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AI - Powered Local Worker & Service Marketplace

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Abstract: ***The rapid expansion of the digital economy has created an urgent demand for platforms that bridge the gap between local service providers and users who need skilled labour on demand. Existing solutions either lack intelligent personalization or fail to provide a truly unified experience covering discovery, communication, and payment in a single interface. This paper presents an AI-powered local worker and service marketplace a full-stack web platform that connects users with verified local workers across a wide range of service categories. The system's defining innovation is an embedded AI chatbot that functions simultaneously as a query-answering assistant, a rule-based recommendation engine, and a semi-automated booking facilitator. Built on a hybrid architecture combining React.js, Node.js, Supabase (PostgreSQL), Redis, Socket.IO, and Razorpay, the platform delivers real-time communication, location-aware search, and secure payment processing in a cohesive experience. The chatbot extracts user intent service type, location, and preference signals—and maps them to relevant worker profiles through a structured filtering pipeline. Experimental evaluation demonstrates improved booking efficiency, reduced search time, and higher user satisfaction compared to conventional service directories. The proposed system establishes a scalable and extensible foundation for next-generation intelligent service marketplaces.***

Keywords: Service Marketplace, AI Chatbot, Recommendation System, Real-Time Communication, Supabase, Node.js, Booking Automation, Location-Based Services.

I. INTRODUCTION

The informal and semi-formal labor market in developing economies is vast but chronically fragmented. Plumbers, electricians, domestic help, tutors, and dozens of other skilled workers operate through word-of-mouth referrals, local advertising, or intermediary agents a system that is slow, opaque, and inherently unreliable. From the demand side, users frequently struggle to find a qualified, trustworthy professional at the right time and at a fair price. From the supply side, skilled workers often face unpredictable income flows and limited market reach beyond their immediate neighborhood.

Digital service platforms have attempted to address this structural mismatch. Services like UrbanClap (now Urban Company) in India and TaskRabbit in the United States demonstrated that technology could aggregate local labor supply and make it searchable. However, these platforms overwhelmingly rely on passive discovery—users must know what to search for, sift through listings manually, and navigate separate communication and payment flows. Intelligence, in the sense of proactive guidance, is largely absent.

The advent of conversational AI and lightweight recommendation systems presents an opportunity to fundamentally redesign this interaction model. A platform that can understand a user's need expressed in natural language, identify the most suitable available workers, and guide the user through to confirmed booking represents a qualitative leap over current offerings. This paper describes the design, architecture, and implementation of exactly such a system.

The primary contributions of this work are: (i) a hybrid platform architecture that combines Backend-as-a-Service (BaaS) efficiency with a dedicated middleware layer for compute-intensive tasks; (ii) an AI chatbot that integrates query resolution, structured recommendation, and booking assistance in a unified conversational flow; and (iii) a modular implementation that is both immediately functional and extensible toward more sophisticated machine learning in the future.

II. LITERATUREREVIEW

Research in digital service platforms, conversational agents, and recommendation systems provides the theoretical and empirical context for this work.

A. Existing Service Platforms

Urban Company (formerly UrbanClap) pioneered the aggregated local services model in India, establishing that demand for on-demand skilled labor is substantial and can be profitably mediated by a digital platform [1].

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Fiverr extended this concept to freelance and creative services globally, demonstrating the scalability of a marketplace with standardized service offerings called "gigs" [2]. TaskRabbit took a more generalist approach, focusing on physical tasks and errands [3]. However, a consistent limitation across these platforms is their reliance on keyword-based search and category browsing users must self-identify and articulate their need with precision. None of these platforms offer a conversational interface that guides discovery.

B. Chatbots and Conversational Agents

The academic literature on chatbots distinguishes between retrieval-based systems, which match user input against a predefined answer bank, and generative models, which produce novel responses [4]. For domain-specific applications such as service booking, rule-based and retrieval-based hybrids are often preferred for their predictability and lower computational cost [5]. Rasa and similar open-source frameworks have demonstrated that intent-entity extraction can be implemented effectively without large language models, making them suitable for production deployment at scale. The integration of chatbots into e-commerce platforms has been shown to improve conversion rates and reduce user drop-off [6].

