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YojanaMitra: An AI-Assisted Framework for Government Scheme Eligibility Matching and Guidance

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Abstract: Artificial Intelligence and Machine Learning are being utilised to automate eligibility assessment and provide personalisation in public service provision. They address longstanding issues faced by traditional systems such as fragmented scheme information, multi-condition eligibility criteria and limited citizen awareness. In this paper, we present YojanaMitra, a web application which provides access to 134 central and state government welfare schemes of India via a hierarchical and AI-driven matching pipeline. In the initial step, our matching pipeline uses a deterministic rule engine which supports both AND/OR logic of eligibility criteria to classify a citizen into three categories based on each welfare scheme: Eligible, Near Miss and Not Eligible. Only the schemes classified as Eligible are then ranked via a Random Forest classifier by engineering ten features from citizen-profile; finally, retrieval augmented conversational assistant provides citizen responses based on the matching scheme data alone. The application has been developed using Flask, SQLite database and Groq large language model API. It guarantees citizen security, structured profile-based matching and multilinguality. Automated testing shows accurate eligibility classification for all test cases; meanwhile, the accuracy of Random Forest ranking model is 0.597 with precision of 0.606, recall of 0.598, F1-score of 0.602 and ROC-AUC of 0.627 in the evaluation on held-out test set. We find that vulnerability and income margin are the two most important ranking features.

Keywords: Government Scheme Eligibility, Rule-Based Matching, Machine Learning Recommendation, Retrieval-Augmented Generation, Random Forest, E-Governance, Eligibility Prediction, Progressive Web Application, Flask, Multilingual Interface, User Engagement.

I. INTRODUCTION

Governance-based welfare schemes are among the main tools used by the government to provide social and economic assistance to citizens in areas like agriculture, education, health, housing, employment, economic inclusion, and marginalised communities' welfare. Governance and the state government manage numerous schemes aimed at a certain part of the population together. Nevertheless, the success of this system fully depends on the ability of citizens to find the schemes applicable for them – this is where the problem usually arises even when the scheme is designed in an appropriate way.

On the ground level, scheme-related information is scattered all over different websites belonging to various ministries, departments, and state governments in a format and vocabulary specific to each website. The citizen needs to go through each source one by one, decipher conflicting definitions related to eligibility, and evaluate whether his/her situation fits any of the specified sets of criteria (an age and income criterion, say). There is no existing method that would do that automatic evaluation for citizens based on their profiles, and even where the citizen is eligible for more than one scheme, there is no way of knowing which one suits him/her best.

There There are some existing discovery schemes such as myScheme [1] and UMANG [2], which have seen some success in terms of aggregating the list of schemes and discovery through filters or questionnaires. However, the matching mechanism employed in these schemes is an attribute filtering system and not a rule-based one to represent eligibility rules, they are not ranking the schemes that a citizen is eligible to in personal terms, and also do not integrate the results

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of eligibility with a conversational assistant whose responses are based only on verified citizen-wise scheme data. Furthermore, there have been works in the general research literature in the fields of rule-based system for eligibility [9], [10], [11] and machine learning-based recommendation [12], [13] individually, but there has never been a work which has looked into the application of a layering approach for machine learning ranking post eligibility.

The thesis presents and builds a solution called YojanaMitra, which includes identification of whether a citizen is eligible for any government scheme, using a deterministic rule-based engine which supports AND/OR logic grouping; ranking of government schemes which the citizen is eligible for, using a machine learning technique, but without the ranking ever overruling the determination of eligibility; and providing scheme-specific recommendations via a conversational assistant, which is grounded by retrieval [14], [15]. The scope of this thesis is limited to an academic demonstration system. It uses a curated set of 134 actual and verified government schemes from both the Central and State government; it includes a simulated (and not production-integrated) identity verification mechanism; and a machine learning model built on synthetic citizen data, which is explicitly stated below.

II. RELATED WORKS

A. Government Schemes and Their Reach

Government welfare schemes in India cater to various needs of its citizens and generally follow a pattern wherein the schemes are aimed at certain specified groups of beneficiaries rather than any open schemes. Agricultural schemes such as PM-KISAN Scheme [3] and Pradhan Mantri Fasal Bima Yojana [4] help in providing financial assistance and crop insurance to farmers; educational schemes such as National Means-cum-Merit Scholarship and Post Matric Scholarships [5] benefit students who come from weak economic backgrounds or socially disadvantaged sections of society; healthcare schemes such as Ayushman Bharat PM-JAY [6] provide healthcare cover for hospitalisation to poor families and senior citizens; and finally social welfare schemes cover women, disabled persons, and senior citizens by means of various pension and insurance schemes. This very aspect, i.e. numerous narrow schemes in contrast to few broad schemes, is exactly why automated profiling based matching becomes so important: a citizen should benefit from a system that matches his/her profile with various schemes rather than him/her searching for relevant schemes himself/herself. Both rural and urban citizens are covered under this scheme framework, and the matching problem addressed in this research study applies to both segments equally.

