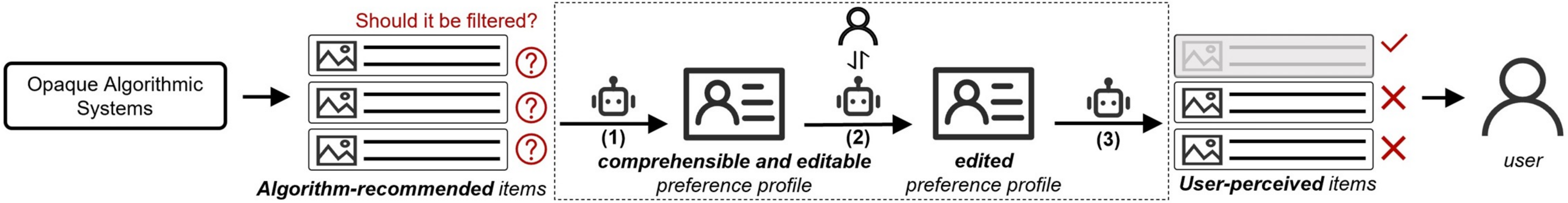

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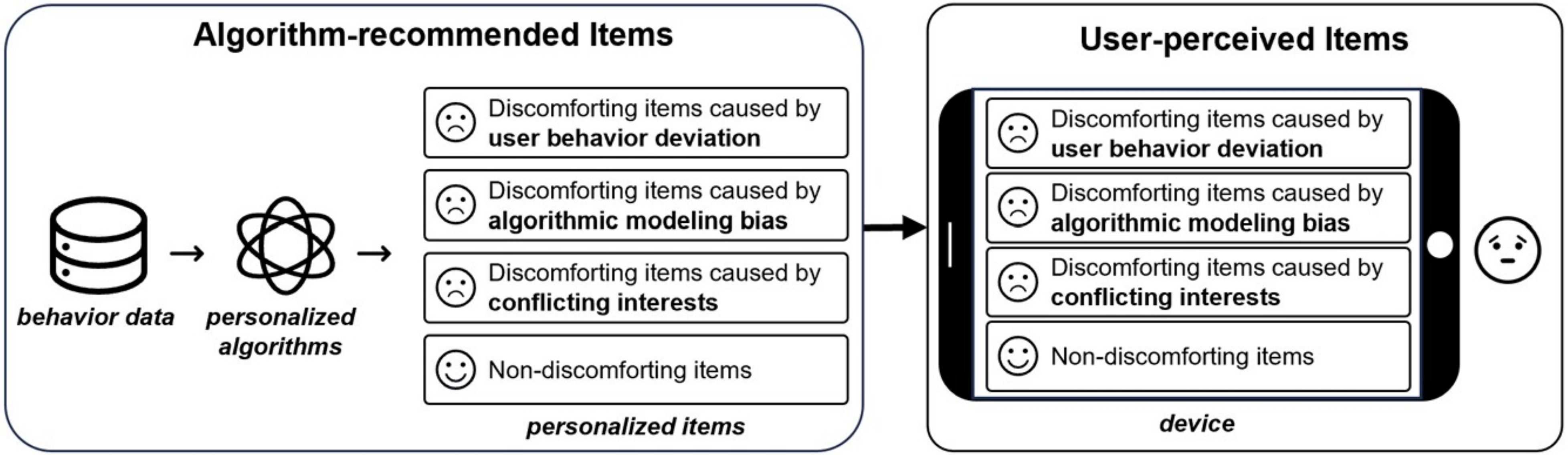
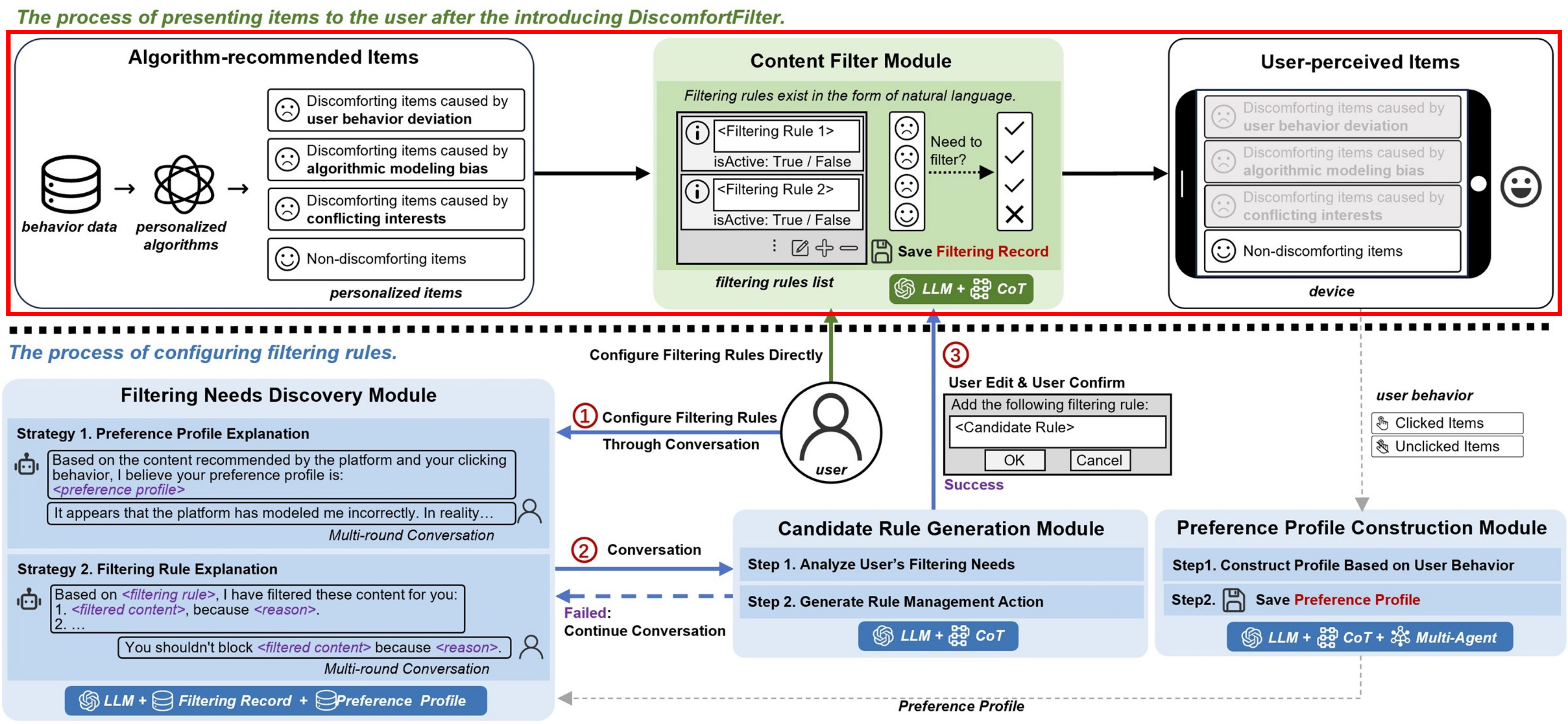
Overall, DiscomfortFilter empowers the user to actively influence the decisions made by personalized algorithms, enhancing control over the algorithms.

