AADHAR Charity Listing Platform: A Technology-Driven Approach to Transparent Charitable Giving in India with Intelligent Recommendation System

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Abstract---*The AADHAR Charity Listing Platform addresses the critical challenge of connecting donors with verified beneficiaries in India's fragmented charitable ecosystem. Traditional charity systems suffer from lack of transparency, verification mechanisms, and centralized access to diverse social causes. This paper presents a comprehensive web and mobile-based solution built on the MERN stack (MongoDB, Express.js, React, Node.js) that consolidates 30+ charity categories including poverty alleviation, education, healthcare, farmer distress, widow welfare, and disaster relief. The platform implements Firebase authentication for secure user management, Razorpay payment gateway for seamless donations, and an admin verification system to ensure listing authenticity. A key extension of this work is the integration of an Intelligent Recommendation System designed to guide donors toward charitable causes that are most relevant and impactful to them. The recommendation engine employs two complementary algorithmic approaches: (1) Location-Based Filtering using K-Nearest Neighbor (KNN) distance metrics and geographic filtering that prioritizes geographically proximate listings for each donor, and (2) Collaborative Filtering using User-Based Collaborative Filtering and Matrix Factorization techniques such as Singular Value Decomposition (SVD) that identifies donors with similar giving patterns and recommends causes accordingly. Together, these strategies work in a hybrid manner -- location filtering handles new users immediately while collaborative filtering deepens personalization over time. By combining modern web technologies, secure payment infrastructure, and data-driven recommendation algorithms, AADHAR aims to revolutionize India's charitable sector through transparency, accessibility, and personalized donor engagement.*

Index Terms---*Charity Platform, Recommendation System, Collaborative Filtering, Location-Based Filtering, KNN, SVD, Matrix Factorization, MERN Stack, Firebase, Razorpay, Transparent Philanthropy, India.*

I. INTRODUCTION

India's charitable landscape is vast and diverse, with millions of individuals and organizations working toward social welfare across numerous domains. However, this ecosystem faces significant challenges that impede effective philanthropic engagement. Donors struggle to identify genuine causes, verify the authenticity of beneficiaries, and track the impact of their contributions. Similarly, individuals and organizations in need often lack visibility and access to potential donors who could support their causes.

The fragmentation of charitable activities across multiple platforms, the absence of standardized verification processes, and limited transparency in fund utilization have created a trust deficit in the charitable sector. Traditional methods of charitable giving rely heavily on personal networks, word-of-mouth references, or regional organizations, which limits the reach and scalability of social impact initiatives.

The AADHAR Charity Listing Platform is designed to bridge this gap by creating a unified, technology-driven ecosystem that connects verified donors with authenticated beneficiaries. The platform leverages modern web technologies, secure authentication mechanisms, and integrated payment systems to provide a seamless, transparent, and trustworthy charitable giving experience. By consolidating diverse charity categories ranging from education and healthcare to disaster relief and farmer welfare, AADHAR creates a comprehensive directory that enables donors to discover causes aligned with their philanthropic interests.

A significant innovation introduced in this paper is the integration of an Intelligent Recommendation System within the AADHAR platform. One of the biggest barriers to charitable engagement is information overload -- a donor landing on a platform with hundreds of listings across 30+ categories often finds it overwhelming to decide where to contribute. A well-designed recommendation engine resolves this by personalizing the donor experience, surfacing causes that are geographically close, thematically aligned, or supported by peers with similar donation histories.

Built on the robust MERN technology stack, the platform ensures scalability, real-time data management, and cross-platform accessibility through both web and mobile interfaces. The integration of Firebase authentication provides secure user management, while Razorpay payment gateway facilitates safe and convenient donation transactions. A dedicated admin

verification system ensures that only legitimate charity listings appear on the platform, thereby building credibility and donor confidence.

This paper explores the design, implementation, and features of the AADHAR Charity Listing Platform including its intelligent recommendation subsystem, demonstrating how technology can transform charitable giving by promoting transparency, accessibility, personalization, and verified connections in India's social welfare ecosystem.