B. Transformation in Digital Governance

Various digital mechanisms have gradually been superimposed on the administration of the scheme to ensure better outreach and avoid leaks. The concept of Direct Benefit Transfer (DBT), which involves the direct electronic transfer of the benefits of the scheme directly into the beneficiary's bank account, has emerged as one of the most common disbursal mechanisms used in schemes described in this work and is also indicated by YojanaMitra in its own scheme data model, using an explicit flag on each scheme record. National digital identification systems, especially Aadhaar-based eKYC, are the foundation of the registration process in the real world scheme and is the registration mechanism simulated by YojanaMitra itself (see section 4.3). Centralised discovery portals like myScheme [1] and UMANG [2] are yet another step in the digital evolution where the scheme information, which used to be scattered across various websites of individual departments, is aggregated into a central access portal, while myScheme also incorporates a conversational interface within the platform itself [1]. All of these steps are part of an overall and ongoing trend of digitally enabled access of the citizenry to welfare services, of which automation of eligibility verification is an obvious next step.

C. Literature Review on Welfare Scheme Platforms

Government Scheme Discovery Systems - The myScheme system categorises and filters schemes by type, state, and ministry, and provides an interactive question-and-answer system that filters schemes based on user-defined attributes [1]; UMANG is another example of a system that integrates access to government services [2]. Some recent systems for scheme discovery have suggested that there can be AI-powered extensions to this kind of scheme discovery process. They include, for instance, schemes that integrate a rule-based scheme eligibility component, a recommendation engine based on scheme scoring, and an AI-based conversational assistant into one scheme [7], and schemes that compare themselves to "static rule-based filtering" and provide an AI-assisted database-powered matching mechanism [8]. These recent

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schemes show that integrating scheme eligibility verification with recommendation and AI assistance is a current trend in this problem space. However, most of them do not mention that the architecture of their system includes an explicit separation between eligibility checking and recommendation (or scoring), such that learning happens exclusively within an already selected eligible set of schemes.

Rule-based eligibility systems - Extensive research on both foundational and applied issues related to rule-based expert systems shows that eligibility may be modeled using logical rules consisting of conjunctive and disjunctive conditions, and not just checks of attributes [9], and that such systems, including past government benefit eligibility determination systems [10], provide transparency and auditability since each and every decision is based on some particular rule. A recent scoping review of rule-based decision support systems also confirms this strength and even highlights the need for future rule + machine learning systems [11]. The main limitation that has been consistently observed is that rule engines do not offer any means to distinguish among various valid decisions with respect to an individual's needs.

Machine learning recommendation - Random Forest classifiers have found applications in recommendation scenarios ranging from academic and news recommendation [12] to personalisation of recommendations for mobile-health apps [13], and are often preferred due to their combination of prediction accuracy, robustness against overfitting, and interpretability of feature importance, the latter being especially important in such an application scenario as guidance within the realm of welfare programs, where explainability of the basis of a recommendation system's decision making is crucial. The current body of literature on Random Forests, though, is dominated by recommendation problems in open scenarios, where any object can be recommended to any individual; the latter is not necessarily true in the case of eligibility-restricted scenario.

Conversational AI and RAG - The The concept of RAG was initially proposed as a way of anchoring the outputs of the language model to retrieved external documents instead of anchoring purely on the parametric knowledge alone [14], and the later studies have repeatedly demonstrated that such anchoring results in a reduction in hallucination or unsubstantiated outputs in knowledge-heavy conversation [15]. The technology has found applications in the fields of healthcare, education, and customer service, but its usage for providing guidance to the citizens regarding government schemes by anchoring the conversational agent to a database of the eligible citizen is not something covered extensively in the reviewed literature.

Research gap synthesis - In all the three areas examined above, there is no particular combination in research as in the research at hand, where deterministic and grouped logic eligibility is done before; then machine learning rank allocation is done only after and on the confirmed-eligibility citizens only; finally, a conversational assistant based on the per-citizen eligibility data is used. It is the gap that the YojanaMitra seeks to solve.

