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GET PLACE GO: An AI-Powered Vibe Based Location Recommendation System Using NLP, RAG and Agentic AI

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Abstract: Conventional location recommendation systems such as, Google Maps and Zomato are mainly depend on ratings, proximity, and keywords, which lead to inefficiency, when considering the subjective intent of the user, like the user's mood, the ambiance of the place, and the contextual preference. Therefore, the user has to wade through numerous results and is more likely to experience information overload. To solve this problem, this paper proposes an intelligent AI-powered personalized recommendation system, GET PLACE GO, to make vibe-based location recommendations and optimize day trips efficiently.
The new system will uses technologies like NLP, RAG and Agentic AI to showcase and guide user interactions with these tech and make sure to enhance intelligent decision-making processes. These system also kind of uses dynamic data collection from platforms such as Google Maps, Zomato and Reddit. Sentiment and semantic analysis techniques are applied to get qualitative attributes like ambiance, among others.

I. INTRODUCTION

Digital platform has greatly influenced the way people look for and choose destination like cafes, restaurants, and travel spots. Current recommendation sites, such as Google Maps and Zomato,depend mainly on measures like ratings, popularity. Although these work well in terms of efficiency, they lack consideration of some important aspects that matter to many people, such as feeling, mood, and purpose[14].

Most of the people search for recommendations like human feeling words like a ‘romantic cafe’, ‘calm office’. These engines cannot recognize these type of context,and intent behind searches, which result in information overload and wrong decision-making processes [12].

New technologies in Artificial Intelligence (AI) technologies, specifically that are in natural language processing and large language models, have enhanced the grammar of language and context by systems [3][11].

With Retrieval-Augmented Generation (RAG), systems can also include present external data and make recommendations with good accuracy and reliability[4].

II. LITERATURE SURVEY

A. *Chat-Based Recommendation Systems*

Conversational recommendation systems helps recommendations by connecting with people through contacting and talking with them. Said by Friedman et al.[15],LLM-powered conversational systems improve user satisfaction by dynamically adapting to preferences. However, conversational recommendation systems less work on real time data.

B. *Retrieval Augmented Generation(RAG)*

As per mentioned by Gao et al[16]. in the references, RAG is an approach to language modeling that both retrieval and output components in producing correct responses within a same region.Such methods proves that effective in dynamically changing contexts where updated information is so much necessary.

C. *Sentiment Analysis and Opinion Mining*

Sentiment analysis methods the extraction of opinions expressed in texts. Matero et al.[13] published pioneering work on a opinion mining, which became a staple of recommendation systems..Most already made solutions concentrate on analysis, ignoring more diffcult aspects of people opinions, such as their “vibe”[6].

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D. Agentic AI Systems

Agent AI systems automaticalys performs planning, and reasoning actions using LLM.Systems like these are capable of handling multiple in row operations and engage with outside resources,which makes them important for creating repetitive and different recommendations [5].

E. Context Aware Recommendation Systems

Context-aware systems consider various factors,which has time, place and different preferences of users. Patel et al. pointed out the critical role of context(word) adaptability in recommendation accuracy improvement [7].

F. Large Language Models as Recommenders

LLM allows zero-shot recommendation by understanding user preferences through natural language without the need or help of the past or historical data or fine-tuning, capturing complex textual and mood-based intent effectively[1][2][11].

G. Knowledge-Agumented Recommendation System

By integrating outside knowledge graphs with LLM's improves recommendation accuracy and optimized by grounding outputs in structured way, real-time information and reducing incorrect suggestions[3].

H. NLP-Based AI Recommendation Systems

In embedding-based NLP approaches outperform keyword and topic-based techniques by also capturing deeper semantic relationships,making them essential for handling and also processing vibe based recommendations[12].

I. Multi-step Planning and Task Execution with Language Agents

LLM-based agents can support complex,multi-step planning tasks like itinerary creation,but it can still cause struggle with maintaining constraints and problems over the longer planning sequences[4][10].

III. COMPARATIVE ANALYSIS

It would be necessary to conduct a comparative analysis of the currently existing recommendation and intelligent systems powered by artificial intelligence algorithms in order to assess the effectiveness, flexibility, and practicality of these systems. The existing system showing features,unlike the proposed system, present smart and recommendation model are designed to solve a range of issues, rather than serve as a broad solution [1][7].

