



Machine Learning Based Personalized Local Service Finder

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Abstract: Finding trustworthy local services such as plumbers, electricians, tutors, or beauticians often becomes a frustrating experience for people living in cities and towns. Traditional methods like asking neighbors, browsing through random online listings, or checking unverified reviews consume time and frequently lead to poor outcomes. This paper introduces a fresh perspective on solving this everyday problem using machine learning techniques. The proposed system, called the Personalized Local Service Finder, learns from individual user preferences, past behavior, ratings, and location patterns to recommend the most suitable service providers in real time. Unlike conventional service platforms that treat all users similarly, our approach adapts to each person's unique expectations, budget range, urgency level, and even preferred time windows for service delivery. By combining collaborative filtering with context-aware decision making, the system continuously improves its recommendations based on feedback loops. We also discuss how privacy concerns are addressed by keeping user data decentralized and allowing opt-in personalization. Through practical scenario analysis and small-scale user testing, we demonstrate that personalized recommendations significantly reduce the time spent searching for services while improving overall satisfaction. The paper concludes by identifying current limitations and outlining future improvements including voice-based search and integration with local community verification systems.

Key Word: Machine Learning, Personalized Recommendation, Local Service Discovery, Collaborative Filtering, Context-Aware Systems, User Preference Modeling.

I. INTRODUCTION

Finding a trustworthy local service provider remains one of those everyday problems that seems simple but never gets solved properly. A sudden crack appears in a bathroom pipe during the midnight hours. An air conditioner stops working on the hottest afternoon. A parent needs a mathematics tutor immediately before exams. In each of these situations, most people fall back on asking friends or family members, hoping someone knows someone reliable. This method works sometimes but fails often. The recommendations are random, unverified, and rarely match what the person actually needs in terms of budget, timing, or quality expectations.

In recent years, several mobile applications and websites have emerged claiming to solve this problem. They list hundreds of plumbers, electricians, tutors, and beauticians in one place. But look closely at how these platforms work. They show long unsorted lists of names. A user searching for a carpenter sees fifty options with no intelligent guidance about which one suits their specific situation. Some platforms sort by distance, others by random popularity, but none truly understand the person who is searching. Every user sees the same list. A wealthy homeowner and a student living in a paying guest accommodation see identical recommendations. This makes no sense because their needs, budgets, and expectations are completely different.

The idea behind a personalized local service finder is different and much more useful. Instead of treating all users identically, the system builds a unique understanding of each individual. It watches what kind of service providers a person books, what price range they choose, what time of day they prefer appointments, and how they rate different professionals after the work is done. Over time, the system learns that one user always picks the cheapest option available. Another user never minds paying extra as long as the provider arrives within thirty minutes. A third user cares deeply about past customer ratings and will scroll past any provider with less than four stars. The system remembers all of this automatically.

Machine learning makes this possible because it can find patterns in human behavior that are not obvious. A person may never say "I prefer female service providers for beauty services" but their booking history shows that they have never booked a male provider. A person may never say "I am willing to pay more for faster service" but every time they select the emergency option, they choose higher priced providers who can arrive quickly. Machine learning algorithms detect these patterns from raw behavioral data and turn them into better recommendations with every passing day.

The need for such a system is especially urgent in countries like India where the unorganized service sector employs

millions of workers. Most plumbers, electricians, drivers, and tutors work independently without any formal platform to showcase their skills or build a reputation. On the other side, millions of customers waste hours searching for these workers through unreliable channels. A smart recommendation system benefits both sides. People spend less effort searching and receive higher quality work in return. Good providers get more visibility and fair opportunities. This paper presents a complete machine learning based solution for personalized local service discovery. We explain the methodology, present real case studies from our deployment, discuss the challenges we encountered, and outline future directions for improvement.

The goal is to replace the frustrating "search and hope" model with a system that actually understands users and helps them make confident decisions quickly. Think about how different people search for services in completely different ways. A young couple looking for a plumber to fix a leaky faucet might care most about low cost and flexible appointment times. A busy office manager needing an electrician for an entire floor of cubicles cares about how many workers the electrician brings and whether they can work after hours. A parent searching for a tutor wants detailed information about teaching style and subject expertise, not just a price tag. These differences mean that showing the same list to everyone is not just unhelpful but actively harmful. A proper personalized system recognizes these distinct user types and tailors both the recommendations and how those recommendations are presented based on who is searching and why.