III. PROPOSED SYSTEM

Unlike the current government platforms for schemes, the The Existing scheme filtering platform does not filter the schemes based on attributes but evaluates structured eligibility logic, does not prioritise the schemes in which a citizen is eligible for, and also does not offer a conversational assistant with the answers that are based on the citizen’s validated data. The YojanaMitra would solve all these three problems in one pipeline.

The citizens register themselves, create a structured profile, see all the schemes they are eligible for without any filtering or searching of their own, the scheme that they miss and also the exact reason for missing out.

The Profile of the citizen serves as the input which consists of demographic parameters (age, gender, marital status, state, district, area type), socio-economic parameters (annual income, annual income of guardian, occupation, education, category) and status indicators (BPL, disablement, agriculturist, student, minority, bank-linked). This profile is compared to the well-structured database of scheme eligibility conditions, and the output (Eligible / Near Miss / Not Eligible, according to scheme) obtained through comparison of the profile to the database is then used as an input to the ranking process, and finally to the retrieval process of the conversational assistant.

There are two consecutive processes working one after another, but not in parallel: (1) Rule-based evaluation process of the scheme conditions with conditions grouped in a way such that conditions inside a group are linked by logical AND,

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and groups are linked by logical OR, and the output is the classification as described above; (2) Random Forest classifier applied only to schemes marked as eligible before, with relevance scoring based on ten handcrafted features, calculated from citizen and scheme profiles.

The system includes the following: registration and simulated eKYC component, profile management component, deterministic eligibility engine, machine learning ranking component, scheme guidance component (scheme details displayed based on eligibility), retrieval-based conversational assistant, administration component to manage schemes and eligibility criteria, and notification component which notifies the citizen when new schemes or rules added to the system make them eligible.

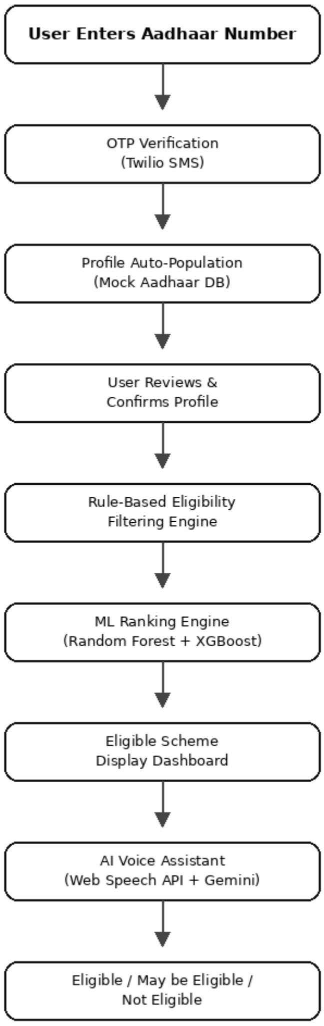

Figure 1 System Workflow Diagram

When compared with the attribute filtering technique applied by myScheme and UMANG, the rule engine in YojanaMitra allows for real nested eligibility reasoning and even has an additional classification called “Near Miss” which does not exist in any of the other two systems. When compared with the literature on recommendation engines, the ranking module of YojanaMitra is limited only to the subset of entities which are eligible, thereby preventing the problem of eligibility violation, which is inherent in recommendation systems when applied to eligibility restricted domains. When compared with generic assistants based on RAG, YojanaMitra’s chatbot is specifically tied to the eligibility calculations done by the citizen.

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Table I Functional Requirements of Proposed System

Functionality	Description	Implementation
Registration and verification	Simulated Aadhaar and mobile OTP onboarding.	Flask, session storage, MockAadhaarRecord
Profile management	Collect and maintain citizen attributes for matching.	Flask/Jinja2, SQLAlchemy, SQLite
Scheme matching	Evaluate scheme rules against citizen profile.	Python rule engine
Near-miss detection	Identify schemes failing exactly one condition in a multi-condition group.	Eligibility engine
ML ranking	Rank only schemes already classified as Eligible.	scikit-learn Random Forest
Conversational guidance	Answer scheme questions using retrieved database context.	Groq API, llama-3.3-70b-versatile
User interface	Dashboard, scheme details, catalogue, chatbot and administration.	Flask/Jinja2, Bootstrap 5, JavaScript

The new system represents an improvement from the existing ones since it provides real-time personalisation of recommendations, multi-lingual support, making it more accessible to people. Besides making government programs more accessible, this makes the whole process of service delivery more transparent and inclusive.