Conversational recommender systems use natural language processing methods and large language models for communication with the user and preferences adjustment during the interaction process. Although such systems significantly increase the people's involvement rate and ensure high levels of personalization,they have issues with connecting to real-time external data and ensuring continuity of context throughout the conversation[1],[3].

Some of these type recommender system that uses machine learning models to make decisions and create recommendations are the most currently existing intelligent systems. Such algorithms can efficiently scale to large datasets and operate effectively; however, they cannot recognize the semantic sense of recommendations or understand such characteristics of a person as mood or vibe [7].

Opinion extraction tools, which are designed to recognize emotions or attitudes of a person towards a particular item of discussion, help understand the perception of the user better; however, these systems usually provide polarity assessment and are incapable of analyzing complex contextual features [6].

Retrieval augmented generation systems help address the issues connected with the usage of machine learning-based models by introducing real-time access to additional external information into the process of generating responses. This feature makes such intelligent mechanism much more precise, but it requires reliable sources of data that are hard to find [4]. Although such intelligent systems perform well in specific applications, such as itinerary planning or decision-making workflows, they still require much computing power [5].

Large language model-based zero-shot recommenders [1] offer the most generalized approach to preference understanding, as they require no task-specific training data and can interpret a wide range of subjective, natural language queries out of the box. However, because of these systems mostly rely on parametric knowledge encoded during pretraining,they cannot be reflected to real-world changes in venue attributes, pricing, or availability ,and they produce no explicit reasoning chain that would allow users to understand or challenge a recommendation.

Sentiment analysis systems [6][13] contribute to a uniquely valuable capability to the recommendation pipeline,the ability to extract qualitative,experiential attributes from a large volumes of an unstructured user reviews.Unlike rating-based systems that collapse all feedback into a single scalar score, sentiment-aware systems can distinguish between a venue that receives high ratings for food quality but poor ratings for ambiance from one that excels on both dimensions. This granularity is important for the vibe-based matching,where as a user seeking a "quiet, intimate setting" requires an aspect-level ambiance scores rather than an aggregate good rating.The primary limitation of sentiment systems, as identified across the literature [6][13],is their tendency to classify the sentiment in an isolation without integrating the resulting of an attributes into a downstream reasoning or recommendation pipeline in a coherent, end-to-end manner.

Agentic AI systems [5][9] represent the most architecturally sophisticated approach among those surveyed, and also the one most directly suited to complex, multi-step recommendation tasks such as full-day itinerary planning.Their ability to decompose the high-level user goal into the sub-tasks,which invokes appropriate tools at each and every step,and synthesizes intermediate results into a coherent final output is unmatched by any of the other system categories.The Reflexion framework [5] further distinguishes an agentic systems by enabling self-correction through trials,allowing the more agents to identify and recover from reasoning errors without any human or user intervention. However, this sophistication comes at a considerable computational cost which is compatible,and the multi-step reasoning chains produced by these systems are very difficult to inspect or audit,which can lead to explainability concerns and also [7][8] that remain largely unaddressed in the current literature.

The integrated and hybrid AI systems [7] attempts to combine the strengths of multiple approaches by typically pairing an NLP-based understanding component with a collaborative filtering. While this combination yields for the measurable and other improvements in accuracy compared to either component individually,the integration is typically short and deep with each of the module operating on its own input-output interface rather than sharing a an unified semantic representation.Then as a result, systems like these often fail to propagate vibe-level semantic signals extracted by the NLP component from user reviews — into the retrieval and ranking stages in a way that would meaningfully differentiate subjective experiences. Patel et al.[7] acknowledge that a achieving deep,semantically coherent integration across heterogeneous AI components remains engineering challenge and research challenge.

TABLE I
COMPARISON OF EXISTING SYSTEMS

System	Technique	Features	Limitations
Conversational Recommender Systems	NLP, LLM	Interactive, personalized recommendations	Limited real-time data integration
Traditional Recommender Systems	ML (Collaborative/Content-Based)	Scalable, efficient filtering	Lack of personalization and semantic understanding
Sentiment Analysis Systems	NLP, Text Mining	Extracts user opinions from reviews	Limited to polarity, lacks context awareness
RAG-Based Systems	Retrieval + LLM	Real-time, fact-based responses	Dependent on external data, latency issues
Agentic AI Systems	LLM + Planning	Multi-step reasoning, autonomous decision-making	High computational cost, complexity
Integrated AI Systems	Hybrid AI	Combines multiple functionalities	Poor scalability and explainability

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IV. RESEARCH GAP

After revolution on the existing literature and compare them with dissimilar AI-based recommendation mechanism,it clears that there are more important gaps that still needed to filled first.These constraint must focus toward for a more levelled up,advanced, integrated, and user–focused approach.