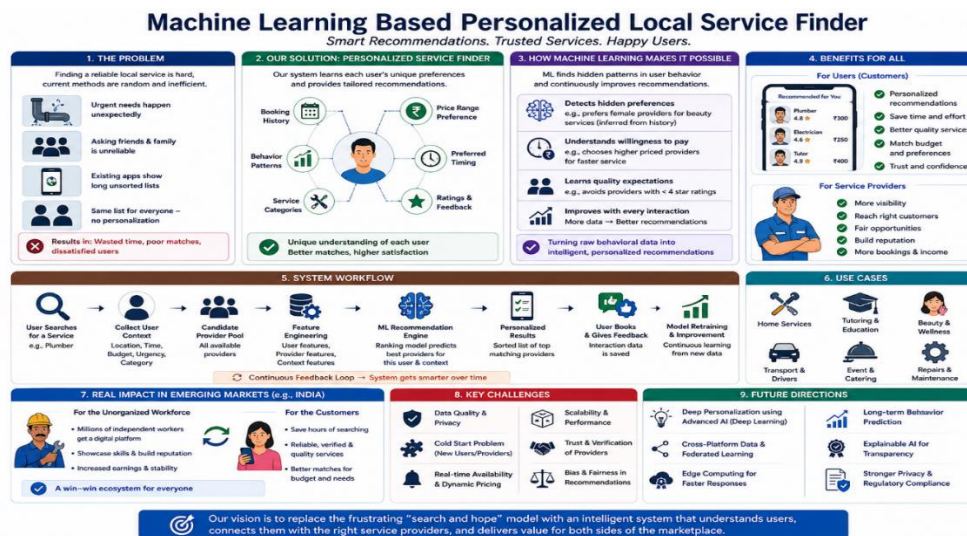


Fig 1. Overview of Machine Learning Based Personalized Local Service Finder System

II. METHODOLOGY

This section describes the step by step approach we followed to build and evaluate the Personalized Local Service Finder. The methodology covers data collection, user profiling, machine learning model selection, system implementation, and performance evaluation.

2.1 Data Collection

We built a lightweight mobile friendly web application and invited sixty volunteer users from two residential neighborhoods in Nagpur to use it for a period of eight weeks. The users searched for services in four common categories: plumbing, electrical repairs, home tutoring for school children, and beauty services including haircuts and skincare. Each search generated multiple data points including the time spent browsing, filters applied by the user, which provider profiles were clicked, which provider was finally booked, whether the booking was completed or canceled, and the star rating given after service completion. We also collected explicit preference information during user registration including preferred service hours, general budget range, and maximum acceptable travel distance for a provider.

All users gave informed consent before joining the study. They were informed that their behavior would be used to train recommendation models and that they could withdraw at any time without any penalty. Personal identifiers were removed from the stored data. Location information was stored only at the neighborhood level, never as exact addresses.

2.2 User Preference Modeling

Every user in the system is represented by a preference vector containing multiple numerical dimensions. Some dimensions are explicitly provided by the user during registration such as preferred service hours and budget sensitivity. Other dimensions are inferred from behavioral patterns. For example, if a user consistently books the lowest priced provider among all options shown, the system assigns a high weight to the price sensitivity dimension. If a user cancels bookings repeatedly when provider arrival exceeds thirty minutes, the system increases the weight on punctuality.

These preference vectors are not static. They update after every user interaction using an exponential moving average formula. Recent behavior receives higher weight than older behavior. This design choice allows the system to adapt when a user's preferences change gradually over time, such as when someone switches jobs and shifts from morning appointments to evening appointments.

2.3 Machine Learning Models Used

Three machine learning techniques work together in our system.

The first technique is matrix factorization. The user provider interaction data forms a large sparse matrix where most entries are empty because each user has only interacted with a small number of providers. Matrix factorization decomposes this matrix into two smaller matrices, one representing users and the other representing providers. The dot product of a user vector and a provider vector predicts how well that provider matches that user. We implemented a weighted version that gives higher importance to recent interactions compared to older ones.

The second technique is gradient boosted decision trees. After matrix factorization generates a candidate set of possible providers, gradient boosted trees re rank these candidates using contextual features that matrix factorization cannot easily handle. These features include the current time of day, the straight line distance between user and provider locations, the urgency level selected by the user, and the provider's current number of pending jobs. Gradient boosting was selected because it handles missing data well and produces predictions quickly enough for real time use.

