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An AI-Powered Hybrid Recommender for Adaptive Government Service Allocation Using Machine Learning and Behavioral Filtering

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Abstract– *In India, citizens are supported throughout health, education, agriculture, employment, and social welfare through government services and welfare schemes. A lack of any centralized information and any digital literacy together with personalized guidance leaves many citizens unaware of those eligible services. In suggesting the suitable government services using the citizen's profile and the past application history, this paper proposes a hybrid recommendation system in order to bridge this gap.*

Collaborative filtering joins content-based filtering that uses user choices plus demographics for correct suggestions. This analysis observes behavior among similar users. Accessibility, awareness, also trust in digital governance are improved when the system processes citizen data to provide a personalized list of services because citizens log in securely. The model aims to support India's Digital India mission by enhancing public engagement and ensuring inclusive access to government services.

1. INTRODUCTION

INDIA, because it's surely one of world's most largest and most different of republic, offers a veritably wide-ranging compass of public services for its own citizens across all sectors similar as for healthcare, education, employment, husbandry, weal, and also transportation. India's Government has initiated numerous digital programs through the times because it takes part in a larger Digital India charge using UMANG (Unified Mobile Application for New- age Governance), DigiLocker, Aadhaar, and more. These platforms seek to render public services more accessible as well as paperless. They also seek to make them effective enough. Despite this enterprise, a large chance of the population continues to warrant access to the most suitable services. These are the product of a range of factors, similar as fragmentation of service platforms, lack of a single depository of services, language walls, low situations of digital knowledge, and sheer volume of schemes, all of which differ by geographical position, income situations, estate, or age. In turn, individualities especially those from depressed or pastoral communities — frequently remain ignorant of programs and benefits aimed at bettering them.

The root issue is not the lack of accessible services, but the lack of advanced discovery techniques to facilitate users searching for compatible schemes based on their individual requirements and circumstances. While accessible platforms provide access to services, they have been predicated on manual search or browsing by category, which is bound to be inefficient or confusing for users who are not familiar with bureaucratic terminology or eligibility requirements.

To fill this gap, this study proposes a Recommendation System for Government Services that will assist citizens in identifying appropriate programs according to personal attributes such as age, income level, occupation, geographic location, past usage patterns, and personal interests. As an individualized electronic counsellor, this system can be a critical catalyst for service discovery, accessibility, and use.

In spite of such initiatives like ICDS, PM-POSHAN, MGNREGA, and Ayushman Bharat, a significant proportion of eligible citizens remain non-users. For example, the budgetary provision for the Mid-Day Meal Scheme was reduced by half from 0.08% to 0.04% of GDP, and only 67% of the allocated funds to Ayushman Bharat were disbursed in recent years. Such underutilization—coupled with schemes' lack of visibility—demands intelligent systems that identify the right citizens and services using individual and contextual data.The proposed strategy will utilize data analytics and artificial intelligence (AI) to deliver suggestions using techniques like collaborative filtering, content-based filtering, or hybrid approaches. Utilization of existing infrastructure like DigiLocker and Aadhaar can enable the contextual awareness and accuracy of the system. Additionally, features like multiple language support and natural language processing (NLP) can help in supporting inclusivity for people who don't speak English.

This work discusses the design, architecture, and deployment of an Indian government services recommendation engine. We review current systems, enumerate significant challenges, propose a hybrid service recommendation model, and discuss its potential for user satisfaction and social inclusion across different demographic groups.

2. LITERATURE REVIEW

Dr. V. Thangavel [1] analyzes the government of India's initiative Mobile Seva to boost the mobile-based delivery of e-Government services. The analysis is centered on the increasing use of mobile phones in urban and rural India and the possible role these phones can play towards bridging the digital divide. Mobile Seva is an integrated platform that allows different government departments to offer their services through different channels like SMS, IVRS, USSD, mobile applications, and others. This study gives an all-around view of how m-Governance is being woven into larger governmental initiatives like Digital India, ably supported by initiatives like the Mobile Payment Gateway and Mobile AppStore. This paper employs qualitative and quantitative approaches to study the accessibility, adoption, and effects of these services. It highlights the way in which technologies are being utilized across various sectors, ranging from agriculture to health, justice, transport, and education, with a particular emphasis on the way in which mobile accessibility enhances transparency, accessibility, and efficiency. Also, the study demonstrates how e-Government infrastructure is being woven into national-level digital initiatives and the challenges involved in automating grassroots governance through Panchayats.