DiscomfortFilter



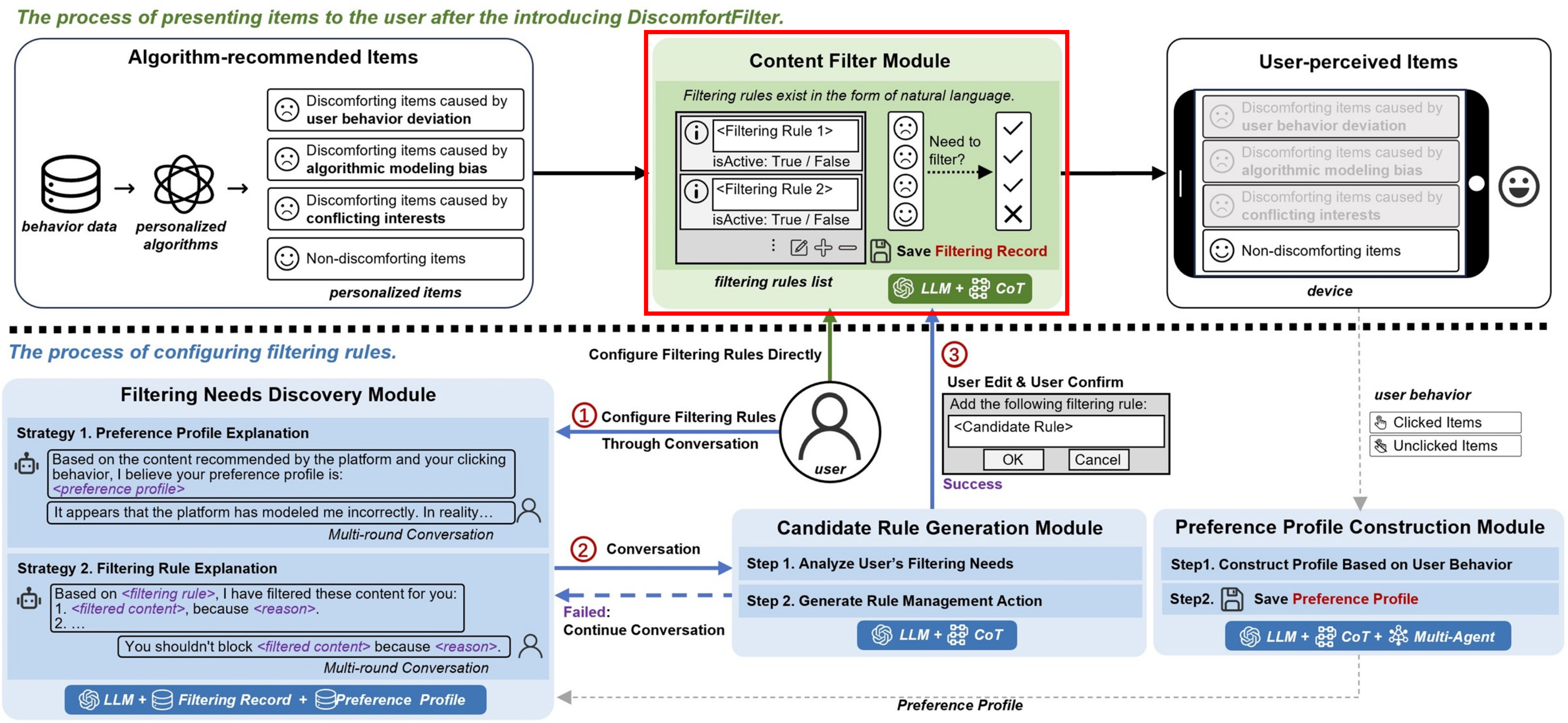
Without DiscomfortFilter, users **passively** consume the content recommended by the algorithm.

DiscomfortFilter



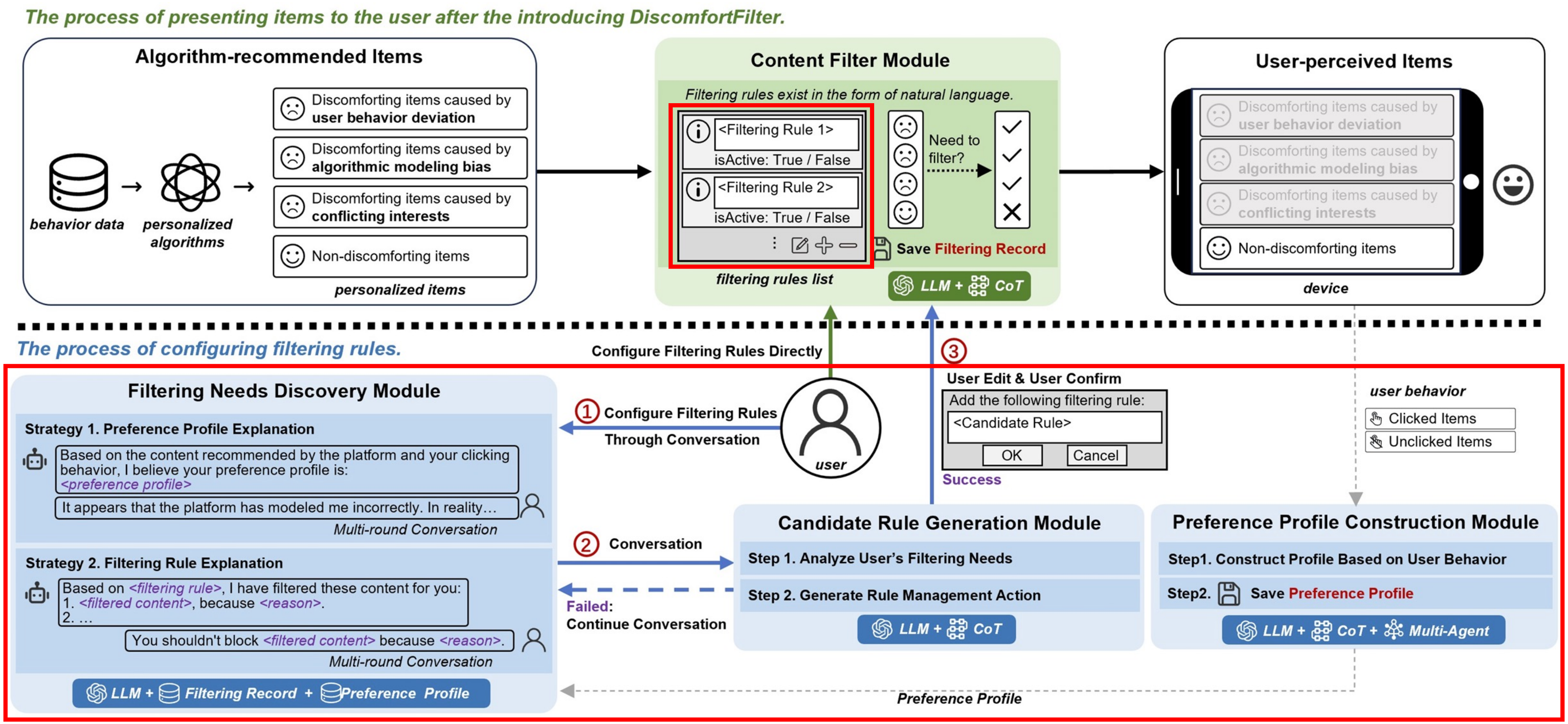
With DiscomfortFilter, users **actively** control the content recommended by the algorithm.