II. MOTIVATION OF THE PROJECT

The charitable sector in India faces several systemic challenges that motivated the development of the AADHAR platform. Donors frequently encounter difficulties in identifying genuine charitable causes and verifying the legitimacy of organizations or individuals seeking support. The absence of a centralized platform means that potential beneficiaries remain invisible to willing donors, while donors waste time and resources searching through fragmented sources of information.

Trust is a fundamental issue in charitable giving. Without proper verification mechanisms, donors risk contributing to fraudulent or non-existent causes, leading to financial loss and erosion of confidence in the philanthropic ecosystem. Legitimate beneficiaries struggle to establish credibility and reach potential donors who could transform their circumstances through timely support.

The lack of transparency in traditional charitable systems further compounds these challenges. Donors often have no visibility into how their contributions are utilized, whether funds reach intended beneficiaries, or what impact their donations create. This information asymmetry discourages sustained philanthropic engagement and limits the potential for meaningful social change.

Additionally, even on digital platforms, the absence of personalization creates a poor donor experience. A donor who has previously contributed to farmer distress relief and education causes should not have to scroll through animal welfare or environmental listings to find the next cause they want to support. This problem -- known as the discovery problem in recommender systems literature -- directly reduces platform engagement and donation frequency.

Geographic proximity is another underexplored dimension of charitable motivation. Research in behavioral psychology shows that people are significantly more motivated to help those in their immediate community. A donor from Nagpur is more likely to feel a personal connection to a cause from Nagpur than one from a distant city. Existing charity platforms largely ignore this spatial dimension of philanthropic preference.

The AADHAR Charity Listing Platform is motivated by the goal of addressing all these challenges through technology -- delivering not just a verified listing directory, but a smart, personalized experience that matches the right donor to the right cause at the right time.

III. OBJECTIVES

The primary objective of this research paper is to explore and analyze how modern web technologies, secure authentication systems, integrated payment solutions, and intelligent recommendation algorithms can be effectively applied to transform charitable giving in India. The specific objectives are as follows:

1. To create a centralized platform that consolidates 30+ charity categories including poverty alleviation, education, healthcare, farmer distress, widow welfare, and disaster relief into a single accessible directory.
2. To implement a robust admin verification system that authenticates charity listings and beneficiaries, ensuring that only legitimate causes appear on the platform.
3. To provide secure user authentication using Firebase, enabling safe registration, login, and profile management for donors, beneficiaries, and administrators.
4. To integrate seamless payment infrastructure through Razorpay gateway, facilitating safe, convenient, and trackable donation transactions with multiple payment options.
5. To design and implement a Location-Based Filtering recommendation module using KNN and geographic distance metrics that surfaces geographically proximate charity listings to donors, improving local community impact.
6. To design and implement a Collaborative Filtering recommendation module using User-Based Collaborative Filtering and Matrix Factorization (SVD) that discovers latent donor preferences and recommends causes aligned with similar users' giving behavior.
7. To combine both recommendation strategies into a unified Hybrid Recommendation Engine that is effective for both new users (cold-start via location) and experienced users (personalized via collaborative filtering).
8. To ensure data security, privacy, and scalability through a centralized MongoDB database architecture managing user profiles, charity listings, donation records, and interaction logs.
9. To democratize access to charitable support for underserved communities by increasing their visibility and connecting them with potential donors across geographic boundaries.

IV. LITERATURE SURVEY

The AADHAR Charity Listing Platform integrates charitable giving, web application architecture, secure payment systems, and intelligent recommendation techniques. This literature review synthesizes relevant findings across these domains.

A. Digital Transformation of Charitable Giving

Contemporary philanthropic platforms increasingly rely on technology to address trust and transparency challenges in traditional charity systems. Research by Bellandi et al. (2025) on knowledge-driven service platforms demonstrates how centralized systems with structured data management can streamline complex ecosystems by providing users with organized, accessible information. Their work on document management platforms highlights the importance of categorization, searchability, and verification mechanisms -- principles directly applicable to charity listing systems.

Davane et al. (2025) explored AI-driven verification and risk analysis systems employing multi-stage validation processes. While focused on legal document verification, the hybrid approach combining automated checks with human oversight provides a valuable framework for charity listing authentication, demonstrating that technology-assisted verification significantly enhances platform credibility.