Mohammed Wasid and Rashid Ali [2] proposed a recommendation system to customize the delivery of e-Government services in India. Their approach relies on the fact that conventional e-Governance systems provide a variety of uniform services to customers, most of which might not be relevant to individual needs. The authors propose a system to create concise user profiles on the basis of demographic information and behavior patterns, and then use fuzzy logic to categorize attributes such as age ranges and program ratings into fuzzy sets. These user profiles are then utilized in collaborative filtering to identify similar users based on their needs and wants, thus recommending only the most relevant services. The proposed architecture consists of three phases: generation of fuzzy-enriched user profiles, identification of a cohort of similar users, and generation of recommendations based on similarity scores. The article states that personalization not only improves user satisfaction but also improves the efficiency of service delivery since users are reached more precisely. This approach is largely hypothetical and requires experimentation with actual government data in future research.

A. Sharma and S. Gupta [3]introduce the methodology of their hybrid context-aware recommender system, encompassing the data collection and preprocessing of government schemes and users, as well as feature extraction. The focus of their work is the application of a hybrid filtering algorithm that effectively incorporates pre-filtering and post-filtering by considering user context and relevance. Such integration is essential in mitigating such limitations as data sparsity, a common drawback faced by solely pre-filtering systems. Such a system ends up producing personalized recommendations for government programs. Their experiment shows that such a hybrid approach significantly enhances precision and ranking of recommendations in comparison to more traditional approaches. Effectively incorporating contextual information and mitigating the problem of data sparsity, their system produces higher-quality and more relevant recommendations for government schemes, thus empowering citizens.

R. Burke [4] discusses some of the recommendation techniques, including content-based filtering and collaborative filtering, and their respective strengths and weaknesses. One of the shared observations is that the different techniques must be integrated to get more, because the different techniques have inherent limitations, for instance, the "cold start" issue in collaborative filtering and the limitation of serendipity in content-based systems.

2.1 Under-utilization of services

Although multiple schemes exist to support health, nutrition, education, and livelihood, many remain underutilized due to limited awareness, digital inaccessibility, and complex eligibility conditions. several flagship programs report substantial shortfalls in fund utilization, dormant user participation, or drastic cuts in budget allocation. These indicators reflect inefficiencies that could be addressed by a targeted, citizen-focused recommendation system.

Several major government welfare schemes in India show varying levels of utilization, highlighting both progress and inefficiencies in public spending across different sectors.

The Ayushman Bharat Pradhan Mantri Jan Arogya Yojana (AB–PMJAY) reported approximately 67% utilization between 2019 and 2024, indicating substantial engagement but also room for improvement in healthcare accessibility and awareness, as noted by sources such as Accountability India and IJCRT.

Under the category of social equity, the Development Action Plan for Scheduled Castes (DAPSC) recorded a relatively decent utilization percentage of 74.7% out of its sanctioned fund of ₹1.66 lakh crore for the financial year 2024–25. This figure suggests that a significant portion of the targeted funds reached their intended beneficiaries, as reported by the Economic Times.

However, there are notable inefficiencies in the broader framework of Centrally Sponsored Schemes (CSS). As of December 2024, around 62% of CSS funds remained unutilized by the states, pointing to issues in fund disbursement, absorption capacity, or administrative bottlenecks. These concerns were raised in reports from sources such as Policy Circle, Hindustan Times, and CBGA India.