DiscomfortFilter



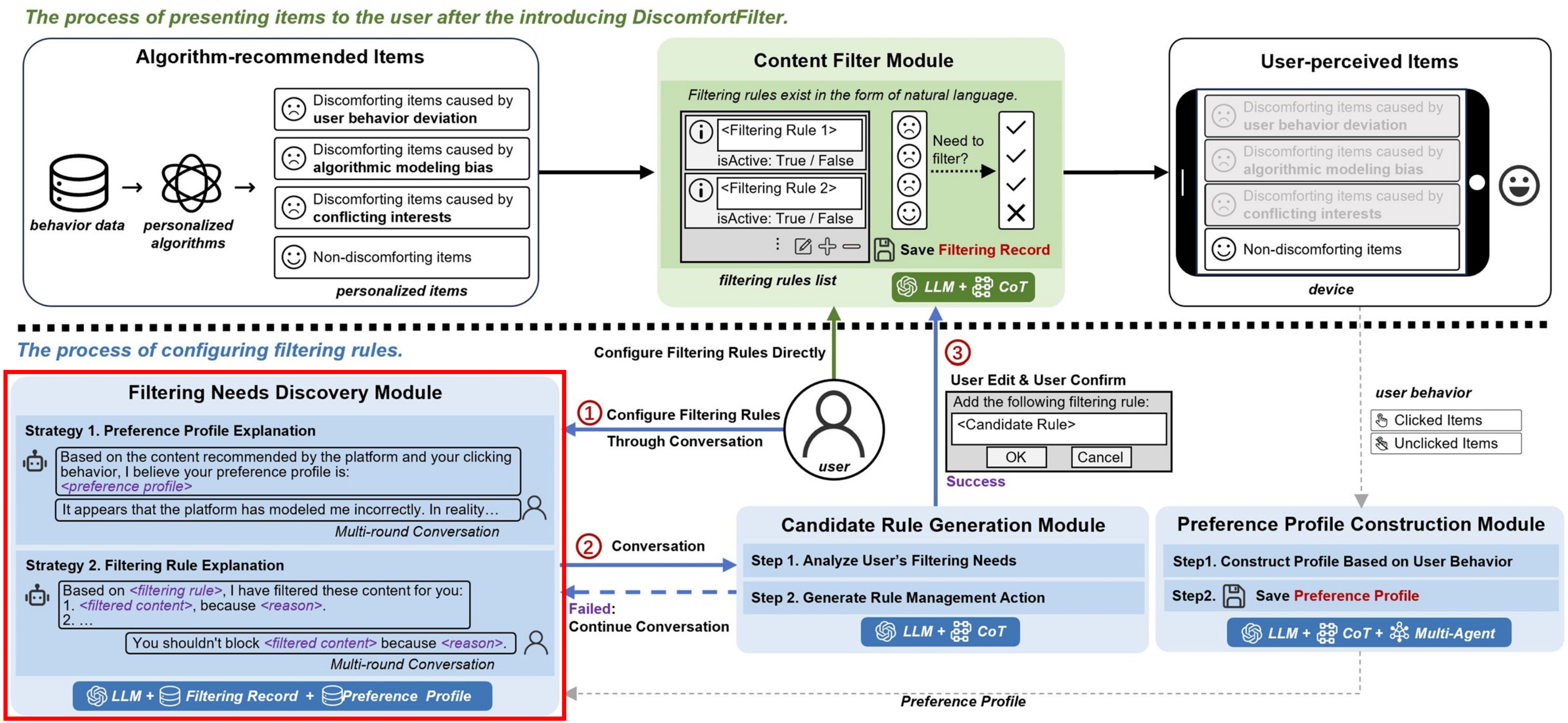
Content Filter Module Identifies and blocks recommended content based on the filtering rules configured by the user.

DiscomfortFilter



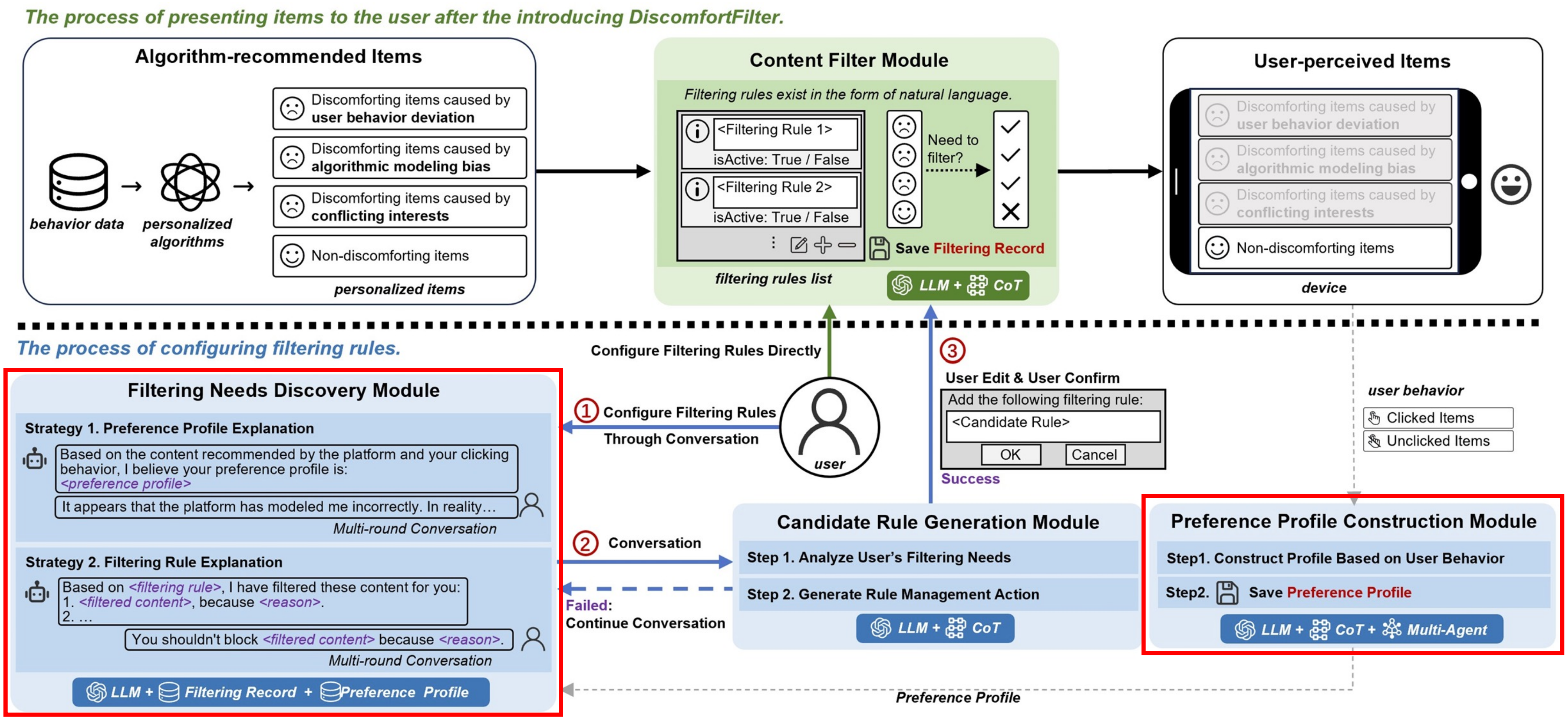
The core is the configuration of the **filtering rules**.

DiscomfortFilter



Filtering Needs Discovery Module helps users express their filtering preferences by explaining the preference profile reflected by their behavior.