B. Web Application Architecture and Scalability

The MERN stack (MongoDB, Express.js, React, Node.js) has emerged as a popular choice for building full-stack applications due to its unified JavaScript ecosystem. React's component-based architecture provides excellent user experience through fast rendering and responsive interfaces, while Node.js with Express.js offers scalable backend services capable of handling concurrent requests efficiently. MongoDB's document-oriented database structure is particularly well-suited for platforms managing diverse data types such as user profiles, charity listings, and transaction records.

C. Secure Authentication and Payment Integration

Firebase Authentication provides enterprise-grade security with support for multiple authentication methods. Research confirms that Firebase's token-based approach using JSON Web Tokens (JWT) ensures secure session management while maintaining user convenience. Razorpay has emerged as a leading payment solution in India, supporting UPI, net banking, cards, and digital wallets. Studies indicate that Razorpay's API-first design and PCI DSS compliance enable easy, secure integration with web and mobile applications.

D. Recommendation Systems in E-Commerce and Social Platforms

Recommendation systems have been extensively studied in the context of e-commerce, streaming services, and social networks. Collaborative Filtering, first formalized by Goldberg et al. (1992), remains one of the most widely used techniques. User-Based Collaborative Filtering identifies users with similar preference vectors and recommends items liked by similar users. Matrix Factorization methods, particularly Singular Value Decomposition (SVD) popularized by the Netflix Prize competition, decompose the user-item interaction matrix into latent factor spaces to uncover hidden patterns in user behavior. These methods have shown strong performance even with sparse interaction data.

K-Nearest Neighbor (KNN) algorithms have been applied broadly in geographic recommendation scenarios. Linden et al. (2003) demonstrated that item-to-item collaborative filtering at Amazon achieved superior scalability, while geographic filtering approaches have been shown to significantly improve recommendation relevance in location-aware applications such as Yelp, Foursquare, and local service platforms. The combination of geographic proximity and behavioral similarity -- a hybrid approach -- has been proposed by several researchers as the most effective strategy for location-aware recommendation systems.

E. Trust and Transparency in Digital Philanthropy

Research in behavioral economics confirms that trust and transparency are primary determinants of donor engagement. Donors are significantly more likely to contribute when they can verify the legitimacy of causes and receive feedback on donation impact. Platforms implementing verification systems, detailed beneficiary profiles, and donation tracking mechanisms demonstrate higher user retention and increased donation volumes. The literature confirms that technology-driven platforms addressing transparency in charitable giving must combine comprehensive verification, secure transactions, and user-friendly interfaces.

V. PROPOSED SYSTEM

The proposed AADHAR Charity Listing Platform is a comprehensive, full-stack web and mobile application engineered to democratize charitable giving by connecting verified donors with authenticated beneficiaries across India. The system addresses the critical challenge of trust, transparency, and personalization through a technology-driven approach combining secure authentication, integrated payments, centralized verification, and an intelligent recommendation engine.

The architecture adheres to a modern MERN stack paradigm ensuring scalability, real-time data synchronization, and cross-platform accessibility. The platform consolidates 30+ charity categories into a unified directory covering poverty alleviation, education, healthcare, senior citizen support, farmer distress, widow welfare, orphanage support, animal welfare, environmental conservation, disaster relief, women empowerment, child nutrition, skill development, and many others.

Central to the enhanced platform design is the Intelligent Recommendation System, which operates in two complementary modes. The Location-Based Filtering module activates immediately upon user registration, using the donor's registered city or pin code to calculate geographic proximity to charity listings and rank them accordingly. The Collaborative Filtering module activates once sufficient donation history is accumulated, building a user-item interaction matrix and applying SVD to identify latent donation preferences and generate personalized cause recommendations.

A multi-tier verification system ensures platform credibility. An admin dashboard enables authorized personnel to review charity listings, verify supporting documents, validate beneficiary information, and approve or reject submissions. Security and privacy are paramount: Firebase Authentication manages user identity with encrypted credentials, all payment transactions are processed through Razorpay's PCI DSS compliant infrastructure, and MongoDB stores user data with encryption at rest and role-based access control.

VI. RECOMMENDATION SYSTEM DESIGN

The Intelligent Recommendation System is the primary novel contribution of this research. It is designed as a hybrid engine combining two algorithms -- Location-Based Filtering and Collaborative Filtering -- to deliver personalized, relevant charity suggestions to donors at every stage of their platform journey.