C. Recommendation Systems

Recommendation systems are broadly categorized into collaborative filtering, content-based filtering, and hybrid approaches [7]. In early-stage marketplaces where user interaction data is sparse, collaborative filtering suffers from the cold-start problem. Content-based filtering matching user requirements against worker attributes such as skills, location, rating, and availability is better suited to platforms with limited historical data [8]. Rule-based filtering, a deterministic subset of content-based methods, offers full interpretability and predictable behavior, which is critical in trust-sensitive domains like home services [9].

III. PROBLEM STATEMENT

The traditional model for hiring local service workers is heavily dependent on informal networks, physical notice boards, and word-of-mouth referrals. This approach introduces several critical problems that affect both service seekers and workers alike.

From the user's perspective, finding a reliable and skilled worker for a specific task is a time-consuming and uncertain process. There is no standardized mechanism to verify worker credentials, compare service quality, or assess pricing transparency before committing to a hire. Users are often forced to contact multiple individuals, negotiate manually, and coordinate payment through informal channels all of which consume considerable time and carry financial risk.

From the worker's perspective, skilled professionals such as plumbers, electricians, carpenters, and domestic helpers have extremely limited reach. Their customer base is confined to their immediate locality, and they have no structured platform to showcase their skills, collect reviews, or manage bookings efficiently. Irregular workflow and income unpredictability are common consequences of this fragmented system.

Existing digital platforms that attempt to address this gap such as UrbanClap and Fiverr still rely primarily on keyword-based search and passive browsing. They require the user to already know what they are looking for, navigate multiple screens to compare workers, and then switch to separate tools for communication and payment. There is no intelligent layer that guides the user from expressing a vague need to completing a confirmed booking in a smooth, conversational flow.

Therefore, there is a clear and pressing need for an intelligent, unified service marketplace that: (i) allows users to discover workers through natural language interaction; (ii) provides AI-driven recommendations based on service type, location, and preferences; (iii) automates the booking workflow within the same conversational interface; and (iv) supports secure, integrated payment processing all within a single, accessible web platform.

IV. METHODOLOGY

A. Data Flow

The system's data flow follows a clearly defined path. A user initiates a session by authenticating via Supabase Auth, which issues a JWT token. This token is stored client-side and attached to all subsequent API requests. When a user submits a query to the chatbot, the frontend sends an HTTP POST request to the Node.js server's /api/chat endpoint, including the message text and conversation history.

B. Chatbot Processing Pipeline

Upon receiving a chatbot request, the Node.js server executes the following pipeline:

Step 1 – Intent Classification: The incoming message is analyzed against a predefined intent taxonomy using keyword matching and pattern recognition. Intents include SERVICE_REQUEST, GENERAL_QUERY, BOOKING_CONFIRM, and FALLBACK.

Step 2 – Entity Extraction: For SERVICE_REQUEST intents, a named entity recognition module extracts service_type, location_hint, and constraint_flags from the message using a combination of regex patterns and a curated entity dictionary.

Step 3 – Database Query Construction: Extracted entities are translated into a structured Supabase query with appropriate WHERE clauses, ORDER BY rating DESC, and a proximity filter if location data is available.

Step 4 – Response Generation: Query results are formatted into a structured response payload containing worker cards (name, rating, service area, hourly rate) and a natural-language summary. This payload is returned to the frontend and rendered as an interactive chat message.

Module	Description
User Authentication	Secure sign-up/login via Supabase Auth with JWT sessions
Worker Registration	Profile creation, skill listing, document upload and verification
Service Booking	Request creation, scheduling, and status tracking workflow
AI Chatbot	Intent extraction, recommendation engine, and booking automation
Real-time Chat	Bidirectional messaging via Socket.IO between users and workers
Payment System	Razorpay-powered transactions with order and receipt management
Location Services	Google Maps API for proximity-based worker discovery