DiscomfortFilter



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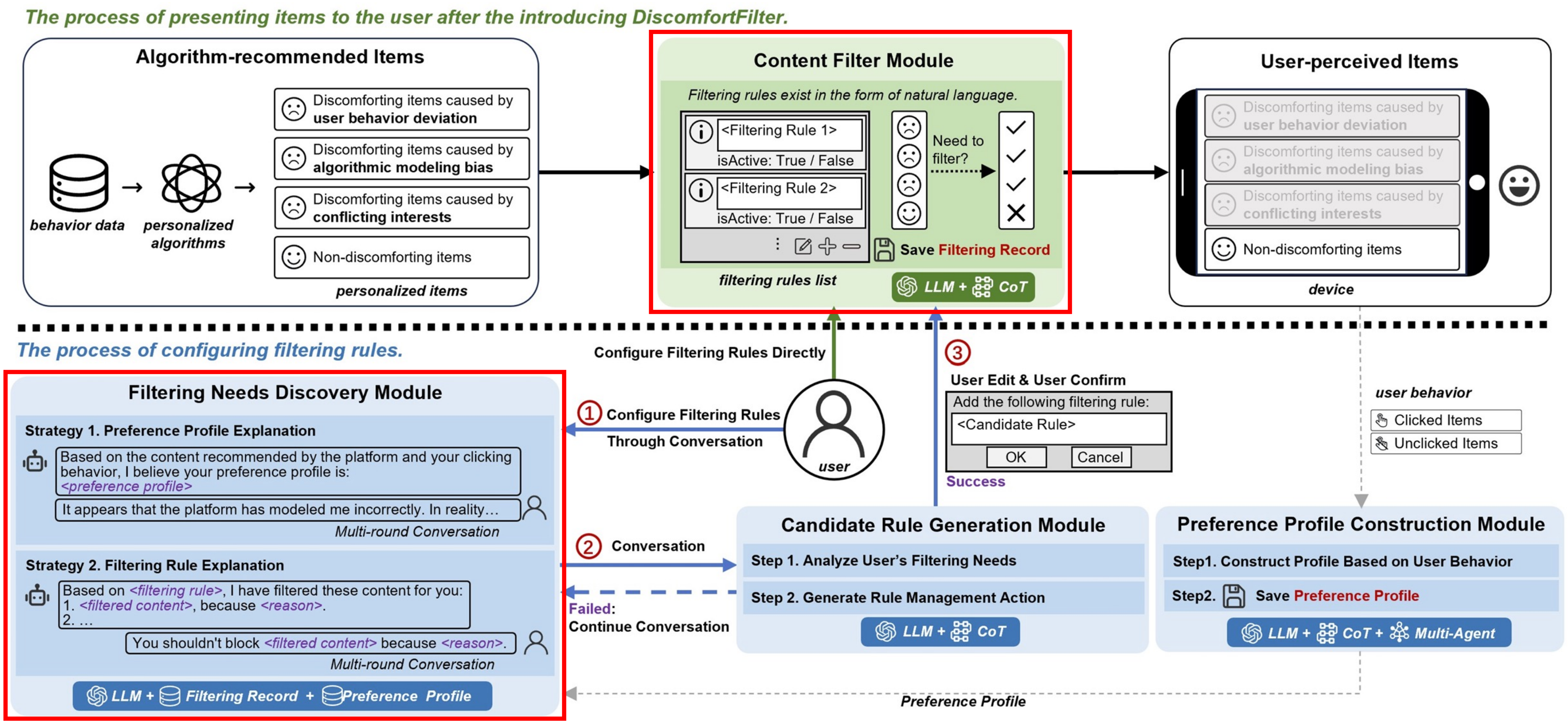

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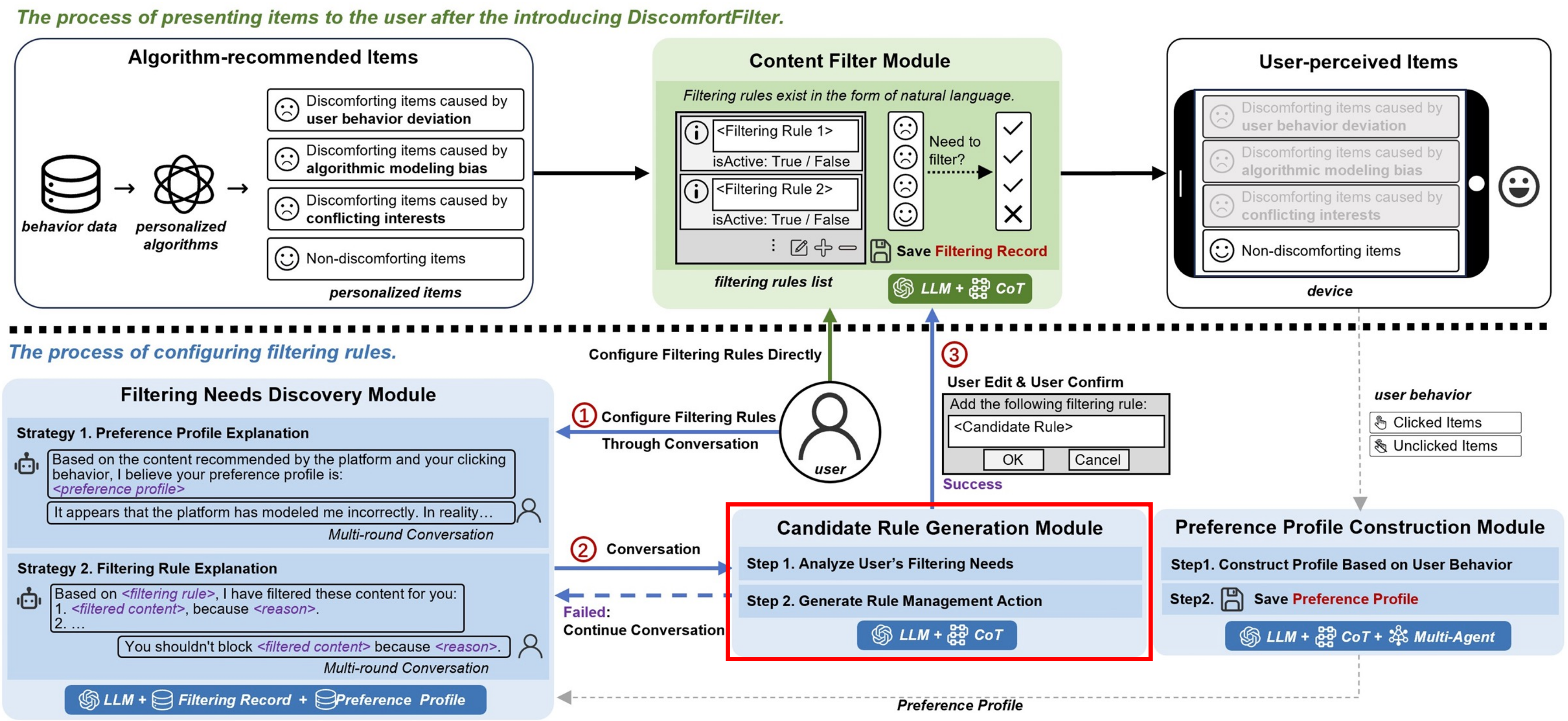
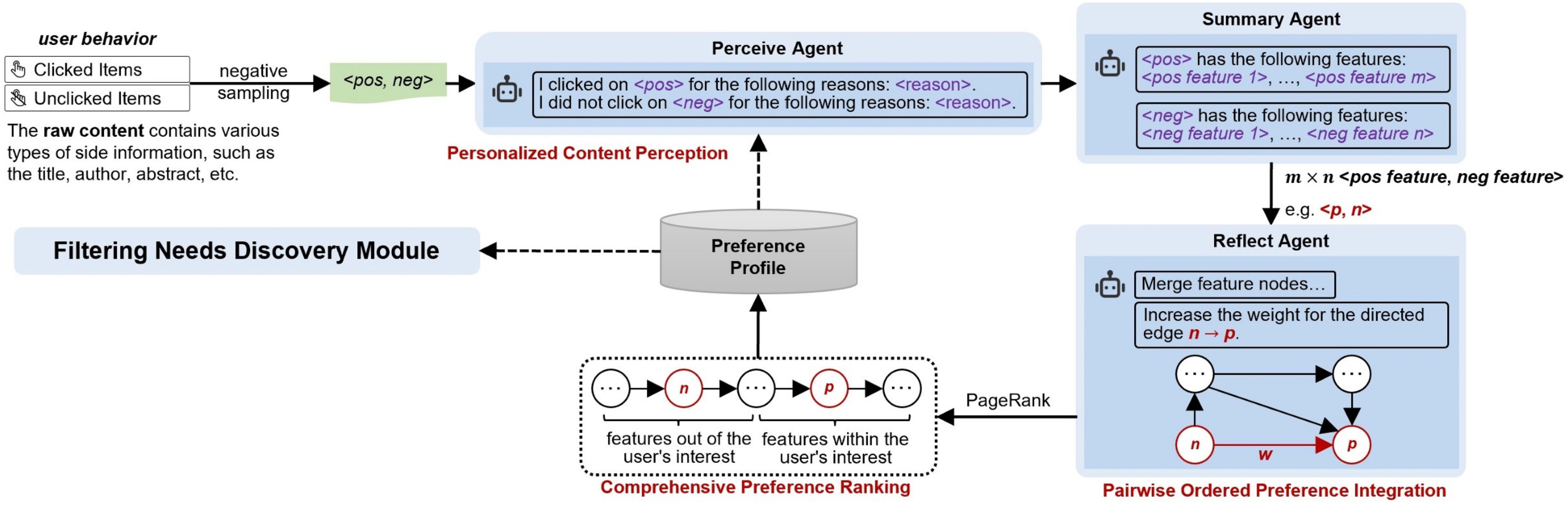