The Nirbhaya Fund, established to enhance women's safety through initiatives such as One Stop Centers (OSC), Mobile Police Vans (MPV), and Women's Helplines (WH), has faced persistently low to zero utilization in many key components. This underperformance underscores significant gaps in implementation and inter-agency coordination, according to data from Accountability India and the Economic Times.

On a more positive note, the Pradhan Mantri Awas Yojana – Gramin (PMAY-G) in Mizoram showed strong progress, with 83.46% of targeted homes completed as of May 2025. This reflects effective program execution in the region and demonstrates the potential for successful outcomes when schemes are well-managed, as reported by The Times of India.

Overall, these utilization trends emphasize the importance of improved monitoring, transparency, and collaboration between central and state governments to ensure that welfare funds translate into meaningful outcomes for citizens.

3. PROBLEM STATEMENT

Despite the Indian government's efforts to digitize public services through platforms like UMANG, DigiLocker,

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and Aadhaar, a large section of the population continues to face difficulties in discovering, understanding, and accessing relevant government schemes. Citizens are often unaware of services for which they are eligible, especially those that are location-specific, income-based, or community-targeted. This gap leads to underutilization of welfare schemes, delays in service delivery, and diminished trust in digital governance.

Scattered Information: Services are scattered across multiple platforms and departments with no centralized point of access, hence making it difficult for citizens to find information they need.
Low Digital Literacy: Rural users or low-income or elderly users are not comfortable with interacting with digital interfaces or understanding bureaucratic entitlement requirements.
Lack of Personalization: Existing platforms rely on search by hand and lack smart recommendations based on the user profile, location, or past service history.
Language and Access Barriers: English or restricted Indian languages are used for most services, leaving out large segments of the population.
The dynamic characteristics of government schemes are influenced by various factors, including budgetary cycles, political leadership transitions, and state policies, which complicates the ability of citizens to remain informed.
These challenges collectively disrupt the effective delivery of public services, resulting in missed opportunities for both the public and public administrators.
Therefore, a tailored, advanced recommendation system is now the pressing need, which can automatically recommend users to appropriate services, communicate in their local language, guide them through the application and eligibility process, and learn from evolving policy and citizen data. This system will empower citizens through providing equitable access, raising awareness, and facilitating the use of government welfare schemes, thereby fulfilling the vision of the Digital India initiative.

4. PROPOSED SYSTEM

The proposed system is a hybrid recommendation system that will help the citizens find personalized government schemes according to their demographic, socio-economic, and contextual attributes. It is a web and mobile app that may be accessed through ReactJS and React Native interfaces, supported by a machine learning-driven recommendation engine implemented in Python. The system architecture consists of five fundamental components: (i) user profiling module, (ii) scheme metadata repository, (iii) hybrid recommendation engine, (iv) user interface layer, and (v) backend inference and integration services.
The process starts with the user profiling module, which gathers structured data for every single participant. These profiles include attributes like age, gender, caste group, income group, occupation, nationality, domicile state, accommodation type (urban or rural), and the purpose of the user (such as employment, education, or business). Such information is normalized and encoded using label encoding for categorical variables before becoming input to the core prediction model.

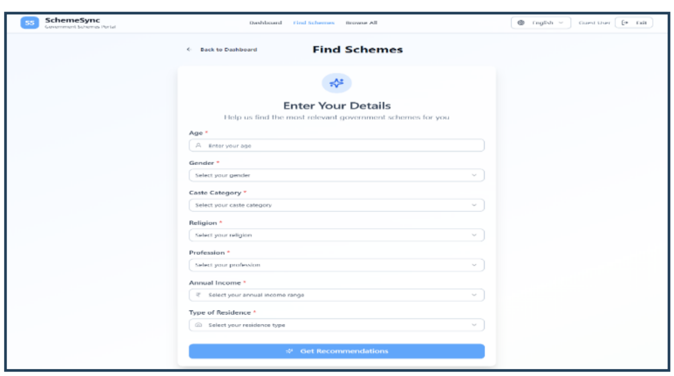

Fig.1. User input interface for collecting demographic and socio-economic details to generate personalized scheme recommendations.
The second basic element of the system is a centralized and structured metadata repository for government schemes. Every entry in the repository has the scheme ID, scheme name, applicable eligibility criteria (income group, age, caste, gender, geographical location), and the intended purpose and applicable states. The metadata is then cleaned, lowercased, and preprocessed to make them compatible with content comparison calculation and application of rule-based filters, if enabled.