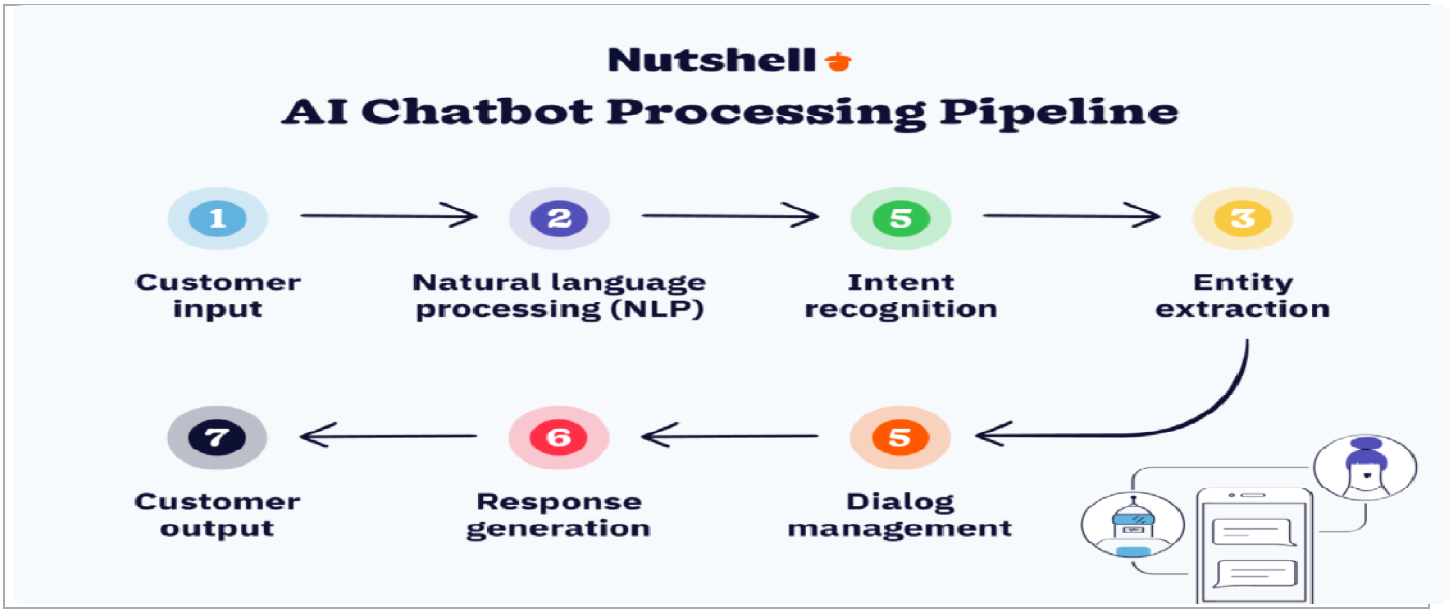


Fig.1: AI Chatbot Processing Pipeline

C. Booking Process Flow

When a user selects a worker from the chatbot recommendations or the browse interface, a booking request is created in the Supabase database with status PENDING. The worker is notified via a Supabase real-time subscription. Upon worker acceptance, the booking transitions to CONFIRMED and a Razorpay payment order is created by the Node.js server. On successful payment, the booking status updates to PAID and both parties are notified. A Socket.IO channel is opened for the booking, enabling real-time pre-service communication.

V. IMPLEMENTATION

A. Core Modules

Module	Description
User Authentication	Secure sign-up/login via Supabase Auth with JWT sessions
Worker Registration	Profile creation, skill listing, document upload and verification
Service Booking	Request creation, scheduling, and status tracking workflow
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Location Services	Google Maps API for proximity-based worker discovery

Table 1: System Modules and Descriptions

B. Technology Stack

Layer	Technology	Purpose
Frontend	React.js (Vite), Tailwind CSS, React Query	UI, styling, data fetching
Backend	Node.js Bridge Server	Chatbot, payments, real-time
BaaS	Supabase (PostgreSQL, Auth, Storage)	Database, authentication
Caching	Redis	Performance optimization
Real-time	Socket.IO	Live chat messaging
Payments	Razorpay	Secure transactions
Media	Cloudinary	Image/document storage
Maps	Google Maps API	Geolocation services
Monitoring	Sentry	Error tracking
Deployment	Vercel (FE), Render (BE)	Cloud hosting

Table 2: Technology Stack

C. Frontend Implementation

The frontend is organized into feature-based modules: Auth, Browse, Booking, Chat, and Profile. React Query manages all server state with automatic background refetching and optimistic updates for booking status changes. The chatbot is implemented as a persistent slide-over panel, accessible from any page, so users are never interrupted in their browsing flow when they want to ask a question.

