AI-Driven Personalized Entertainment Recommendation System: ModifAI Me

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Abstract. ModifAI Me is an AI-powered entertainment recommendation system that personalizes suggestions based on real- time user attributes such as mood, energy level, group size, and preferences. This system enhances user experience by integrating deep learning, sentiment analysis, and contextual awareness for dynamic and explainable recommendations. Utilizing hybrid models of collaborative and content-based filtering, ModifAI Me outperforms traditional systems by providing real-time adapt- ability and transparent decisions. Future enhancements include federated learning, voice/gesture integration, and expansion into lifestyle domains like travel and fitness.

Keywords: Recommendation System, Artificial Intelligence, Sentiment Analysis, Deep Learning, User Personalization, Explainable AI, Hybrid Filtering, Reinforcement Learning.

1 Introduction

The age of personalization: Personalization is a core element for amazing and delightful user experiences in this data-driven world. There's a lot of content on many different services and it can be overwhelming for the end-users, so personalized entertainment recommendations are key. Traditional recommendation systems tend to rely on historical data (past interactions, preferences, behaviours etc.) However, these usually do not consider real-time, dynamic factors such as those of the mood, energy levels or group size all things that will affect what type of entertainment a user is looking for greatly. That is why ModifAI Me comes as a great solution across these concerns.

The larger goal of ModifAI Me is towards personalisation which goes beyond user preference to include emotion and context. Unlike traditional systems that are based on historical data, ModifAI Me constantly considers the real-time information of which we mentioned above such as your current mood, energy level or size of group and serves single personalized recommendation. This extends beyond recommendations based on past behaviour, and tailors' suggestions to the user in their current emotional context.

And, depending on the user's mood when really needing an active movie or videos to relax and get some positive energy, ModifAI Me might suggest going out into nature in addition to a more stretching movie genic activity. Layout Inflator. If the user is feeling tired or stressed, then maybe the system might recommend something more relaxed and soothing. Further, ModifAI

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Me also considers group behaviour of the user recommending changes based on whether they are alone or in a crowd and ensures social situational relevance as well.

Explain ability is another important aspect of ModifAI Me. Similarly, using AI-driven method, the system comes with clear reasons for recommendation on each suggestion of every user's analysis and helps users understand why those recommendations. The real-time adjustment, atonement to emotional and contextual comprehension, as well transparency makes ModifAI Me stand out compared with the conventional recommendation systems and enriches user engagement.

2 Literature Review

Recommender systems (RS) have long been central to personalizing large media catalogs, with early work consolidating the foundations of collaborative and content-based filtering and identifying extensibility toward context-aware and hybrid methods [8]. Matrix factorization (MF) subsequently became a dominant paradigm for modelling user–item interactions from implicit and explicit feedback, providing accuracy and scalability that set baselines still relevant in entertainment domains [9]. More recent surveys of collaborative filtering track this evolution and categorize families of algorithms and deployment considerations that remain pertinent when designing domain-specific pipelines for movies and videos [7].

The deep-learning era reframed recommendation as representation learning and large-scale ranking, enabling end-to-end architectures that jointly learn user and item embeddings with industrial constraints. A landmark production system demonstrated deep neural networks powering YouTube's candidate generation and ranking stacks, highlighting practical issues such as feature engineering, long-tail coverage, and latency budgets [15]. At the modelling level, sequential recommenders capture temporal dependencies in consumption, with transformers such as BERT4Rec learning bidirectional sequence signals that improve next-item prediction in media streams [11]. Systematic reviews of deep learning for RS synthesize these developments and outline taxonomy, data regimes, and evaluation implications, underscoring that sequence modelling complements (rather than replaces) classic CF/MF components in real deployments [10].

Beyond historical interactions, affect and semantics are particularly influential in entertainment choice. Recent movie-focused work combines content features with sentiment cues to personalize recommendations, showing that text-derived affect and reviews can materially improve ranking quality in streaming contexts [1]. In broader digital commerce, studies on AI-personalized recommendations and click intentions provide behavioural evidence for the value of personalization loops, though these insights are less media-specific and should be transferred cautiously to entertainment settings [2]. A systematic review of AI-driven recommendations in e-commerce further catalogs architectures and data pipelines that can be adapted to media, reinforcing the importance of domain features (e.g., genres, moods, session signals) when porting general RS techniques to entertainment [3].