Candidate Rule Generation Module analyzes the dialogue content to extract the user's filtering needs.

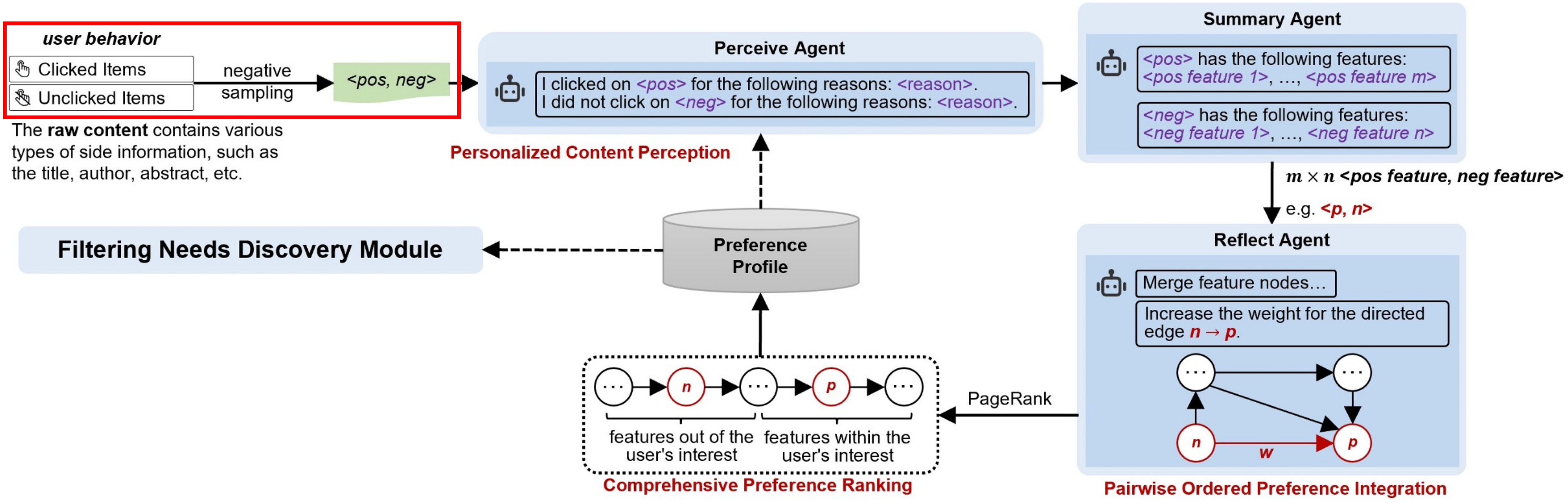
DiscomfortFilter



Preference Profile Construction Module constructs a user's preference profile by analyzing the user's clicking behavior on recommendations.

Pairwise Ranking	Personalized Perception	Feature Extraction	Preference Aggregation	Preference Ranking
Negative Sampling	Perceive Agent	Summary Agent	Reflect Agent	PageRank Algorithm

DiscomfortFilter



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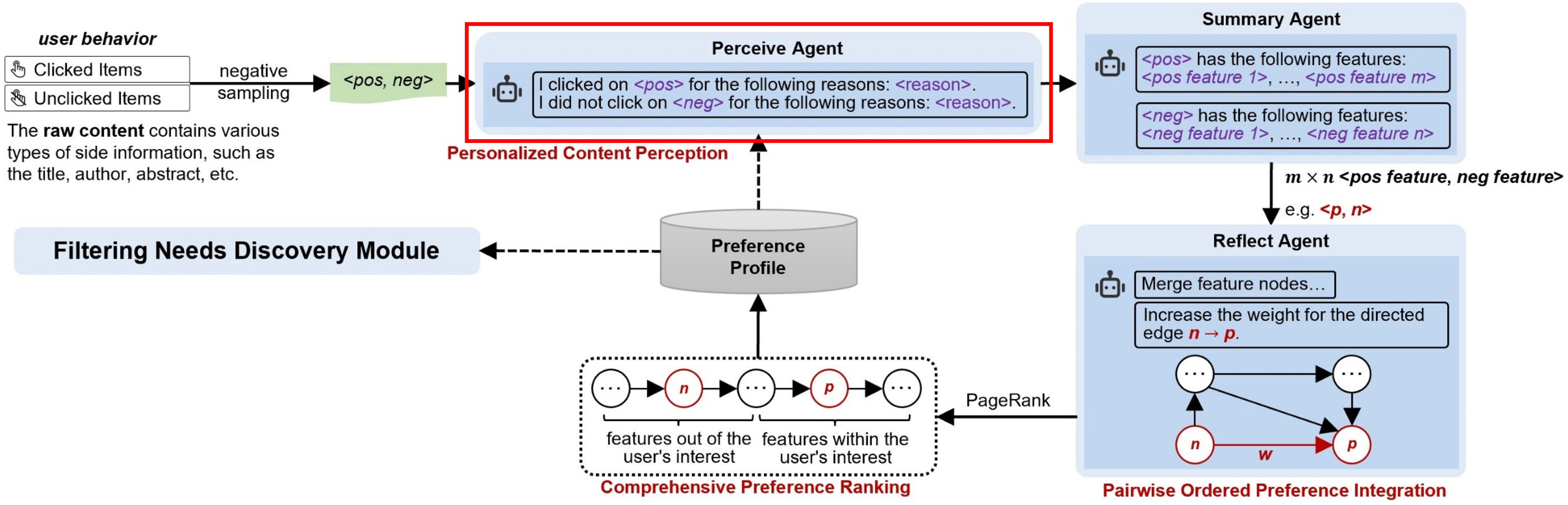