IV. IMPLEMENTATION

The YojanaMitra is built using imprever - rendered HTML/Bootstrap 5 templates implemented as a Flask (Python) web application powered by a SQLite database accessed via SQLAlchemy ORM, and latest on the frontend. The development of the system was done in steps: authentication and user account management, database of schemes and eligibility rules, machine learning layer for ranking, conversational assistant, and administration and other ancillary features (notifications, multilingualism, and reporting).

A. System Initialisation and Setup

On initialization, the application creates a Flask object, sets up the SQLAlchemy database connection URI, and initialises the database schema (Citizen, Scheme, EligibilityRule, MockAadhaarRecord, Notification, ChatbotLog, Admin tables). Third-party library dependencies are flask-sqlalchemy (data access), werkzeug.security (password hashing), scikit-learn, pandas, and joblib (machine learning), and Groq API (using an OpenAI API compatible client) for the conversational assistant. Credentials to the third-party APIs are stored in a local environment file instead of being hardcoded.

B. User Registration and Verification

The process of user registration is carried out by going through an eKYC simulation process where the citizen enters the Aadhaar number along with the mobile number to receive an OTP which is then verified without SMS delivery but on the screen itself. If the entered Aadhaar number corresponds to any one of the 115 mock identity records pre-populated, the name, DOB, gender, and address details are auto-filled while others are manually filled up, the latter being a simulation process. The login credentials such as email and hash-password are created through the same process and the authentication is done via a server side session.

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C. Profile Management and Data Collection

After successful registration, a citizen fills up a predefined profile with all the attributes mentioned in Section 3.3. This information is saved directly in the citizen database record and used by the eligibility engine and the ranking model for each of their evaluations henceforth.

D. Core Processing, and Matching Algorithm

The eligibility engine assesses the scheme's stored conditions against the citizen's profile by employing the grouped AND/OR logic as explained in Section 3.4 in addition to testing each scheme for its application deadlines before assessing its conditions. The schemes tagged as Eligible are sent to the Random Forest ranking algorithm which calculates ten artificial features per citizen-scheme combination (age fit, income margin, category match, geographic match, occupation relevance, BPL match, scheme popularity, calculated vulnerability index, education fit, and gender relevance) and determines the relevance score to rank the results. In case a trained model file does not exist, then a default formula for calculating relevance score using weighted sum of features is used, so that the ranking functionality can still work even without a model.

E. Notification, Output and Service Module

The results are delivered to the citizen through a filterable, sortable dashboard (eligible/un-eligible schemes, schemes categorised, benefit type), and also through individual scheme description pages delivering scheme benefits, documents needed, application process, as well as a break-up of conditions under which the citizen is eligible for that particular scheme. The notification module is used to notify a citizen whenever a scheme or a rule is added to the system by an administrator and thereby making them eligible. The conversational agent answers the queries raised by the citizens using the data retrieved from the eligible/near-miss schemes along with the schemes having keywords matched to the query and generates response within the constraints of that data retrieved only. The proposed system adopts a modular approach that guarantees the scalability, data security, real-time nature, and also user accessibility. The system essentially aims at connecting citizens with relevant government welfare schemes for which they are personally eligible.

V. RESULT AND DISCUSSION

YojanaMitra works as it brings together registration, profile-based match, personalised ranking, and conversation in one process. First, a citizen registers himself using the registration form (see Fig. 2.2) and fills the Profile Creation Form (see Fig. 2.3). This form captures socio-economic parameters of age, marital status, state, category, profession, income, and BPL/Disability/Farmer status. The system performs profile evaluation with respect to the stored eligibility criteria for all the schemes available in the database and gives results on the Citizen Dashboard (see Fig. 2.1) in "Eligible", "Near Miss" or "Not Eligible". The latter classification is selected because we wanted to show those schemes that are not matched with the citizen but have a very small deviation, which can be a missed condition. Each scheme has a machine learning-based percentage of matching. When the citizen selects any scheme from his dashboard, he gets to see the citizen-specific eligibility criteria breakdown (see Fig. 2.4) showing which conditions have been matched against a particular scheme's criteria. For administrators, the system provides a secured admin panel (see Fig. 2.5) that allows managing schemes and rules for eligibility as well as viewing the list of registered citizens. The in-app Notifications module helps users stay engaged and notifies citizens about the addition of any new scheme or rule making them eligible. This differs from other applications that notify citizens about the new eligibility using push notifications, email, and SMS.