One of the most seen issues is the lack of integration among the variety intelligent components.Many builded mechanism are designed to perform only single function-such as giving recommendations to the people, analyzing sentiment,or simple basic conversational talk.However,these features sometimes work.

independently rather than a single together mechanism.[5]This fragmented design limits the overall effectiveness of the system and which leads to negative impacts user experience.

Here big bothering factors is the limited depth of personalization.Factors like human's mood,context,feeling, or the overall "vibe" a human is looking for is rarely considered here.[2][7]Because of which the recommendations generated by the system may not truly reflect, what user actually wants in that particular present moment.

In addition,many mechanism find difficult in understanding natural language in a very meaningful way.A large number of models still based on normal keyword matching techniques,which are not capable for interpreting difficult or conversational human input.As result in,many people get common or different suggestions that does not match there beliefs and not satisfy them[6].

Most of the AI models operates as black boxes,which also mean they only provide answers without clearly explaining,how those results were created.This lack of transparency can broke user trust and make it hard for users do not rely on the system recommendations[7][8].

Talking about real-time adaptability is also limited in many solutions.Several systems depend on correct datasets and do not effectively incorporate unstructred,real-world data such as live user reviews, social media trends and many more factors.This can head to the less relevant recommendations[4].

Moreover,most of the systems are not designed to handle multi-step or tricky decision-making processes.These usually just give one recommendations instead of whic it must be doing bigger tasks like planning an task,effecient routes,or making step-by-step decisions or guide based on multiple factors.[5]Finally,issues with scalability,data quality,and performance are still hurting these system's reliability.

V. METHODOLOGY

These system will make use of a multi–stage pipeline in processing the data provided by the users.

A. Data Collection

The data collection phase involves the systematic aggregation of the structured and unstructured data from of multiple online platform's such as Google Maps, Zomato,and Goibibo.These includes user reviews,star ratings,pricing metadata,geolocation tags,and many more such as textual descriptions of ambiance.As said by Kumar and Sharma [12], AI-based recommendation systems using the NLP rely mostly on collected textual data quality.Social platforms and also review sites serve as rich sources of real-world opinion that capture nuanced, qualitative attributes of places.Additionally,Matero et al.[13] highlights the point that social media data and review platforms provides a dense signal for opinion mining that goes beyond numeric ratings.Data that is being collected using the API integrations and also through web-based pipelines,ensuring that a broad range of user generated content is available for processing in downstream.

B. Data Preprocessing

Raw data collected from the above sources is inherently noisy,complex and unstructured.The preprocessing pipelines apply the standard NLP techniques including such as a stopwords removal,lemmatization,and normalization and tokenization.There are some special characters, HTML tags, and also irrelevant metadata are stripped from the text.Sentences segmentation is being performed to isolate an individual opinion units,which are being more consistent with the approach used in sentiment aware recommendation frameworks[6].This step also ensures that subsequent feature extraction and semantic analysis modules operates only on clean and clear,semantically meaningful text rather than raw,inconsistent inputs.

C. Feature Extraction

Feature extraction plays a central role in the converting the preprocessed text into dense,meaningful and logical representations.Pre-trained transformer based models such as BERT (Bidirectional Encoder Representations from Transformers) and SBERT (Sentence-BERT) are emplies to generate contextual embeddings.These embeddings capture the semantic relationships between words in a sentence, going far beyond traditional bag-of-words or TF-IDF approaches [3],Some of that knowledge-augmented LLMs significantly improves the context aware recommendations,by enriching the features space with domain-specific semantic signals. This also helps in resulting vector representations serves as an inputs to both the semantic analysis module and the retrieval-augmented generation pipeline.