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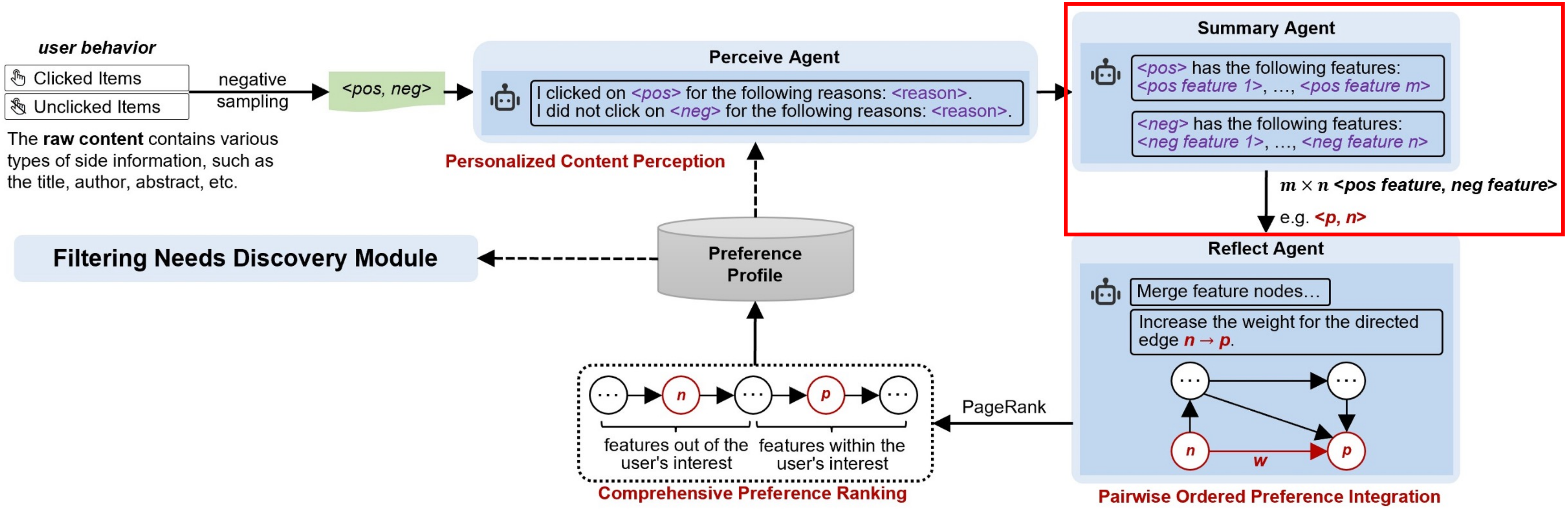

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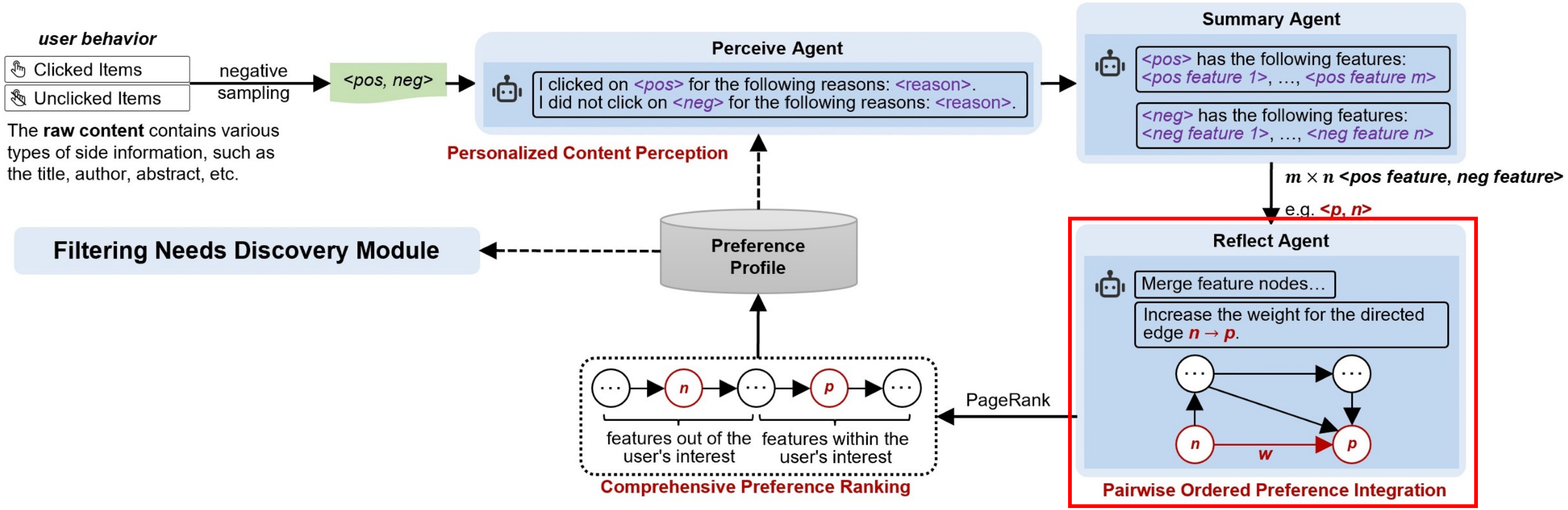

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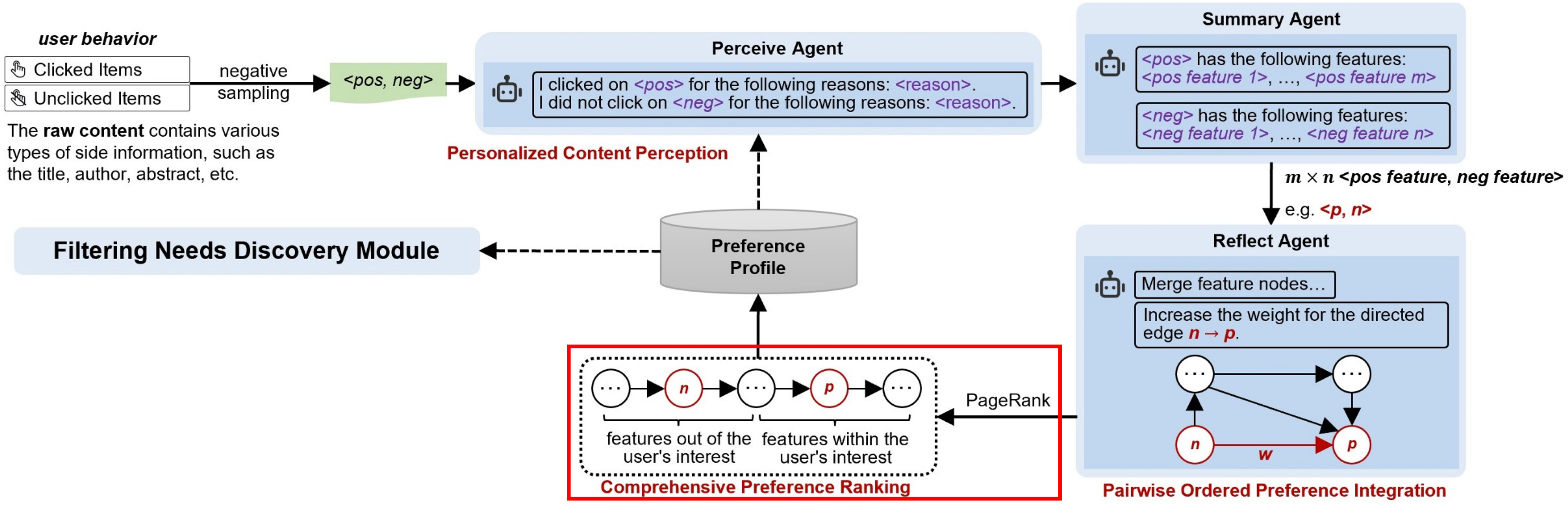