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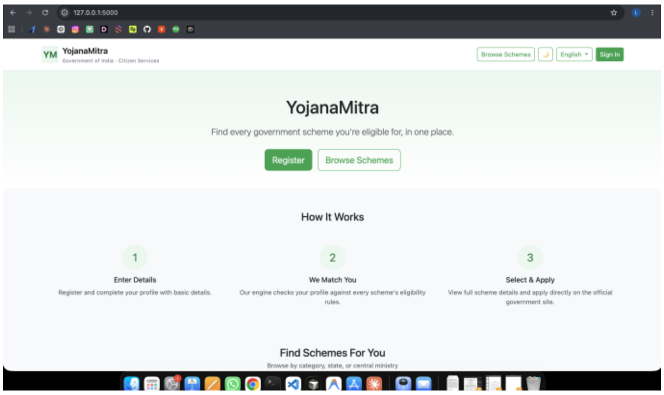

Figure 2.1 System dashboard

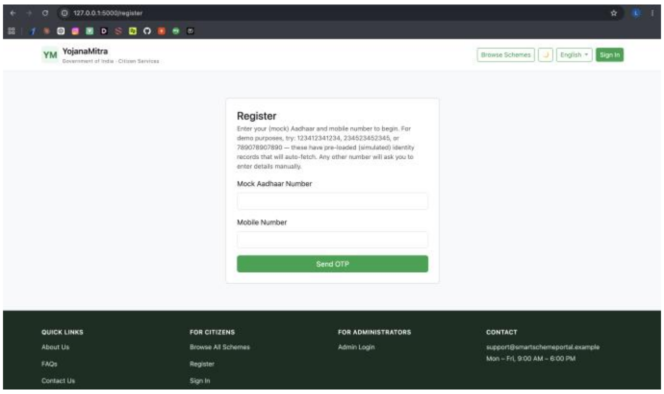

Figure 2.2 User Registration form

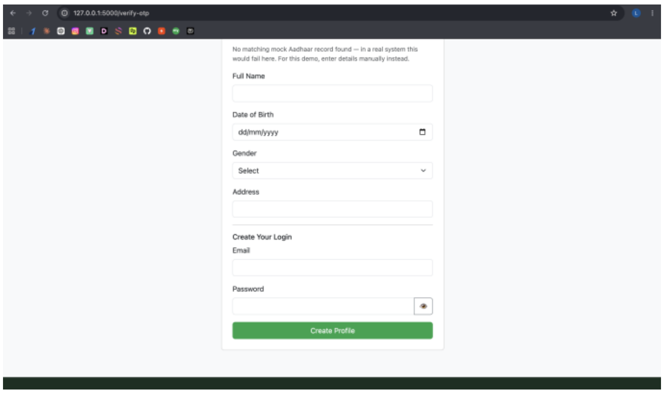

Figure 2.3 User Profile Creation Form

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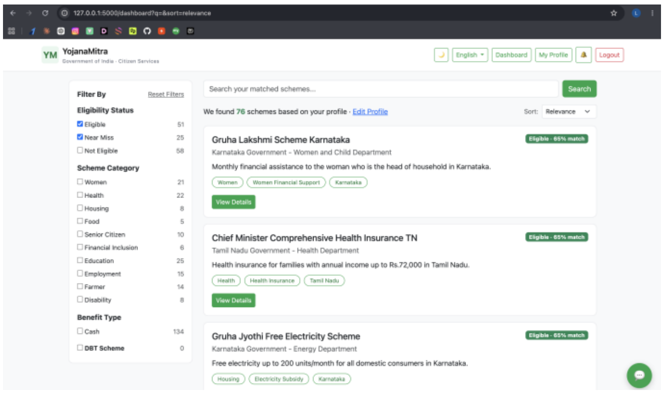

Figure 2.4 Scheme Eligibility

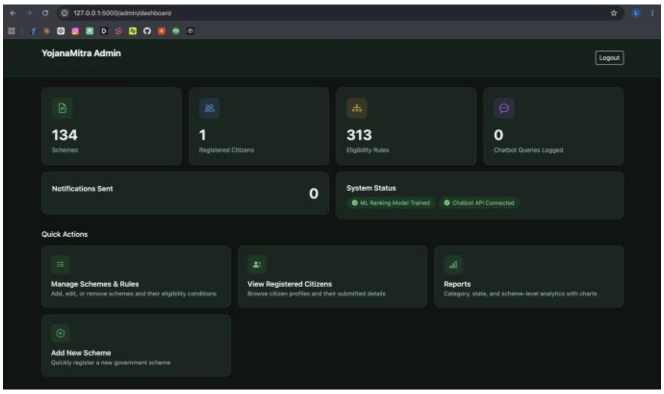

Figure 2.5 Admin panel

A. Technical Assessment of the Eligibility Engine, Ranking Model, and Chatbot.

Unlike those assessment procedures that require the participation of a citizen or expert in a survey, the assessment done in this research was not a field-based exercise but rather a technical exercise since a citizen-participant survey did not fall within the scope of an individual academic work; therefore, software testing and functionality checking of all three main modules were done.