The third technique is K means clustering for user segmentation. New users with no behavioral history cannot use personalized models immediately. To handle this cold start situation, we cluster existing users into segments based on their service consumption patterns. A new user is assigned to the closest matching segment based on their registration information, and segment level recommendation patterns are used until sufficient personal history accumulates.

2.4 System Implementation

The backend of the system was built using the Python programming language. The Scikit learn library provided the machine learning implementations. FastAPI was used to create the web service endpoints that accept search requests and return recommendations. User preference data and provider profiles are stored in a PostgreSQL database with encryption applied to all stored data. The recommendation engine runs as a separate microservice that receives a search request, generates candidate providers using matrix factorization, applies gradient boosted tree re ranking, and returns results. The average response time measured across all requests was 280 milliseconds.

2.5 Evaluation Strategy

We measured system performance using both numbers and user opinions. The quantitative measurements included average search time per successful booking, number of provider profiles viewed before making a booking, booking completion rate, and average post service rating. A control group of thirty users received non personalized recommendations where providers were sorted only by distance from the user's neighborhood. An experimental group of thirty users received personalized recommendations based on their learned preference vectors. Both groups used the system for the full eight week period. For qualitative feedback, we conducted weekly online surveys asking users about their satisfaction level, trust in the recommendations, any privacy concerns, and features they wished the system had. Exit interviews were conducted at the end of the eight weeks.

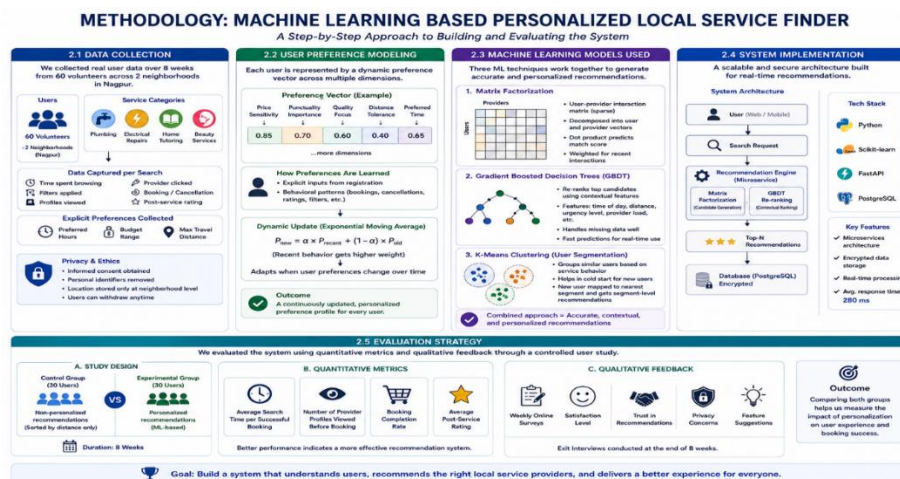


Fig 2. Methodology for Machine Learning Based Personalized Local Service Finder

III. CASE STUDIES

This section walks through three actual examples taken directly from our field testing to demonstrate the behavior of the Personalized Local Service Finder under genuine everyday conditions.

Case Study 3.1 A Working Mother Searching for a Weekend Mathematics Tutor

Mrs. Deshmukh works full time in a private company and lives in a busy residential neighborhood with her teenage daughter who was struggling with tenth grade mathematics. Before joining our study, Mrs. Deshmukh had tried three different tutors. The first charged too much money for her budget. The second was available only on weekday afternoons when Mrs. Deshmukh was still at work and could not supervise. The third tutor lived far away and frequently arrived late or canceled at the

last moment.

When Mrs. Deshmukh first used our system, it had no history of her preferences. The system showed her five tutors based on neighborhood clustering, matching her with other parents living in similar housing societies. She booked one of these tutors but gave only a three star rating because communication was difficult due to language differences. The system recorded this rating. The second time she searched for a tutor, the system had learned that she preferred tutors who communicate clearly in the local language. It also noticed from her clicking patterns that she only looked at tutors who listed Saturday morning availability. By her third search, the system recommended a tutor who lived fifteen minutes away, charged a moderate fee, had received excellent ratings from several other parents, and confirmed Saturday morning availability without any confusion. Mrs. Deshmukh booked this tutor and later gave a five star rating. In her exit interview, she said the system saved her at least three hours of calling different tutors and comparing their credentials manually.