D. Semantic and Sentiment Analysis

This phase bridges and also shows the gap between literal text and the underlying experiential qualities that users associate with a place or any location.Sentiment analysis techniques,specifically those leveraging transformer architectures as described by Chen et al.[6],here are applied to classify reviews along dimensions beyond simple positive as well as negative polarity.The system identifies the aspect-level sentiments for example,separating opinions about ambiance,noise level,crowd density,and service quality.Words as well as phrases that carries an experiential meaning such as ‘cozy’, ‘lively’,’romantic’,or ’peaceful’ are thoroughly detected and mapped to semantic "vibe" categories.This vibe tagging approach aligns with a context-aware methodology proposed by Patel et al. [7],where multidimensional contextual signals are used to improve recommendation accuracy. Explainability of these semantic scores is also considered, consistent with Nandi et al. [8]to ensure the systems output remain interpretable.

E. Retrieval-Augmented Generation (RAG) Pipeline

The RAG module in this forms the knowledge backbone of the recommendation process.As per the Gao et al.[16], RAG combines a dense retrieval mechanism with a generative language model to produce responses that are both logically grounded and also contextually relevant.A vector store is built from the preprocessed and embedded place data, enabling fast approximate nearest-neighbor searches at inference time. When an user query is being received by,the retrieval component that fetches the most semantically relevant documents from the store.These retrieved documents are then being passed as context to the language model, which synthesizes a coherent and the personalized recommendation response.This architecture also mitigates the hallucination problem commonly seen in stand alone generative models,as the outputs are anchored to real data or retrieved data [4][16].

F. Agentic Planning and Multi-Step Reasoning

There are also some complex user queries,such as planning a full-day itinerary or comparing multiple locations on an across different criteria the system also employs an agentic AI framework. Drawing from Shinn et al. [5], the Reflexion paradigm enables language agents to perform the verbal reinforcement learning:reflecting on the past outputs and a self-correcting reasoning chains across multiple steps.And similarly,the ReAct framework proposed by Yao et al. [9] is also being referenced,which interleaves reasoning traces with the action steps to produce structured and helps in decision making.The agent dynamically or randomly selects from which tools to invoke (e.g., sentiment retrieval, mapping API, itinerary planner) and also chains these outputs into the coherent multi-step response.TravelPlanner [4] later demonstrates that LLM-based agents can successfully handle the more complex and difficult,constraint-driven planning tasks, making them well suited for a day trip optimization scenarios.

G. Output Generation

In output generation final recommendations are rendered in an user friendly,explainable format.Rather than presenting a plain ranked list,the system also provides structured explanations to describe why a particular place or location was recommended,which vibe attributes is being matched with user's query,and what specific review evidence supports the recommendation according to the query. This design is informed by the explainability principles articulated by Nandi et al.[8],which show that transparent recommendatios reasoning significantly increases and develop user trust and satisfaction.Natural language interfaces,as discussed by Verbert et al. [14], are used to present results the conversationally, making the interaction feels intuitive more than that of transactional.

H. Conversational Interaction Layer

The systems incorporates a conversational recommendation interface that maintains the dialogue context across multiple turns in this layers.As studied by the Friedman et al.[15],large language models in the conversational recommendation systems improve the user satisfaction by dynamically refining preferences through interaction.The system also tracks the prior turns in a session to resolve unclear follow-up queries(e.g., "Show me something similar but quieter") without requiring of an user to again specify their entire context. Hou et al. [1] further demonstrate that LLMs operating as zero-shot recommenders can generalize effectively across diverse user requests without requiring fine tuning on task specific data,which helps in reducing deployment complexity.

VI. CHALLENGES IN EXISTING SYSTEMS

From above already mentioned in the literature review section, these are following difficulties and limitations were faced in the existing AI-based recommendation systems:

1) Lack of Integration: Most AI system are developed for specific functionalities such as recommendation, sentimental-analysis, conversation l interaction, but they operate independently. These type of approach results in a lack of co-ordination between modules and show the limits of overall system capability.[5]
2) Only Limited Personalization: The type of traditional mechanism mostly rely on the basis and features like ratings, historical data, and user behavior, which also make them fail to capture subjective preferences of user or human such as mood, ambiance,or context, leading to common and less relevant recommendations.[2][7]
3) Keyword-Based Processing: Many of the system in present still depend on keyword(text data) matching techniques, which are unable to interpret natural language effectively, whic may also results in poor understanding of user intent and input text and reduces the accuracy of recommendations.[6]
4) Lack of Explainability: Modern AI tools mainly functions as black boxes providing result without clear reasoning, which may also lacks in transparency reducing user trust and makes it difficult to evaluate mechanism or system decisions.[7]
5) Limited Real-Time Adaptability: The existing system were not able to provide real-time feedback, which is also become more challenge task to grow.
6) Scalability Problems:: Handling big and different amount of unstructured data and processing these remains as challenge. High computational and dependency on external APIs can lack in the performance.
7) Limited Interaction: The existing systems were not able to provide the facility of voice.