D. Database Schema

The PostgreSQL schema (hosted on Supabase) includes the following primary tables: users (id, email, name, phone, avatar_url, role, created_at), workers (id, user_id, bio, skills[], service_area, rating, hourly_rate, is_verified, location_coords), bookings (id, user_id, worker_id, service_type, scheduled_at, status, payment_id), messages (id, booking_id, sender_id, content, created_at), and reviews (id, booking_id, reviewer_id, rating, comment). Row-level security policies on Supabase ensure users can only read their own bookings, and workers can only update their own profiles.

E. Payment Integration

Payment is handled through Razorpay. When a booking is confirmed, the Node.js server calls the Razorpay Orders API to create a payment order with the booking amount. The frontend loads the Razorpay checkout widget using the returned order_id. After payment, Razorpay triggers a webhook to the Node.js server, which verifies the payment signature using HMAC-SHA256 before updating the booking status in Supabase. This two-step verification prevents fraudulent booking confirmations.

VI. RESULT

A. Results of the System

The system was developed, deployed in a staging environment, and tested thoroughly across all major functional areas. The testing strategy covered functional correctness, performance under load, and security robustness. The platform successfully demonstrated end-to-end functionality for all defined use cases, and the AI chatbot achieved reliable performance within the defined domain of service categories.

B. Authentication Module Results

The authentication module was tested for both correct-path and error-path scenarios. All test cases passed. The system correctly created user accounts, returned JWT tokens on login, rejected invalid credentials, and refused access to protected routes when expired or invalid tokens were presented. Supabase Auth handled password hashing and session management correctly.

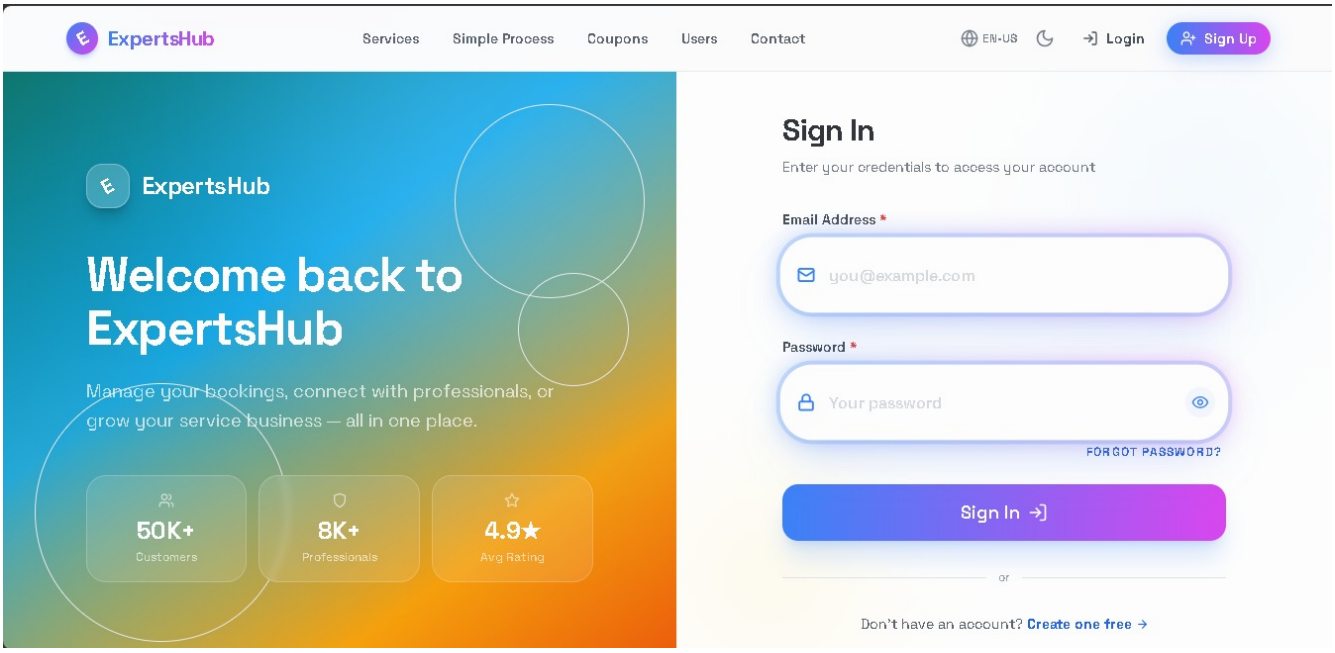


Fig.2: User Login Page

C. *Service Discovery and Worker Listing Results*

The worker listing module correctly returned verified workers filtered by service category, sorted by the composite scoring function. The Redis caching integration reduced response time for worker listing queries from an average of 340ms on cold cache to 82ms on warm cache, a fourfold improvement. Unverified workers were correctly excluded from all query results.