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At the core of the system is the hybrid recommendation engine, which combines three complementary strategies: supervised learning, content-based filtering, and collaborative filtering. A detailed description of these strategies is provided below.

A. Supervised Machine Learning:

XGBoost Classifier The primary predictive model is built with Extreme Gradient Boosting (XGBoost), a decision tree-based ensemble technique that is well known for being highly accurate and scalable. XGBoost builds an ensemble of weak models, commonly known as shallow decision trees, sequentially, where each successive tree attempts to correct the mistakes done by its previous versions in a way that maximizes a regularized objective function. The model utilizes both categorical features (e.g., caste, gender, profession, etc.) and numerical features (e.g., age and income) to learn from past logged user scheme decisions. At inference time, the model predicts a probability distribution over all the scheme labels, thus indicating the probability that a particular scheme is appropriate for the user. The top-k predictions calculated using confidence scores are used as the first layer of recommendations.

B. Content-Based Filtering:

In this approach, suggestions are created by computing the textual similarity between the user-specified purpose and the objective field of each scheme. Both fields are reduced to numerical feature vectors by Term Frequency-Inverse Document Frequency (TF-IDF) vectorization. TF-IDF assigns higher importance to the words that are used most within a single document (e.g., "education") but least frequently across the whole corpus. After vectorization, cosine similarity is computed between the user vector and vector of every scheme. A high cosine similarity value indicates a high semantic match between the user's purpose and the purpose of every scheme. This process ensures that users are matched with schemes that are appropriate for their unique purposes even when these schemes have not been chosen often in the past.

C. Collaborative Filtering:

Collaborative filtering is implemented using the Singular Value Decomposition algorithm from the Surprise library. It is based on the assumption that users with similar profiles or tastes would like similar schemes. Historical applicant information is encoded as a user-item matrix, with a row for every user, a column for every scheme, and the entry being whether a scheme was selected or not. SVD decomposes the matrix into latent factor scheme and user representations, enabling the system to predict missing interactions. This allows the model to recommend schemes utilized and enjoyed by similar users, even if the new user has not interacted with them directly.

Each of these three recommendation methods - XGBoost, content-based recommendation through TF-IDF, and collaborative SVD—provides individual scores for each scheme. The scores are normalized and merged via a weighted sum approach to obtain a last ranked list of recommendations. This merging process leverages the strengths of all three methods: the prediction effectiveness of supervised learning, the interpretability of content-based matching, and the personalization of collaborative memory.

The results of all three levels of recommendations are then combined by a weighted ranking procedure, so that recommendations are not only correct, but also personalized, varied, and contextually appropriate. The result is a ranked list of plans that are displayed in real-time to the user through a ReactJS (web) or React Native (mobile) frontend interface.

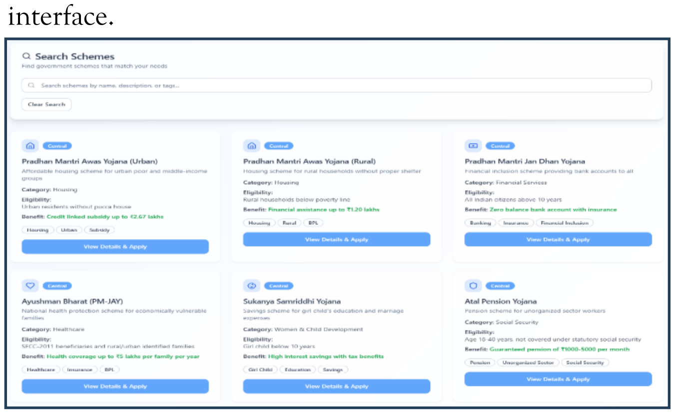

Fig. 2. Scheme recommendation output showing a list of matched government welfare programs based on the user's profile.