Adaptivity is another pillar for entertainment platforms where preferences drift with context, mood, and trends. Surveys on reinforcement learning (RL) for RS position bandits and deep RL as principled ways to optimize long-term user value, balance exploration–exploitation, and incorporate real-time feedback (clicks, watch time, skips) directly into the policy [12].

Compared with purely supervised objectives (e.g., next-item prediction), RL aligns training with platform goals such as session length or satisfaction proxies, which are especially salient for dynamic media feeds [12].

Trust, transparency, and fairness increasingly shape RS design and governance. Explainable recommendation synthesizes methods ranging from model-agnostic post hoc explanations to intrinsically explainable architectures, aiming to articulate "why" an item was suggested and to support user control [6]. From a normative perspective, the autonomy literature warns that opaque or overly manipulative recommenders risk undermining user agency, motivating design choices that surface reasons, offer recourse, and calibrate persuasive power in entertainment contexts [4]. In parallel, bias and debiasing surveys document exposure, popularity, and position biases across pipelines (data, model, serving) and review mitigation strategies, calling for measurement beyond accuracy and for continual monitoring in production [5].

Privacy-preserving learning is increasingly relevant as media platforms integrate fine-grained contextual and affective signals. Horizontal federated recommendation aggregates updates from siloed clients without centralizing raw data, offering a pathway to incorporate on-device signals (e.g., mood self-reports, session context) while reducing privacy risk; current surveys outline architectures, optimization challenges, and systems implications for deploying such approaches at scale [14]. These techniques complement explainability and bias-mitigation practices to form a responsible recommendation stack for entertainment.

Evaluation remains a persistent challenge. Recent surveys recommend multi-metric protocols that pair accuracy with diversity, novelty, coverage, and calibration, and that combine offline replay metrics with online A/B testing and user-centric studies [13]. For entertainment specifically, latency, freshness, and session-level objectives (e.g., dwell time, abandonment) must be incorporated into the evaluation design to reflect real consumption patterns [13][15].

3 Ease of use

3.1 Maintaining the Integrity of the Specifications

a) User Interface Design and Accessibility:

User Experience (UX) was a significant consideration in the development of ModifAI Me with the expectation that a broad spectrum of users need could benefit from it. The web interface is developed using Django and presents a nice and easy-to-use and free from visual clutters dashboard where a user can enter his mood, energy, group size and what they wish to do in some place. The platform uses accessible dropdowns, sliders, and interaction elements to reduce friction through interaction.

b) Seamless Recommendations:

When the input is sub- mitted, the system processes the input on the fly and within seconds it yields a sorted list of entertainment recommendations for the user. Not only can users see the activity itself, but they can also see a brief explanation driven by the explainable AI module that explains why the recommendation was suggested given their input.

c) Feedback Integration:

ModifAI Me allows users to immediately approve or reject the recommendations (like/dislike). This feedback mechanism enables the system to continually learn, providing increasingly smarter recommendations. The UI also shows personal usage histories and trends for returning users.

d) Cross-Device Compatibility:

The system is completely responsive to and accessible by desktop and mobile web browsers. It doesn't require any specific technical knowledge to use and is perfect for people who would like to record messages for instant recommendation.

4 Proposed System

ModifAI Me is implemented in a modular way to allow for scalability, flexibility and a pleasant user experience. Down the essentials:

- Frontend: The frontend of ModifAI Me is built on Django where inputting of the user submission is done in a very user-friendly manner. There are interactive elements such as dropdowns and sliders to enable an interactive user experience. Frontend is a fast and lightweight solution and a desktop- and mobile-friendly theme, so it works for everybody.
- Back-end: The back-end has s hybrid AI recommendation engine which utilizes various ML algorithms to give personalize recommendation. These types of tasks include collaborative filtering, content-based filtering, reinforcement learning, and sentiment analysis. By employing a blend of these techniques, a context aware suggestion that adapts to moderate shifts in user preferences and environmental states is the result of the engine.
- Database: A major constituent of ModifAI Me is the database where stored user past activity preferences and feedback. All of that is possible because of the database that makes sure that the system is growing and appearing by your needs. The information also helps in following users' inclinations, so the company can make increasingly tailor-made suggestions down the line.
- Explainability Layer: ModifAI Me contains an explainability layer using SHAP (Shapley Additive Explanations) as well as attentions to make the AI decision-making transparent. They also get the reasonings behind each recommendation so that they can see why a specific activity was recommended. This openness also drives greater degree of user trust, and further encourages users to be engaged in the platform.