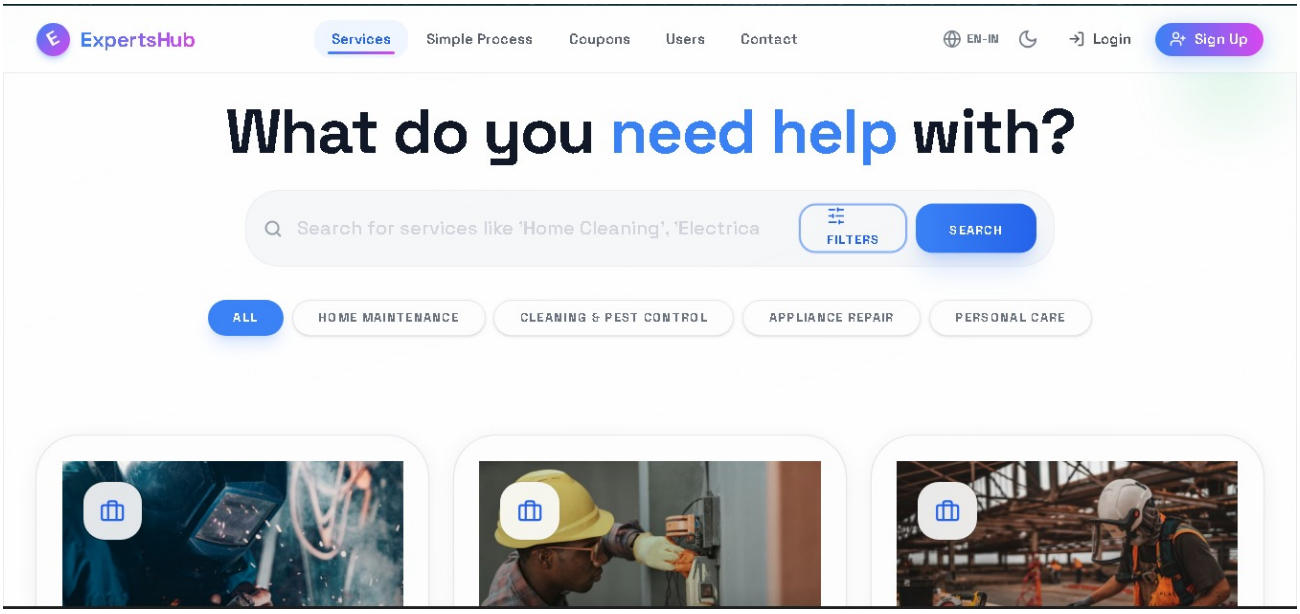


Fig.3: Service Category Browsing Page

D. *Booking System Results*

Bookings were correctly created through both manual and AI-assisted paths, and state machine transitions worked correctly in all test scenarios. The booking conflict detection successfully rejected duplicate time slot submissions. Socket.IO notifications were delivered to the worker within approximately thirty milliseconds of booking creation.