VII. FUTURE SCOPE

The proposed system can be made efficiently upgraded further by learning and building with advanced technologies and those features are as follows:

1) In the real-time data integration,they can also be upgraded by incorporating with live traffic,weather conditions,and basic ongoing events to generate more dynamically,correct and accurate recommendations.[4]
2) Talking about voice-based interaction can also be introduced to allow users to communicate with the mechanism using natural speech these may also improving accessibility and user experience.[3]
3) Talking about the multimodal analysis can be implemented by merging text,images,and videos to improve the accuracy of "vibe" detection and overall recommendation quality.
4) In future advanced personalization techniques such as reinforcement learning can be used to continuously adapt recommendations based on user;s actions,behavior and feedback.[5]
5) AI can be integrated to provide clear picture(sceanrio) behind recommendations, increasing transparency and user trust.[7]

VIII. CONCLUSION

These paper studies according to us how today's AI-based recommendation systems are improving but also where older methods are not working as well.As per my study on past mechanism mostly depend on ratings,user feedback and simple keyword matching.These methods are useful,but they don't always
understand what as a user actually wants.User's most of the time makes choices depending upon their mood,feelings,and overall experience.It also make difficult the to analyze these factors in cleay way and also quite challenging.

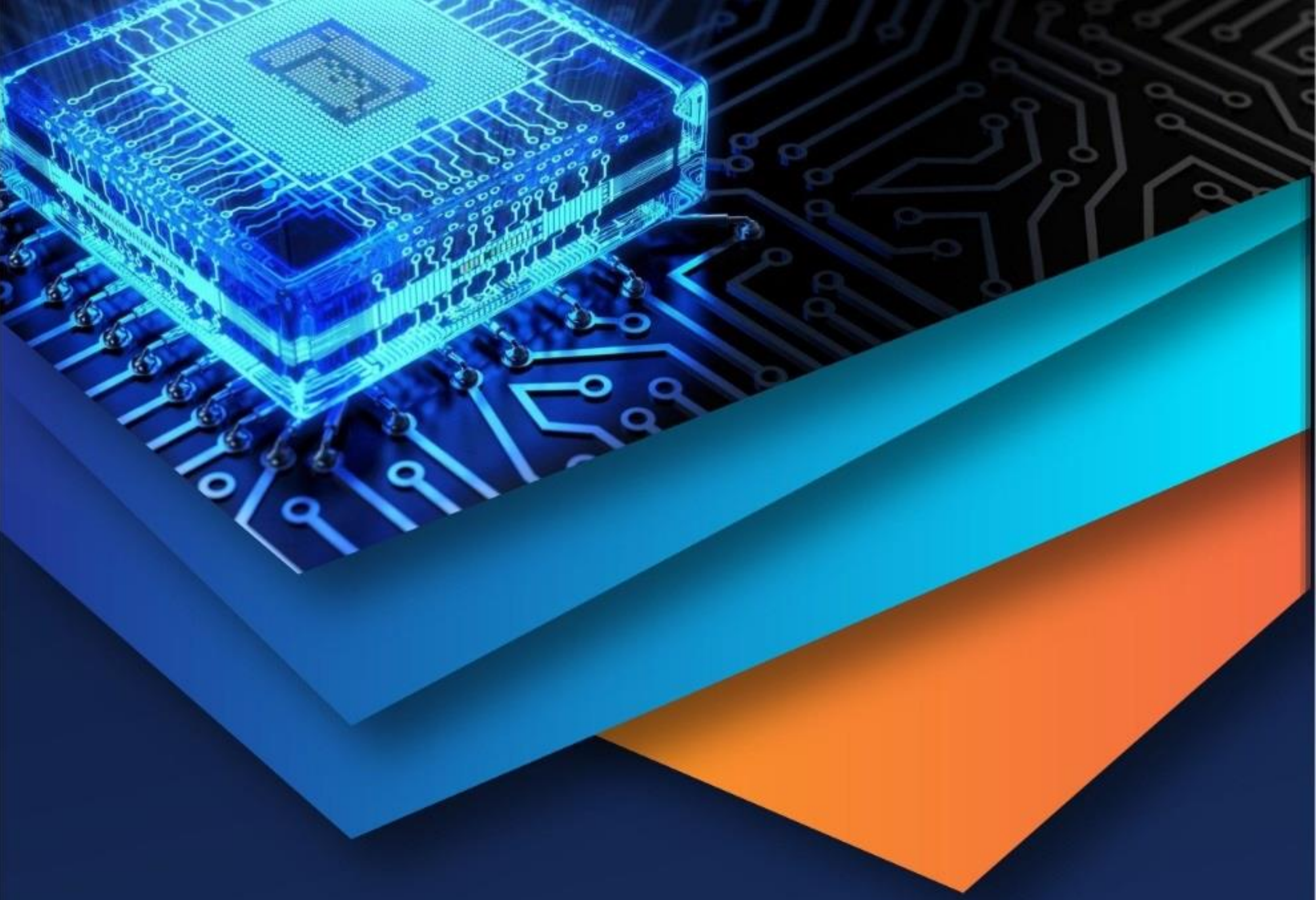
Generally what happen is how newer technologies are helping to solve this problem. AI tools along with methods such as Natural Language Processing (NLP), Retrieval-Augmented Generation (RAG), Generative AI, and Agentic AI, are making recommendation systems more creative,flexible,shaper as well as smarter. These technologies help in understanding systems and also user intent better in meaningful way and adjust responses based on context,suggestions are more precisive manner and way,which improves personalization [3][5][16].