A. Location-Based Filtering

Location-Based Filtering is treated as the most critical component of the recommendation system. Since charitable giving has a strong geographic motivation -- people instinctively want to help their immediate community -- surfacing locally relevant causes dramatically increases donor engagement and conversion.

Algorithm Design: Upon registration, each donor provides their city, district, or pin code. Each charity listing similarly records the beneficiary's location. The recommendation engine computes the geographic proximity between each donor and every active charity listing using either Haversine distance (for latitude-longitude coordinates) or categorical matching (city/district level).

K-Nearest Neighbor (KNN) Implementation: The platform applies KNN with k=10 to 20 (configurable) to select the closest charity listings to the donor's location. The KNN algorithm computes distance d(donor, listing) using the Haversine formula:

$$d = 2r \times \arcsin(\sqrt{\sin^2(Dlat/2) + \cos(lat1) \times \cos(lat2) \times \sin^2(Dlon/2)})$$

where r is the Earth's radius (6,371 km), lat1 and lat2 are the latitudes of donor and listing respectively, and Dlat, Dlon are differences in latitude and longitude. The output is a ranked list of charity listings sorted by distance, with the closest listings appearing first. For example, a donor registered in Pune will first see charity listings from Pune, followed by listings from nearby cities such as Nashik or Solapur, before listings from distant cities like Chennai or Kolkata.

Cold-Start Advantage: Location-Based Filtering requires no prior donation history, making it immediately effective for new users who have just registered on the platform. This directly addresses the cold-start problem -- a well-known challenge in recommender systems where new users have no historical data to base recommendations on.

Fallback Mechanism: If a donor's location cannot be determined or no charity listings are available within a specified radius, the system falls back to state-level filtering, then national-level listings sorted by recency and urgency.

B. Collaborative Filtering

Collaborative Filtering is applied when sufficient interaction data is available on the platform -- typically after a donor has made two or more donations or after the platform accumulates a meaningful number of active donors. It captures latent patterns in donor behavior to recommend causes that a donor is likely to support based on the preferences of similar donors.

User-Based Collaborative Filtering: This approach builds a user-item interaction matrix M where rows represent donors and columns represent charity listings. The value M[i][j] represents whether donor i has donated to charity j (binary), or the donation amount (continuous). The similarity between two donors is computed using cosine similarity:

$$sim(A, B) = (A \cdot B) / (||A|| \times ||B||)$$

For a target donor A, the system identifies the top-k most similar donors (k=5 to 15), collects the charity listings those similar donors have supported that Donor A has not yet donated to, and ranks these unseen listings by weighted average similarity score to generate recommendations. For example, if Donor A and Donor B have both donated to 'Farmer Distress Relief - Vidarbha' and 'Child Education - Pune', they are identified as similar users. When Donor B subsequently donates to 'Widow Welfare - Nashik', that listing is recommended to Donor A, since Donor A has shown aligned philanthropic preferences.

Matrix Factorization (SVD): For platforms with larger datasets, User-Based CF can suffer from scalability issues. Matrix Factorization using Singular Value Decomposition (SVD) offers a more scalable approach. The interaction matrix M is decomposed as:

$$M \sim= U \times S \times VT$$

where U is the user latent factor matrix, Sigma is the diagonal matrix of singular values, and VT is the item (charity) latent factor matrix. The latent factors capture hidden dimensions of donor preference -- for example, a donor's affinity for health-related causes vs. education-related causes -- without explicitly labeling these dimensions. Predictions for unrated items are computed by reconstructing the matrix using reduced-rank approximation. This allows the system to identify non-obvious connections between donor preferences and cause types.

Practical Implementation: The system uses Python's Surprise library or scipy.sparse.linalg.svds for SVD computation, which runs as a background batch job (e.g., every 24 hours) and updates the recommendation index stored in MongoDB. Real-time requests query this precomputed index rather than computing SVD live, ensuring fast response times for the recommendation API.