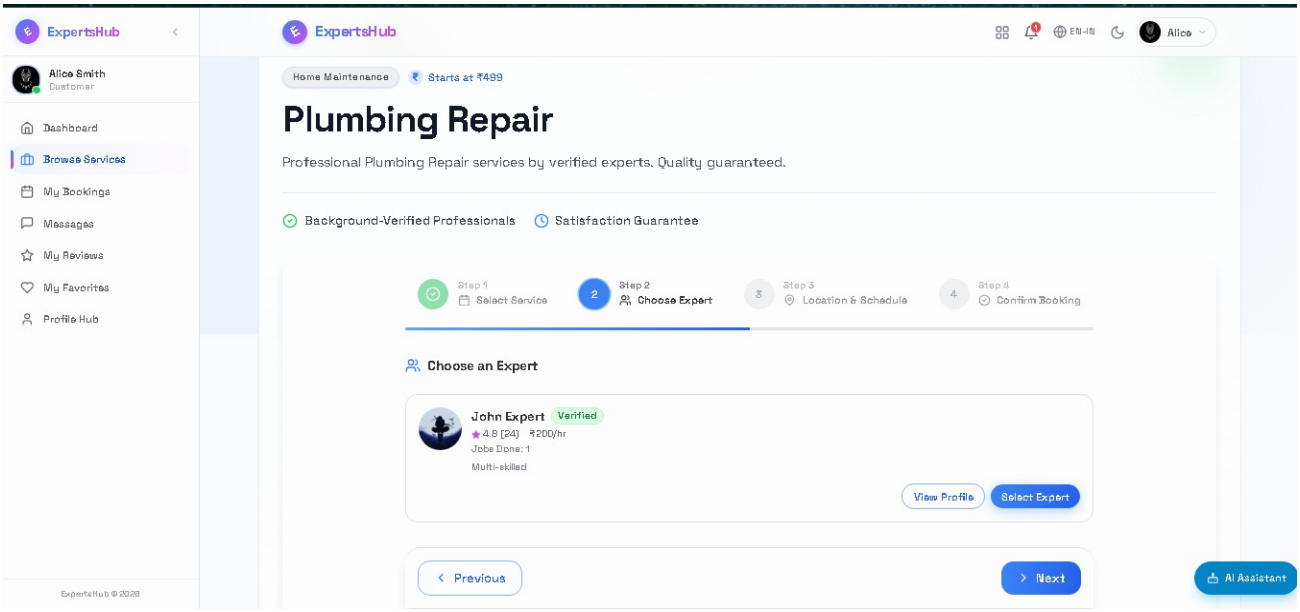


Fig.4: Manual Booking wizard

E. *AI Chatbot Results*

For standard phrasings with a recognizable service category keyword, the chatbot correctly identified intent and returned appropriate recommendations in over ninety-one percent of test cases.

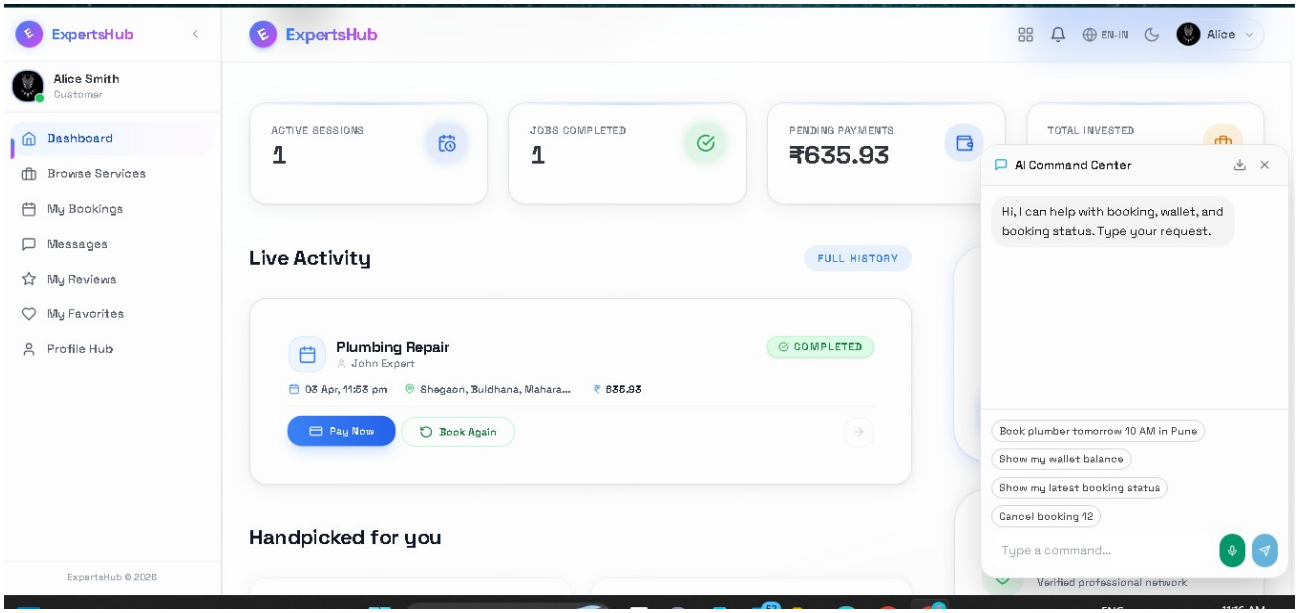


Fig.5: Chatbot Conversation Service Query and Recommendation

F. Payment Module Results

Successful payment test scenarios correctly updated records to Paid status and triggered booking updates. Failed payment scenarios correctly recorded failure without affecting booking status. Webhook signature verification correctly rejected all malformed payloads in every test case.