Many systems are not able to use real-time data properly, and some do not explain how they generate recommendations. Because of this,users may not trust the system and also do not agree with the results in practical real-time situations[6][7].

Most of the time generally,together these modern AI approaches can headed to the better recommendation mechanism in the future. The aim is must not only be to improve accuracy but also to make sure about the framework that feel more natural, easier to understand by human, and also closer to how humans so that it can actually make decisions.

REFERENCES

[1] Y.Hou, S.Zhang, and X.Zhao,"Large Language Models as Zero-Shot Recommenders." Proc. ECIR 2024.
[2] OpenAI,"GPT-4 Technical Report." arXiv:2303.08774, 2023.
[3] J.Baek et al.,"Knowledge-Augmented LLMs for Context-Aware Recommendation." Proc. WWW Conference 2024.
[4] J.Xie et al."TravelPlanner- A Benchmark for Planning with Language Agent." arXiv:2402.01622 2024.
[5] N.Shinn et al.,"Reflexion: Language Agents with Verbal Reinforcement Learning." NeurIPS 2024.
[6] W.Chen et al.,"Sentiment-Aware Recommendation Systems Using Transformers." IEEE Access 2023.
[7] R.Patel et al.,"Context-Aware Intelligent Recommendation Systems Using Hybrid AI." IEEE Transactions on AI, 2024.
[8] S.Nandi et al.,"Sankalp: Explainable AI-Based Recommendation System." IEEE Access 2025.
[9] S. Yao et al.,"ReAct: Synergizing Reasoning and Acting in LLMs." arXiv 2023.
[10] J. Xie et al.,"Planning with Large Language Models for Real-World Tasks," arXiv 2024.
[11] H. K. Naing et al., "AI-Driven Recommendation Using LLMs." IEEE Conference, 2025.
[12] A. Kumar and S. Sharma, "AI-Based Recommendation Systems Using NLP." IJACSA 2023.
[13] M. Matero et al.,"Opinion Mining from Social Platforms for Recommendation." IEEE/ACM 2023.
[14] K. Verbert et al.,"Natural Language Interfaces for Next-Gen Recommender Systems."Springer 2023.
[15] L.Friedman, S. Ahuja, D. Allen, T. Tan, H. Sidahmed, C. Long, J. Xie, G.Schubiner,A.Patel, H. Lara, et al., "Leveraging Large Language Models in Conversational Recommender Systems," arXiv:2305.07961, 2023.
[16] Y.Gao,Y.Xiong, X.Gao, K. Jia, J. Pan,Y.Bi,Y.Dai,J. Sun, M. Wang,and H.Wang,"Retrieval-Augmented Generation for Large Language Models: A Survey," arXiv:2312.10997, 2023 (revised Mar. 2024)



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