C. Hybrid Recommendation Engine

The two algorithms are combined into a unified Hybrid Recommendation Engine using a weighted scoring approach. Each charity listing receives a composite recommendation score:

Score(listing) = alpha x LocationScore + (1-alpha) x CollaborativeScore

where alpha is a dynamic weight parameter. For new users (no donation history), alpha = 1.0 (pure location-based). As a user accumulates more donations, alpha decreases toward 0.4, giving increasing weight to the Collaborative Filtering signal. This gradual shift ensures a smooth transition from cold-start to personalized recommendations.

The hybrid engine also incorporates a diversity mechanism to prevent recommendation bubbles -- situations where a donor is only ever shown causes from one narrow category. Up to 20% of recommendations are diversified by category, ensuring donors discover causes outside their immediate history while remaining anchored to their primary interests and geographic area.

Table 1: Comparison of Recommendation Approaches

Aspect	Location-Based (KNN)	Collaborative (SVD)	Hybrid Engine
Data Required	Location only	Donation history	Both
Cold-Start	Excellent	Poor	Excellent
Personalization	Low	High	High
Scalability	High	Medium (batch)	High
Example Use Case	New donor in Pune	Experienced donor, 5+ donations	All donors

VII. ARCHITECTURAL DESIGN

The AADHAR Charity Listing Platform follows a five-tier architecture that extends the original three-tier MERN design with dedicated layers for authentication, payment processing, and intelligent recommendation.

A. Presentation Layer (Frontend)

The React 18+ frontend provides an intuitive, responsive interface. Donors can browse 30+ charity categories, view personalized recommendation sections ('Causes Near You' powered by Location-Based Filtering and 'Recommended For You' powered by Collaborative Filtering), search for specific causes, and initiate donations. The interface implements component-based architecture with reusable UI elements, responsive design for desktop and mobile, and real-time state updates via React hooks.

B. Application Logic Layer (Backend)

The Node.js with Express.js backend serves as the core orchestrator, managing RESTful API endpoints for user registration, charity listing creation, donation processing, admin verification, and recommendation serving. A dedicated /api/recommendations endpoint accepts the donor's user ID and returns a ranked list of charity listings based on the hybrid recommendation engine. Express.js middleware handles request validation, authentication token verification, error handling, and response formatting.

C. Recommendation Engine Layer

A separate Python microservice handles computationally intensive recommendation operations. This service exposes REST endpoints consumed by the Node.js backend. It maintains two models: (1) a KNN geographic index built from charity listing coordinates using scikit-learn's BallTree structure for efficient radius queries, and (2) a precomputed SVD model updated via nightly batch jobs. The service stores recommendation results in a Redis cache or MongoDB collection for fast retrieval during live requests.

D. Data Persistence Layer

MongoDB serves as the primary database with the following collections: users (donor and beneficiary profiles with location data), charities (listings with category, description, location, verification status), donations (transaction records linking donors to charities), interactions (implicit feedback logs for recommendation training including listing views, saves, and donations), and recommendation_cache (precomputed recommendation lists per user for fast API responses).

E. Authentication and Payment Layers

Firebase Authentication manages all user identity operations including email/password registration, Google social login, and phone authentication. JWT tokens are issued per session and validated by the backend on every protected API call. Razorpay processes all payment transactions through PCI DSS compliant infrastructure. Payment webhooks confirm transaction completion and trigger donation record creation in MongoDB, recommendation model updates (adding the new interaction), and beneficiary notifications.

VIII. SYSTEM REQUIREMENTS

A. Functional Requirements

User Management: Support registration for donors, beneficiaries, and administrators. Implement Firebase authentication with email/password and social login. Enable profile management and password reset functionality. Capture and store donor location at registration for recommendation use.

Charity Listing Management: Allow beneficiaries to create listings with category, description, target amount, location, and supporting documents. Support 30+ charity categories. Enable listing search and filtering by category, location, and keywords.

Verification System: Provide admin dashboard for reviewing pending listings. Enable document verification and beneficiary validation. Support approval/rejection workflow with feedback.

Donation Processing: Integrate Razorpay for secure multi-method transactions. Generate receipts and confirmation notifications. Track complete donation history per donor and beneficiary.

Recommendation System: Location-Based Filtering must rank charity listings by geographic proximity to the donor using KNN or Haversine-based distance. Collaborative Filtering must activate when a donor has 2+ donations and identify similar donors using cosine similarity or SVD. The hybrid engine must smoothly blend both signals using a dynamic alpha parameter. Recommendations must update within 24 hours of new donation events. Cold-start scenario must be handled gracefully via location-only recommendations.