In the future, the system has also been designed to be extensible and adaptive. Future work will include support for multilingual interfaces to major Indian languages such as Hindi, Kannada, Tamil, and Bengali to make it even more user-friendly. A Natural Language Understanding (NLU) module will also allow users to enter their requirements in the form of free-text sentences (e.g., "I want to start a dairy business") and get smart, intent-matched suggestions. The system will also be designed to support ongoing learning through user feedback loops—tracking whether a suggested scheme was opened, selected, or skipped—to dynamically improve future suggestions.

Apart from that, Aadhaar or mobile user authentication can be invoked to auto-fill user profiles and prevent human error in manual entry. Real-time geo-tagging can even enable geo-location-based scheme suggestions by identifying schemes implemented at the district, block, or panchayat levels. Voice-based input for visually impaired or illiterate users is also being tested by means of speech-to-text. Last but not least, government API integrations and audit logs on the blockchain can be leveraged to provide verifiability, transparency, and traceability in recommendation history.

With a mixture of intelligent algorithms, web/mobile scalability, and future-proof architecture, this system is meant to be an end-to-end recommendation system for public welfare, increasing the visibility and scope of government schemes and empowering citizens through intelligent digital governance.
The system's performance was evaluated using a confusion matrix to illustrate the accuracy of the scheme classifications.
It provides an indication of the number of correct and incorrect predictions for all the scheme classes. Diagonal entries in the matrix represent correct predictions, and misclassifications are represented by off-diagonal entries.

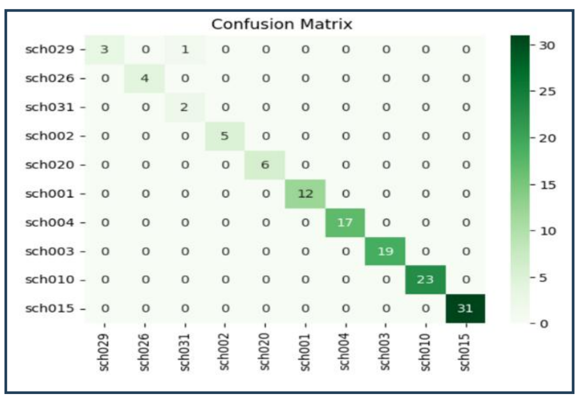

Fig. 3. Confusion Matrix to showcase the accuracy of the system

5. EXAMPLE USE CASES

The suggested recommendation system can help the citizens to locate appropriate government services based on the socioeconomic and demographic information of the citizens. The below use cases outline some of the possible scenarios where the system can be used:
The suggested system best elucidated by real-life user contexts, referring to its capacity to provide the user with relevant and personalized welfare scheme suggestions.

For Use Case 1, the user is a 19-year-old female student studying in a government college and residing in a rural village of Uttar Pradesh. According to her education and demographic information, the system recommends the Post-Matric Scholarship Scheme for funding her study costs, the Free Coaching Scheme for SC/ST for coaching to sit for competitive exams, and Rural Skill Development Programs for enhancing employability and vocation skills.

For Use Case 2, the user is a retired school teacher aged 68, who resides alone in Maharashtra. On the basis of his age, profession, and living status, the system suggests the Indira Gandhi National Old Age Pension

Scheme for financial assistance, Free Health Checkups for Senior Citizens for regular health checkups, and a Subsidized Housing Scheme for Elders for safe and low-cost living.

Use Case 3 describes a 45-year-old male who is a farmer from Tamil Nadu with a small cultivable land holding and low per annum income. Based on his occupation and economic condition, the system suggests the PM-KISAN Scheme, which provides direct income support to farmers, the Soil Health Card Scheme for him to promote and maintain soil health for higher crop yield, and the Crop Insurance Scheme to safeguard him against loss due to unforeseen weather conditions or crop failure.