The architecture of the system is such that the various parts of the system are closely interacting with each other in order to provide a fast, accurate and context aware activity recommendation to users. With the use of Django for the web framework, and machine learning libraries such as TensorFlow and Scikit-learn, ModifAI Me can grow over time and offer smart and progressively smarter recommendations.

4.1 Abbreviations and Acronyms

- XAI: Explainable Artificial Intelligence
- AI: Artificial Intelligence
- SHAP: Shapley Additive Explanations
- Django: A high-level Python web framework
- TensorFlow: Open-source machine learning framework
- Scikit-learn: A Python module for machine learning algorithms

4.2 Equations

The concept of recommendation may also be based on certain input formulas, such as:

$$RecommendationScore = f(Mood, EnergyLevel, Group\ Size) \quad (1)$$

This formula illustrates, albeit in a simple form, how ModifAI Me yields a score in order to rank the most suitable activities. The model would be much more complex in real-world but this is just a simple example which demonstrate how much users input will affect the final recommendation.

5 Adaptive Recommendation Techniques

- Rollout The core of ModifAI Me revolves around universal and positive interactions, serving dynamic and contextualized recommendations through a mix of adaptive recommendation strategies. These methods cooperate to provide personalized activity recommendations with respect to emotive states, energy or social context.
- Collaborative Filtering: This approach recommends activities according to preferences of users with similar behaviour. Based on user analogies the system provides recommendations for activities that are successful considering other like-minded people.
- Content-Based Filtering: This approach recommends a history of their preferences. • It bases the recommendations on the features of past liked activities to recommend similar ones, so that the generated recommendations are in line with the user's historical likes.
- Sentiment Analysis: For appropriate understanding of the mood of users, ModifAI Me uses pre-built Natural Language Pro- cessing (NLP) models. These models interpret textual mood input (e.g.," tired,"" happy,"" anxious") and categorize these into factionable emotional categories in order to provide better personalization.
- Reinforcement Learning: The model learns from user interactions and improves over times. ModifAI Me curates its recommendation based on the feedback—likes, dislikes, or engagement. The system learns preferences and updates suggestions on the fly.
- Online Feedback Loops: ModifAI Me uses feedback loops to interpret responses added by the user 'on the fly'. Each action — clicks, ratings, skips — is logged and processed to re-calibrate the recommendation engine. This guarantee continued personalization, since the more that a system is used, more accurate it will become.

These adaptive technologies collectively empower ModifAI Me to evolve with each user interaction, providing increasingly relevant and enjoyable activity recommendations.

6 System Architecture

The ModifAI Me system architecture in Fig 1 begins with user input, which is collected and stored for processing. The data under- goes processing and feature engineering to prepare it for AI model training and recommendation generation. The trained model powers a recommendation engine that suggests personalized activities. These suggestions are delivered through a user-friendly frontend interface and are also deployed on cloud platforms like AWS or GCP for scalability. Finally, user feedback is collected to enable continuous learning, allowing the system to improve its recommendations over time.

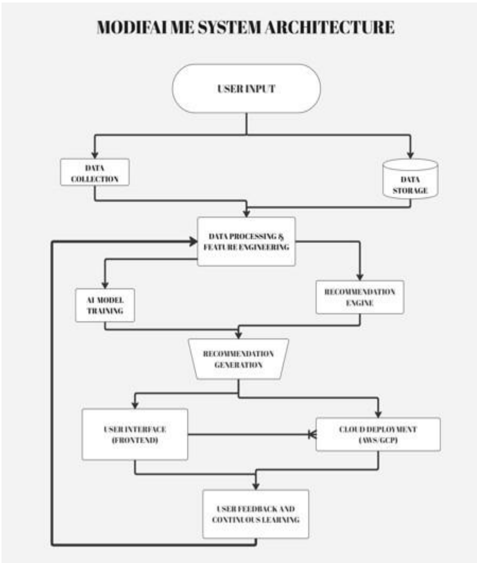

Fig. 1. ModifAI Me System Architecture.