B. Non-Functional Requirements

Performance: Support 500+ concurrent users. Load charity listing pages within 2-3 seconds. Serve recommendation API responses within 500ms (using precomputed cache). Process donation transactions within 5-10 seconds. Database query response under 100ms for indexed searches.

Security: Encrypt all data in transit using HTTPS/TLS. Store sensitive data with encryption at rest. Implement JWT-based authentication. Comply with PCI DSS standards through Razorpay. Enforce role-based access control for admin operations.

Scalability: Design horizontal scaling capability for increased user load. Support efficient recommendation batch recomputation as donation history grows. Enable addition of new charity categories without code modifications.

Recommendation Quality: Location-Based Filtering must achieve geographic precision at city level or better. Collaborative Filtering must achieve a minimum precision@10 of 0.4 (40% of top-10 recommendations are relevant) when sufficient data is available. Hybrid engine must outperform either individual algorithm on precision and diversity metrics.

IX. APPLICATION FEATURES

A. For Donors

Category Exploration: Donors can explore 30+ charity categories organized into intuitive sections -- Education Support, Healthcare Assistance, Poverty Alleviation, Farmer Distress Relief, Widow Welfare, Senior Citizen Care, Orphanage Support, Animal Welfare, Environmental Conservation, Disaster Relief, Women Empowerment, Child Nutrition, Skill Development, and many more.

Personalized Recommendation Feed: A dedicated 'Recommended For You' section on the donor dashboard surfaces listings ranked by the hybrid recommendation engine. The section is labeled 'Causes Near You' for new users and transitions to 'Based on Your Giving History' as personalization data accumulates.

Advanced Search and Filtering: Donors can search by keywords, location, category, donation target, urgency, and verification status. Location-smart search automatically boosts results near the donor's registered location.

Secure Donation Processing: Razorpay integration supports credit/debit cards, UPI, net banking, and digital wallets. Donors receive instant payment confirmation and digital receipts.

Donation History and Impact: Complete donation history with dates, amounts, beneficiaries, and causes. Aggregated impact metrics showing total contributions and category-wise distribution.

B. For Beneficiaries

Easy Registration and Listing Creation: Beneficiaries can register and create charity listings by selecting categories, writing descriptions, specifying target amounts, setting their location, and uploading supporting documents. Accurate location data improves listing visibility in Location-Based Filtering recommendations.

Real-Time Notifications: Beneficiaries receive instant alerts on listing verification status, incoming donations, and milestone achievements.

C. For Administrators

Verification Dashboard: Comprehensive view of pending listings with document review tools, approval/rejection workflow, and feedback mechanisms. Platform analytics including total users, active listings, verification rates, donation volumes, and recommendation system performance metrics (precision, coverage, diversity).

D. Recommendation-Specific Features

Recommendation Transparency: Each recommended listing displays a brief explanation -- 'Near You: 4.2 km away' or 'Similar donors also gave to this cause' -- building user trust in algorithmic suggestions. Donors can dismiss recommendations they find irrelevant, and this negative feedback is incorporated into the collaborative filtering model.

Geolocation Consent: Donors are prompted to share precise browser location (with consent) to enhance geographic recommendation accuracy beyond the registered city level.

X. IMPLEMENTATION DETAILS

A. Technology Stack

Table 2: Complete Technology Stack

Layer	Technology	Purpose
Frontend	React 18+, React Router, Axios, CSS Modules	User interface and state management
Backend	Node.js, Express.js, Mongoose ODM	REST API, business logic
Database	MongoDB Atlas	User data, listings, donations, interactions
Authentication	Firebase Auth, JWT	Secure user identity management
Payments	Razorpay SDK, Webhooks	PCI-compliant donation transactions
Recommendation	Python, scikit-learn, Surprise, scipy	KNN, SVD, hybrid engine
Caching	Redis / MongoDB cache collection	Fast recommendation API responses
Deployment	Vercel (frontend), AWS EC2 (backend, Python service), MongoDB Atlas	Production hosting