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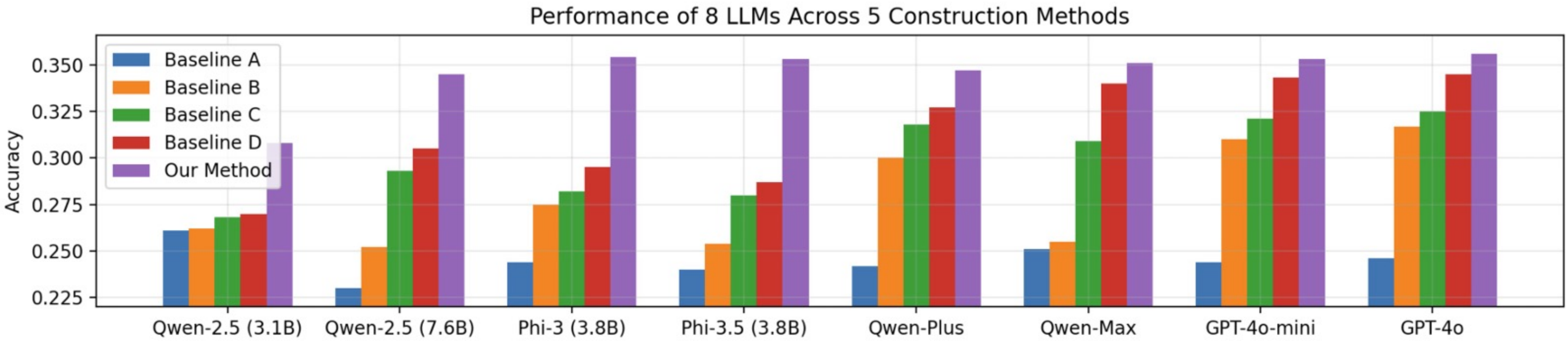
Evaluation

Offline Proxy Task

Task: Predict a user's next click from K options based on their preferences

Metric: Accuracy

Dataset: MIND [1]



Result: The constructed preference profile not only delivers state-of-the-art performance across various LLMs, but also empowers open-source models with fewer parameters to compete with proprietary commercial models.

[1] Wu, Fangzhao, et al. "MIND: A Large-scale Dataset for News Recommendation" Proceedings of the 58th annual meeting of the association for computational linguistics. 2020.

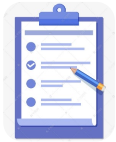
Evaluation

User Study

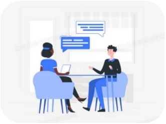
Platform: **Zhihu** 知

Duration: **one week**

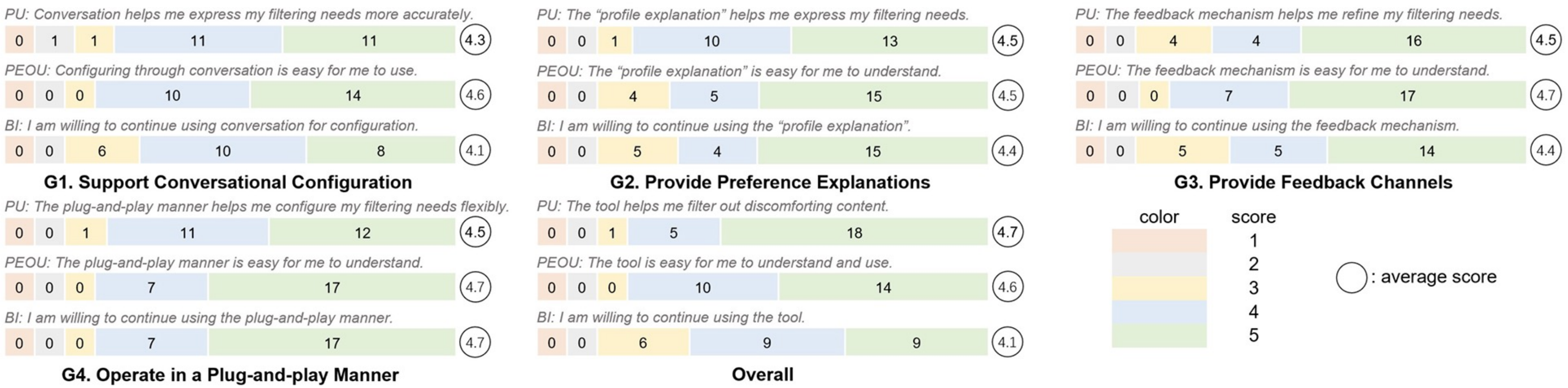
Number of participants: **24**



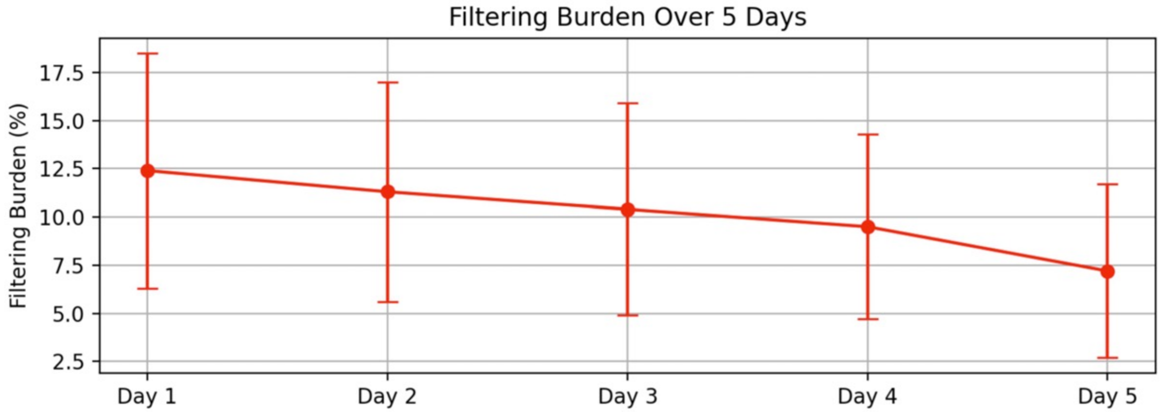
Quantitative analysis: survey



Qualitative analysis: semi-structured Interview



Result 1: DiscomfortFilter effectively help users express their filtering needs and filter out discomforting recommendations



Assuming DiscomfortFilter processes *N* items using a filtering rule, with *n* items identified as discomforting, we define *n/N* as the **filtering burden** of this rule. Over time, the filtering burden steadily declined, indicating that the **platform was recommending progressively fewer discomforting items**.