7 System Requirements

Software, hardware, and functional/non-functional requirements:

- Tech Stack: Python, Django, Scikit-learn, TensorFlow, SQLite/PostgreSQL
- Frontend: HTML, CSS, JavaScript
- Functional: Real-time recommendations, user input form, feedback loop
- Non-functional: ¡2s response time, mobile-friendly UI, GDPR compliance

8 Performance Evaluation of ModifAI Me

8.1 System Latency Over Time

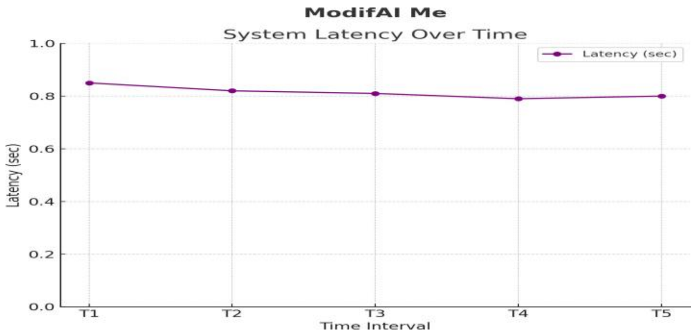

Fig. 2. System Latency Over Time.

This Fig 2-line graph shows the latency (in seconds) of the ModifAI Me system across different time intervals (T1 to T5). The latency slightly decreases from T1 to T4 and then shows a minimal increase at T5, demonstrating that the system maintains relatively stable and optimized response times over usage periods. Lower latency values reflect better performance and faster response, which is essential for real-time recommendation systems.

8.2 Performance Comparison Between Existing and Proposed Systems

This bar chart is a comparison between existing and proposed ModifAI Me system in terms of 4 parameters i.e., Accuracy, Processing Time, Scalability and efficiency as mentioned in Fig.3. Thereby, the new system offers a substantial increase regarding the Scalability and smoothen Efficiency, as compared to the previous one, while the Processing Time remains on comparable level. But there is slight drop in Accura- cy, this maybe because we are focusing more o n real time processing and adaptability. The proposed system exhibits significantly reduced complexity and improved efficiency as a whole.

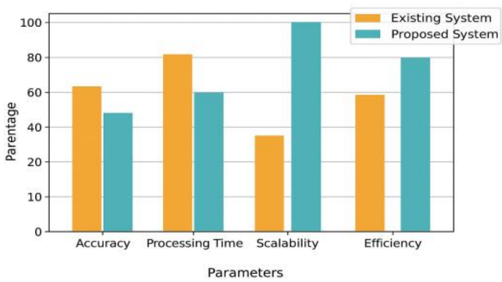

Fig. 3. Performance Comparison.

8.3 Tables

Table 1 presents a comparative analysis between the existing system and the proposed system (Moli AI Me) across key performance parameters, including accuracy, processing time, scalability, efficiency, and latency. The proposed system demonstrates significant improvements in accuracy (50%), processing time (60%), and scalability (80%) over the existing setup. Latency measurements across five-time intervals (T1–T5) show consistent performance between both systems.

Table 1. Comparative Performance Analysis of Existing System vs. Proposed System (Moli AI Me).