B. Database Schema Design

Users Collection: { _id, firebaseUid, email, name, userType (donor/beneficiary/admin), phone, city, district, state, pinCode, latitude, longitude, createdAt }

Charities Collection: { _id, title, category, description, targetAmount, raisedAmount, beneficiaryId, city, district, state, latitude, longitude, verificationStatus (pending/approved/rejected), documents[], createdAt, updatedAt }

Donations Collection: { _id, donorId, charityId, amount, paymentMethod, razorpayOrderId, razorpayPaymentId, status, createdAt }

Interactions Collection: { _id, donorId, charityId, interactionType (view/save/donate), weight (view=0.1, save=0.5, donate=1.0), timestamp } -- This collection feeds the Collaborative Filtering training pipeline.

Recommendation Cache Collection: { _id, donorId, locationRecommendations[], collaborativeRecommendations[], hybridRecommendations[], computedAt, expiresAt }

C. Recommendation Engine Implementation

Location-Based Filtering Code Flow: (1) On donor registration or location update, compute latitude/longitude from city/pinCode using a geocoding API. (2) Build a BallTree index over all approved charity listing coordinates using scikit-learn. (3) For a recommendation request, query the BallTree with the donor's coordinates and radius r (start with 50km, expand to 200km if fewer than 10 results found). (4) Return ranked results sorted by distance ascending.

Collaborative Filtering Code Flow: (1) Nightly batch job queries the Interactions collection and builds the donor-charity interaction matrix M using implicit feedback weights. (2) Apply TruncatedSVD (n_components=50) via scipy or the SVD algorithm from the Surprise library to decompose M. (3) For each donor, compute predicted scores for all charity listings not

yet interacted with. (4) Store top-20 recommendations per donor in the Recommendation Cache. (5) On API request, retrieve and return cached recommendations.

Hybrid Scoring: For each candidate charity listing, compute: hybridScore = alpha x (1 / (1 + distanceKm)) + (1-alpha) x collaborativeScore, where alpha = max(0.4, 1.0 - 0.15 x donationCount). This formula ensures alpha decreases by 0.15 for each donation made, reaching the minimum of 0.4 after four donations.

D. API Endpoints

Table 3: Key API Endpoints

Method	Endpoint	Description
GET	/api/recommendations/:donorId	Returns hybrid recommendation list for donor
GET	/api/charities/nearby	Returns location-filtered charity listings
POST	/api/donations	Records donation and triggers interaction log update
POST	/api/auth/register	Registers new user with location data
GET	/api/charities/search	Search with category and location filters
POST	/api/charities	Create new charity listing (beneficiary)
PUT	/api/admin/verify/:id	Admin approves or rejects listing
POST	/api/interactions	Logs view/save/donate interaction for CF model

XI. RESULTS AND EVALUATION

The AADHAR platform with Intelligent Recommendation System was evaluated across multiple dimensions: platform functionality, recommendation quality, system performance, and user experience.

A. Platform Functionality

The full-stack MERN application successfully delivered all core features including 30+ charity categories, admin verification workflow, multi-method payment processing through Razorpay, and complete donor and beneficiary dashboards. Firebase Authentication provided zero-downtime user management with support for email/password and Google login. The admin panel's verification system correctly processed approval and rejection workflows with audit trails.

B. Recommendation System Performance

Location-Based Filtering (KNN): Evaluation on a simulated dataset of 500 donors and 300 charity listings across 15 Indian cities demonstrated that the KNN geographic filter correctly surfaced same-city listings as top recommendations for 94% of donors. Average distance of top-5 recommendations from donor location was 8.3 km, compared to 347 km for random baseline recommendations. Cold-start performance was excellent -- all new users received meaningful recommendations immediately upon registration.

Collaborative Filtering (SVD): Evaluated using leave-one-out cross-validation on a simulated interaction dataset of 200 donors with 5+ donations each. The SVD model (50 latent factors) achieved Precision@10 = 0.42 and Recall@10 = 0.38, significantly outperforming the random recommendation baseline (Precision@10 = 0.11). User-Based CF achieved similar Precision@10 = 0.39 but with higher computational cost at inference time, making SVD the preferred production choice.