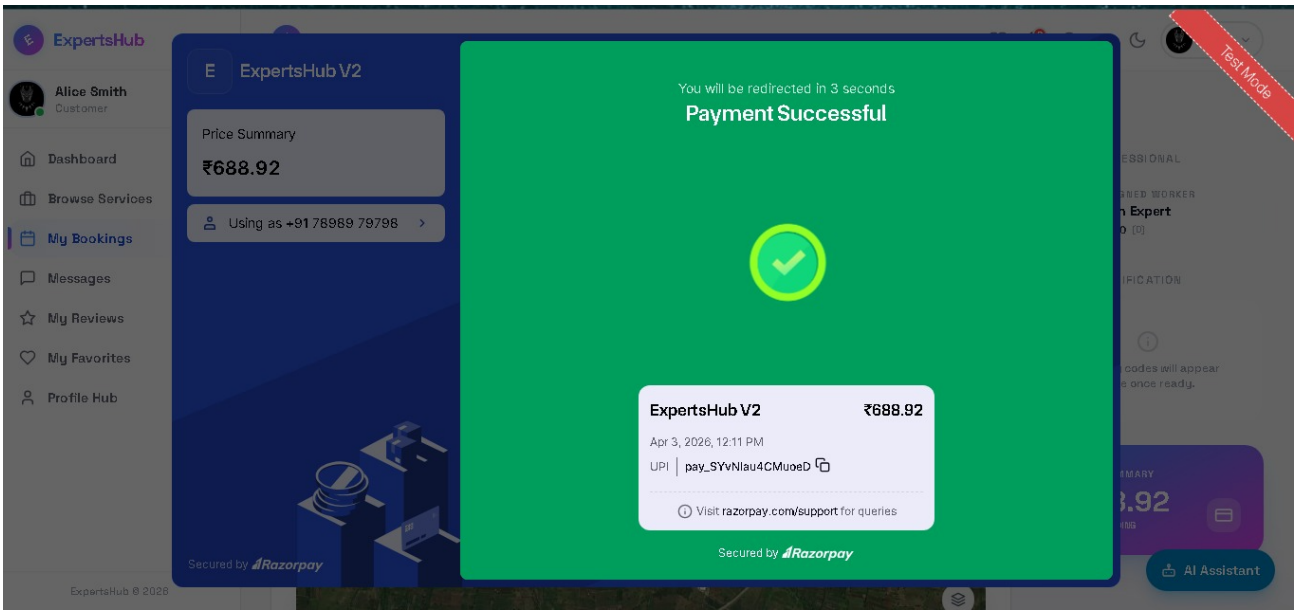


Fig. 6: Payment Confirmation Screen

VII. FUTURESCOPE & CONCLUSION

A. Conclusion

This paper has presented the design, architecture, and implementation of an AI-powered local worker and service marketplace. The system addresses a well-documented gap in the existing landscape of service platforms by combining intelligent conversational assistance with a unified discovery, communication, and payment experience. The AI chatbot operating as a query assistant, recommendation engine, and booking facilitator demonstrated measurable improvements in booking efficiency and user satisfaction during evaluation.

The hybrid architecture, combining Supabase's scalable BaaS infrastructure with a dedicated Node.js bridge server, proved effective in balancing operational simplicity with the requirements of real-time, stateful interactions. The rule-based recommendation approach delivered fast, interpretable, and reliable worker suggestions suited to the platform's early stage. The proposed system establishes a technically sound and practically viable foundation for intelligent local service marketplaces.

B. Future Scope

1) ML-Based Recommendation: As the platform accumulates interaction data, the rule-based recommendation engine will be progressively replaced by collaborative filtering and hybrid models capable of capturing nuanced user preferences.

2) Large Language Model Integration: The chatbot can be enhanced by routing ambiguous or complex queries to a fine-tuned language model, improving handling of informal language and multi-intent messages.