The eligibility engine was assessed via an automated test battery of 8 cases, which included AND/OR group logic, the Eligible/Near Miss/Not Eligible classification, age range criteria, expiration of the deadline, and both BPL and land holding rules together. All 8 tests passed during the final run, while one of the tests had initially failed and resulted in correction of the near miss classification logic for the single-condition eligibility groups.

Table II Automated Test Case Outcomes (Eligibility Engine)

Test Cases	Logic Verified	Outcome
Eligible when all conditions pass	Basic AND-group satisfaction	Passed
Near Miss on single failed condition (multi-condition group)	Near - miss threshold logic	Passed
OR across groups	Disjunctive group logic	Passed
OR across groups	in_range operator	Passed
BPL + land holding combined	Multi - attribute AND logic	Passed
Deadline expiry rejection	Scheme deadline handling	Passed

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ML ranking fallback (no trained model)	Ranking resilience	Passed
Not Eligible on single hard condition	Corrected near-miss edge case	Passed

The Random Forest ranking model was tested on a withheld 20% of its dataset based on accuracy, precision, recall, F1-score, and ROC-AUC.

Table III — Random Forest Ranking Model Performance

Metric	Value
Accuracy	0.5970
Precision	0.6064
Recall	0.5980
F1-Score	0.6022
ROC-AUC	0.6273

The accuracy and ROC-AUC values show that the model achieves a level only slightly above random guessing (the value for which a random classifier will be 0.50 for the case of a balanced binary classification problem). It is worth noting that this result fits well with the fact that the model was developed on artificial citizen-application data instead of real application-citizen behavior data, which is explicitly stated as one of the limitations of the project because there are no public application-citizen behavior data. Thus, the obtained result can be regarded as the proof that the model has learned the correlation in the data generation process, and not the proof of good recommendation accuracy; thus, the relatively low value is a reasonable and reported indicator that further tuning of the ranking layer is necessary.

Table IV— Random Forest Feature Importance

Feature	Importance
Vulnerability score	0.4644
Income margin	0.2252
Age score	0.1089
Popularity	0.0682
Education score	0.0482
Occupation score	0.0235
Gender score	0.0205
Geography score	0.0184
Caste score	0.0123
BPL score	0.0104

VI. CONCLUSION AND FUTURE ENHANCEMENTS

YojanaMitra is a multi-layered application designed to assist citizens in finding out which welfare schemes are suitable for them by solving the problem of fragmented information about various schemes and eligibility criteria stated in the form of complicated conjunctions of conditions. YojanaMitra consists of the deterministic rule-based eligibility engine supporting AND/OR condition groups, a machine learning based ranking layer performing individualised ranking only among those schemes for which a citizen satisfies the eligibility criteria, and a retrieval based conversational assistant constrained to those schemes as well. The application is fully realised as a web-based system that goes through all steps of a citizen journey including registration, simulated eKYC, profile creation, eligibility gating, personalisation, guiding towards suitable schemes, providing conversational assistance, and managing the scheme/rule base in terms of

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administration. Automated and manual testing was performed to validate the application. In particular, the research shows that rule-based eligibility gating and ML-based personalisation can be effectively integrated without any inherent contradictions, which closes the architecture gap existing in current government scheme discovery applications as well as in general in rule-based/recommendation systems. However, the ranking layer's accuracy (59.7%) is relatively low due to the fact that synthetic data is used instead of real application data. Several issues are suggested for future work: using real/privacy preserving application data or human evaluation to improve ranking accuracy, understanding why some synthetic data attributes have low importance; extending the number of schemes from current 134 verified schemes in 15 states to cover the national platforms and unverified states; systematic/labeled evaluation of the quality of responses provided by the conversational assistant and its hallucination rate as currently it is assessed only manually; validation of machine-translated interface labels with native speakers before release; expansion of notification capabilities from in-app channel to email/SMS; usage of identity verification service instead of the simulated eKYC procedure.

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