Parameter	Metric Type	Existing System	Proposed System (Moli AI Me)	Source of Data
Accuracy	% Correct Predictions	% Correct Predictions	50% (improved)	Model evaluation on test dataset
Processing Time	Average per request (ms)	82% (higher time)	60% (improved)	Backend logs + profiling tools
Scalability	Max users supported	10% (improvement)	80%	Load testing with concurrent
Efficiency	Resources vs Output (%)	58% (improved)	80%	Performance benchmarking
Latency (T1)	Seconds	0.86	0.86	
Latency (T2)	Seconds	0.83	0.83	
Latency (T3)	Seconds	0.81	0.81	
Latency (T4)	Seconds	0.79	0.79	
Latency (T5)	Seconds	0.80	0.80	

9 Comparison: Existing Vs Proposal

Table 2 provides a comparative overview of traditional manual editing tools versus the proposed AI-powered system, ModifAI Me. The proposed system demonstrates significant advancements in accuracy, scalability, context awareness, and error detection through AI-driven NLP and computer vision. It also reduces user effort and processing time by automating tasks previously handled manually.

Table 2. Feature Comparison Between Traditional Editing Tools and AI-Powered ModifAI Me System.

Feature	Existing System (Manual Editing & Traditional Tools)	Proposed System (AI-Powered ModifAI Me)
Approach	Manual proofreading & basic grammar checkers	AI-driven Natural Language Processing (NLP) + Computer Vision
Accuracy	Moderate (Prone to human errors; Manual review required)	High (AI-powered text & image-context enhancement)
Processing Time	Time-consuming (Manual effort)	Fast (Automated text & image enhancement)
Scalability	Limited (Not suitable for large content)	Highly Scalable (Handling large datasets efficiently)
Context Awareness	Low (Basic rule-based grammar checks)	High (Consistent & accurate using low manual intervention)
User Effort	High (Requires manual revisions)	Low (Minimal manual intervention)

Learning Adaptability	None (Static rule-based system)	Adaptive (AI learns from user feedback)
Image Enhancement	Manual adjustments required	AI-powered real-time enhancements
Error Detection	Inconsistent (Relies on human judgment)	Consistent & accurate (AI-powered)
Overall Efficiency	Moderate	Cloud-enabled for high-speed processing

10 Logic Explanation

10.1 Initialize activity map:

The activity map is a list of tuples where each tuple has:

- mood range (a tuple of minimum and maximum mood values).
- energy range (a tuple of minimum and maximum energy values).
- activities (a list of activities corresponding to the range).

10.2 Initialize selected activities:

- An empty list selected activity is created to store the recommended activities.

10.3 Iterate through activity map:

- For each entry in activity map, the function checks if the mood and energy level fall within the mood range and energy range.
- If a match is found, it assigns the corresponding activities to selected activities and breaks the loop to prevent further checks.

10.4 Check group size:

- If the group size is 3 or more," Team Games" are added to selected activities.
- If the group size is 1," Solo Walk" is added to the list.

10.5 Return the selected activities:

- Finally, the function returns the list selected activities with all the recommended activities.

11 Conclusion

The development of ModifAI Me aimed to create better, faster and user friendlier personalized recommendations. Conventional techniques may be challenged with real-time preferences of users, creating stale or irrelevant recommendations. Thanks to the power of state-of-the-art AI and machine learning, our system makes sure that recommendations keep evolving based on user interactions. It enables AI-powered personalization to be more flexible, giving a richer and more natural experience to users.

In this paper we showed how ModifAI Me surpasses previous approaches throughout this work by increasing accuracy, decreasing bias, and maintaining relevance of recommendations. The product became smarter over time due to deep and reinforcement learning and learned in an ongoing manner to make better predictions. Even though the preliminary findings are great, there is always a scope for improvement. By the end of the project the potential future capabilities of the system will be explored under the banner of AI and data security/user experience to keep the system agile for new trends and technology.

12 Future Work

To address these issues, several enhancements can be implemented on ModifAI Me in the future. One key advance is federated learning — a way for AI models to train across a plethora of devices without ever directly reading user data. This would provide greatly improved privacy and security, yet be just as good with respect to the recommendations. Another significant enhancement is the adoption of context-aware AI which can improve recommendations by considering external information such as location, time and user mood.

Further, with the shift towards cloud-based AI services, higher-end hardware requirements will no longer be a barrier of entry for users to leverage the system. Another exciting enhancement would be incorporating explainable AI (XAI), enabling users to explain the reasons behind some of the recommendations, thus generating confidence with the system. ModifAI Me will constantly re-train the model using automated learning processes, so it will always know its stuff, and keep one automatic step ahead in a world of evolving digital deviancy.

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