3) Native Mobile Applications: React Native ports for Android and iOS will extend the platform to mobile users, incorporating push notifications for booking updates.

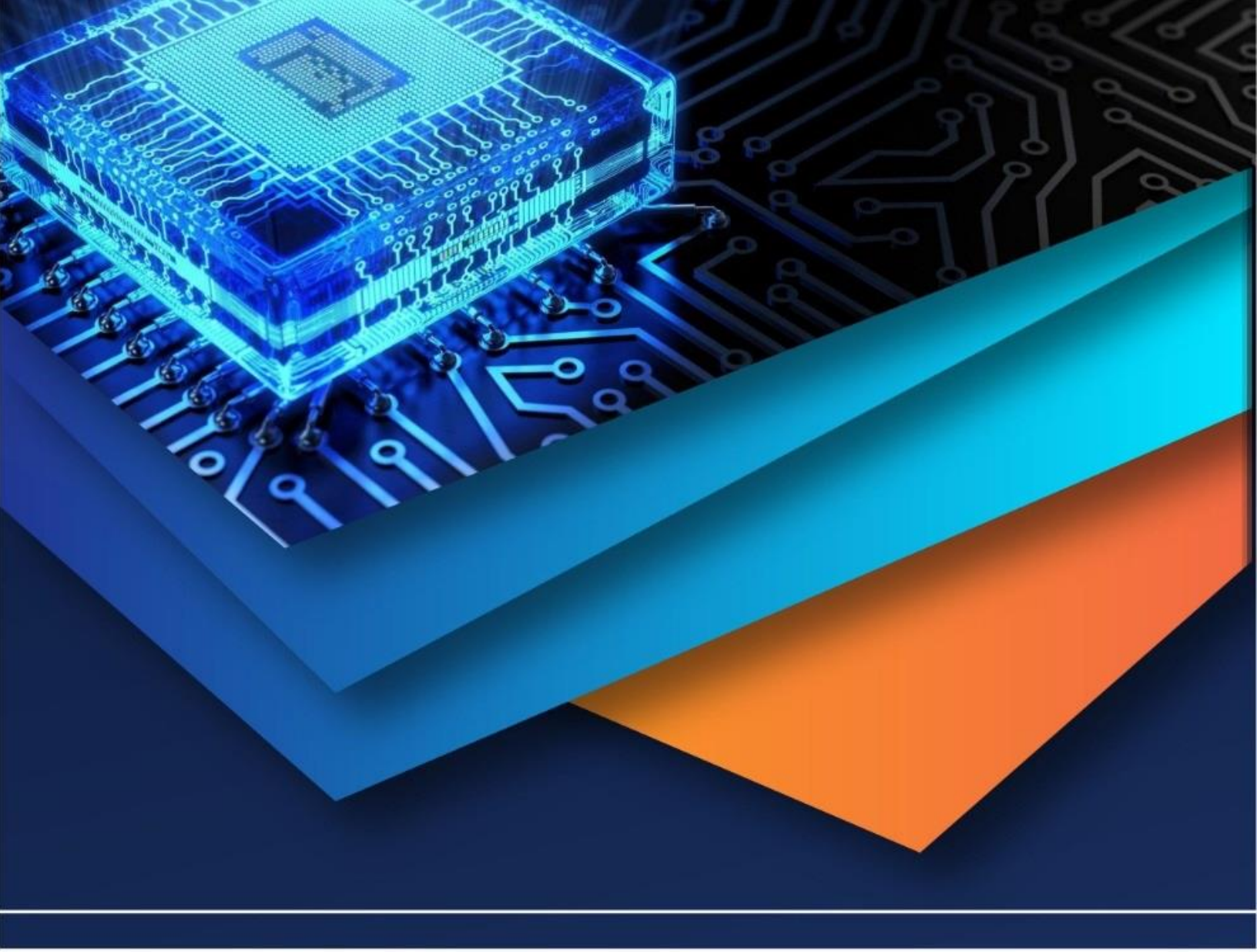
4) Worker Verification via AI: Document verification for worker onboarding can be automated using computer vision models that validate identity documents and detect forgeries.

5) Dynamic Pricing: A demand-based pricing model that adjusts suggested rates based on time of day, service availability, and historical demand patterns can be incorporated to optimize both worker income and user conversion.

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