Result 2: DiscomfortFilter impacts platform recommendation outcomes by influencing the exposure of discomforting items.

Limitations & Future Work

Limitations: From seeing to perceiving — still a long way to go

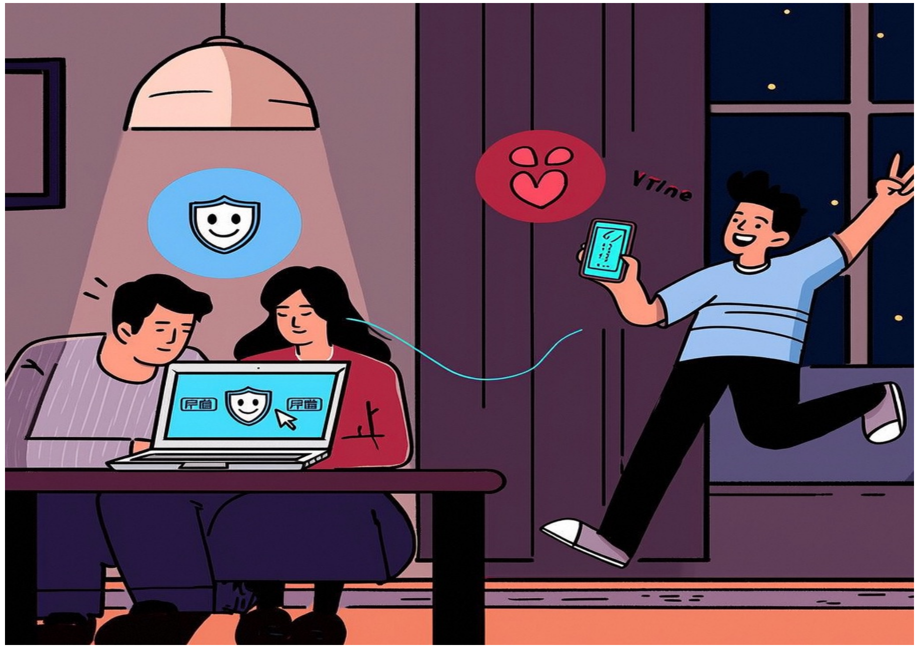
False Association in LLMs

Insufficient Perceptual Alignment

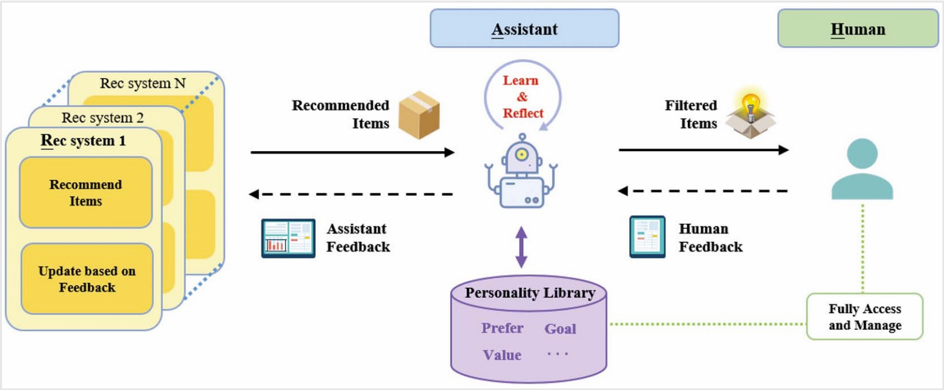
Future Work: Parental Control Over Children's Online Content

configured by parents and used by children

requires targeted design (e.g., legal and ethical considerations)



Related Work



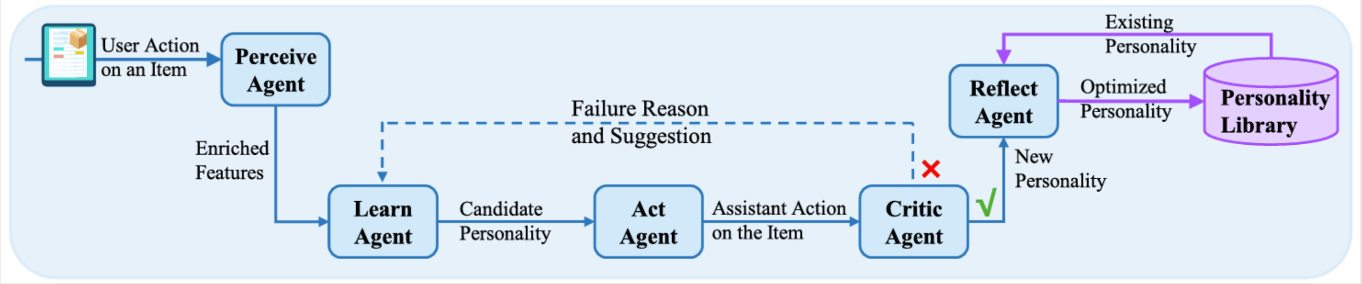
RAH! (*RecSys*–*Assistant*–*Human*)

A human-centered recommendation framework

Assistant Features:

1. Aligning with User Preferences
2. Filtering Items Recommended by the System
3. Simulating User Clicks

The framework utilizes the **learn-act-critic loop** and a **reflection mechanism** for improving user alignment:



Perceive Agent: Analyzes recommendations and feedback.
Learn Agent: Captures user personalities from behaviors.
Act Agent: Filters and personalizes content.
Critic Agent: Evaluates and adjusts actions.
Reflect Agent: Optimizes personality data.

[Human]
User Action: Like The Depression Cure: The 6-Step Program to Beat Depression without Drugs
[Assistant]
It can have a potential risk of privacy leakage. Suggest two personality confusion strategies.
- **Strategy I** (pretend a psychologist) Assistant will automatically express more Like on professional psychology textbooks to the recommender system.
- **Strategy II** (pretend a shared account) Assistant will automatically express random Like and Dislike.

[Human]
(select and enable a protection strategy)
[Rec System]
(recommend several items)
[Assistant]
Act
- For the user: filter recommended items from the recommender systems to remain accurate.
- For the recommender system: selectively express user real feedback and create some extra feedback to protect privacy.

1. Protecting Privacy

[Human]
User Action: Dislike the Incredibles (Pixar film)
User Comment: *Usually **watch films with my kid**. The film is **too dark for children**, yet **too childish for adults**. It's pretty much for the most part just **mindless violence** throughout the film.*
[Assistant]
Learn:
| **Prefer:** family movies | **Disprefer:** heavy dark elements, too childish, lots of violence | ……
[Rec System]
Recommend: (1) Coco (2) Ironman (3) Batman: The Dark Knight
[Assistant]
Act
(1) Like, pass to the user
(2) Not Sure, pass to the user to learn from human feedback
(3) Dislike, proxy feedback to the recommender system

2. Enhancing Control

More Capabilities:

3. Debiasing
4. Cold Start
5. ……

RAH! RecSys–Assistant–Human: A Human-Centered Recommendation Framework With LLM Agents. IEEE TCSS 2024.
Yubo Shu, Haonan Zhang, Hansu Gu, Peng Zhang, Tun Lu, Dongsheng Li, and Ning Gu.

Thanks!