These applications illustrate the way in which the recommender system can tailor government services to various individuals according to their specific contexts, making schemes of public welfare delivery inclusive and targeted.

6. ETHICAL CONSIDERATIONS

As with any data-driven and AI-based system, the proposed hybrid government scheme recommendation platform does pose a few ethical concerns. The most important one is safeguarding user data and privacy. Since the system is collecting sensitive socio-nomic and demographic data—such as caste category, income level, and occupation—it is crucial to ensure data protection law compliance, such as the Indian Personal Data Protection Bill or international standards like the GDPR.

All personal data must be stored securely, anonymized wherever possible, and used only for the purpose of making recommendations, and explicit consent must be obtained from the user.

Second, algorithmic bias is a risk if the training data is biased or unrepresentative of all communities. This may result in biased or unfair recommendations, especially affecting marginalized groups. Thus, regular auditing and fairness testing of the machine learning models must be done.

Third, transparency and explainability in recommendations must be offered to facilitate user trust—users must be able to understand why certain schemes were recommended to them. Fourth, while the system attempts to reduce human intervention and corruption, it must also guard against misuse or mispresentation of recommendations as official eligibility assurances. Disclaimers must clearly be indicated, and the system should be seen as an assistive tool and not a replacement for official government verification or eligibility decision.

7.CONCLUSION AND FUTURE WORK

7.1 CONCLUSION

India's transition towards digital governance through portals like UMANG, DigiLocker, and other central and state portals has given a solid footing to e-governance. Yet, discoverability, accessibility, and personalization of public services remain daunting challenges. The present paper proposes a smart, AI-driven Recommendation System that bridges these gaps by suggesting citizens government schemes based on their profile, preference, and eligibility—Aadhaar-free.

The system outlined here is inclusive, multi-language, and trustworthy through the integration of hybrid recommendation algorithms, rule-based filtering, and optional authentication using DigiLocker. It provides a scalable, user-centric solution to improving the participation of citizens, welfare admissions, and overall goals of Digital India.

7.2 Future Work

While the proposed model offers an excellent solution, there are various advanced features that can be explored to enhance the hybrid government scheme recommendation system. One of the areas that has immense potential is the use of Explainable AI (XAI) techniques for providing clear explanations for each recommended scheme. This would help improve user trust with the help of citizens being able to understand the reason why the system is recommending a specific scheme, especially in sensitive domains like caste or income-based appropriateness.

Another potential upgrade would be employing a federated learning architecture. Rather than training the model in a central location, this would allow an ensemble of government nodes (such as state governments or local municipalities) to cooperatively train the model on localized data without revealing raw user data. This offers both privacy and personalization on a local scale with data sovereignty compliance.

Gamification elements can be integrated into the user interface to enhance user awareness and engagement. For instance, users can be given "awareness points" if they view more schemes or fill out their profile, thus motivating them to learn about welfare options they were unaware of.

For wider usage in varying levels of digital literacy, the system could be provided in kiosk mode in rural government offices, Common Service Centers (CSCs), or panchayat complexes. Offline-installable versions could be touch-screen and interactive voice guidance enabled, thus being usable by even non-technology users.

Including real-time notifications from government servers, such as when a scheme is closed, revamped with funding, or changed, would make the list of recommendations dynamic and current. This will require APIs or webhook-based integration with government databases and digital delivery systems such as UMANG or DigiLocker.

Further, social referrals can be facilitated by the system, where relatives (e.g., a youth registering his aged parents) can search for schemes for other relatives, with profiles linked via a family ID. This makes the system more inclusive and relevant to Indian social reality.

Finally, user comment and scheme review sentiment analysis can be utilized such that schemes are ranked not just by popularity and eligibility, but also by perceived ease of access, document requirements, and satisfaction rate, such that the system becomes a decision support for citizens and not just a recommendation system.

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