Hybrid Engine: The hybrid recommendation engine combining both signals with dynamic alpha weighting outperformed both individual algorithms. On users with 3+ donations, the hybrid achieved Precision@10 = 0.51 -- a 21% improvement over collaborative filtering alone -- attributed to the geographic diversity injected by the location component. Donor engagement simulations showed 34% higher click-through rate on recommended listings compared to non-personalized listing feeds.

C. System Performance

Load testing with 500 concurrent simulated users showed average page load times of 1.8 seconds for charity listing pages. Recommendation API responses averaged 210ms using precomputed cache (well within the 500ms target). Razorpay payment processing completed within 6-8 seconds end-to-end including webhook confirmation. MongoDB query times for indexed searches averaged 45ms.

Table 4: Recommendation System Evaluation Summary

Metric	Location KNN	Collaborative SVD	Hybrid Engine
Precision@10	N/A (distance)	0.42	0.51
Recall@10	N/A	0.38	0.44
Cold-Start Handling	Excellent	Poor	Excellent
Avg. Rec. Distance (top-5)	8.3 km	347 km (random)	23.1 km
API Response Time	180ms	240ms	210ms (cached)
Simulated CTR Improvement	+22%	+19%	+34%

XII. DISCUSSION

The results confirm that integrating an Intelligent Recommendation System into the AADHAR platform significantly enhances the donor experience beyond what a plain listing directory can provide. The most impactful finding is that Location-Based Filtering -- despite being algorithmically simpler than SVD -- contributed substantially to hybrid engine performance. This supports the hypothesis that geographic proximity is a primary driver of charitable motivation in India, where community identity and regional solidarity are strong cultural factors.

The cold-start problem, which is a major limitation of pure Collaborative Filtering approaches, is effectively neutralized by the location component. New donors receive immediately relevant recommendations without any historical data, making the platform engaging from the very first visit. This is particularly important for donor acquisition and retention.

The SVD-based Collaborative Filtering component revealed interesting latent patterns in donation behavior. Donors who supported farmer distress causes also tended to support rural healthcare and water conservation listings -- connections that would not have been discovered through simple category matching. These cross-category connections represent genuine latent preferences that the SVD model successfully captured.

The hybrid weighting mechanism (dynamic alpha) proved to be an effective solution for transitioning between cold-start and personalized recommendations. The gradual shift ensures continuity in the user experience and prevents abrupt changes in recommendation quality as donors accumulate more history.

One limitation observed is that the Collaborative Filtering model requires a minimum dataset size to function effectively. On the AADHAR platform in its early deployment phase, where the number of donors with 5+ donations may be limited, the system relies more heavily on Location-Based Filtering. This is an acceptable trade-off given the strength of the geographic motivation discussed above. As the platform scales, the collaborative signal will strengthen, and the hybrid engine will become increasingly effective.

XIII. CONCLUSION

This paper presented AADHAR, a comprehensive charity listing platform for India that combines verified listings, secure donation infrastructure, and an Intelligent Recommendation System to address the critical challenges of trust, transparency, and donor engagement in the philanthropic sector.

The platform's two-algorithm recommendation engine -- Location-Based Filtering (KNN) and Collaborative Filtering (SVD) combined in a dynamic hybrid -- represents a significant practical contribution to the domain of charitable technology. The location-first approach ensures immediate value for new donors while the collaborative component deepens personalization as the platform grows. Evaluation results demonstrated a 34% improvement in simulated click-through rate over non-personalized feeds and Precision@10 of 0.51 for the hybrid engine on experienced donors.

The MERN stack foundation provides a scalable, maintainable, and cross-platform architecture that can accommodate rapid user growth. Firebase Authentication and Razorpay integration ensure enterprise-grade security and payment reliability. The admin verification system maintains platform integrity by ensuring only authenticated causes receive donor visibility.

Future work will focus on (1) integrating Natural Language Processing (NLP) for content-based filtering to complement the collaborative and location signals, (2) building a real-time feedback loop that updates collaborative models incrementally rather than in batch, (3) expanding the platform to support multilingual content for broader pan-India accessibility, and (4) developing a mobile application with native push notifications for donation reminders and recommendation alerts.

AADHAR demonstrates that technology, when thoughtfully applied, can restore trust in charitable giving, remove information asymmetries between donors and beneficiaries, and ultimately amplify the social impact of India's philanthropic ecosystem.

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