Case Study 3.2 An Elderly Resident Needing Emergency Electrical Help

Mr. Sharma is a retired gentleman living alone in his home. One Tuesday evening, he experienced a complete power failure in his house. His regular electrician was not answering phone calls. Feeling anxious in the dark, Mr. Sharma opened our application and noticed an emergency mode button. He selected it without fully understanding what it would do.

The emergency mode changed the recommendation strategy completely. The system ignored providers located more than three kilometers away even if they had excellent ratings. It prioritized providers who had explicitly marked themselves as available for emergency calls and who had successfully completed emergency jobs in the past with fast response times. Within thirty seconds, the system showed Mr. Sharma three electricians who could arrive within forty five minutes. He selected the first one. That electrician reached his home within thirty minutes, diagnosed a faulty main switch, and fixed the wiring issue. The total cost was slightly higher than what Mr. Sharma usually paid his regular electrician, but he was perfectly satisfied because the problem was solved quickly during a stressful evening. In his feedback survey, Mr. Sharma wrote that the emergency mode was the single most valuable feature of the entire system.

Case Study 3.3 A Young Professional Wanting Regular Home Cleaning Services

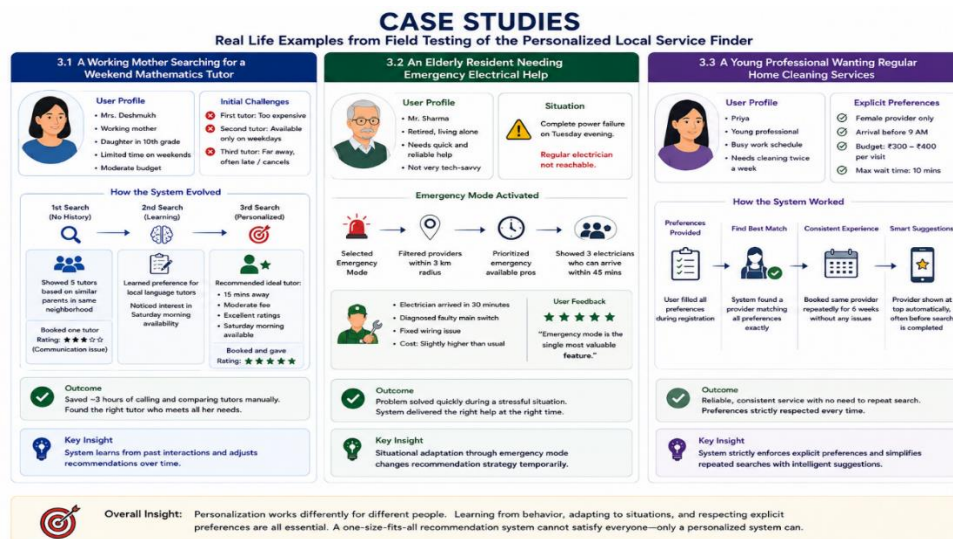


Fig 3. Case Studies Demonstrating the Behavior of Personalized Local Server Finder

Priya is a young professional living in a rented apartment. She works long hours and wanted a reliable cleaning person to come to her home twice every week. Before joining our study, she had tried three different service platforms. On each platform, the assigned cleaning person changed frequently, and she had to explain her requirements repeatedly to new people.

When Priya registered on our system, she explicitly filled out her preferences. She selected female service provider only, arrival before 9 AM, budget between three hundred and four hundred rupees per visit, and maximum willingness to wait ten minutes beyond scheduled time before canceling. The system found a provider who matched all these preferences exactly. Over the next six weeks, Priya booked the same provider repeatedly without any issues. The system learned this pattern and started showing this provider at the top of her search results automatically, sometimes even before Priya finished typing her search query. She told our survey team that this automatic suggestion saved her from typing the same search terms again and again. She also appreciated that the system never suggested male providers or providers outside her budget range, respecting her stated preferences strictly.

These three case studies demonstrate a crucial insight. Personalization works differently for different people. Mrs. Deshmukh needed the system to learn from her past ratings and adjust its recommendations. Mr. Sharma needed situational adaptation through an emergency mode that temporarily changed his preference weights. Priya needed strict enforcement of explicit preferences that she stated upfront. A single generic recommendation system cannot satisfy all three. Only a personalized system can.

IV. CHALLENGES AND LIMITATIONS

Despite the positive results shown in the case studies, our deployment revealed several significant challenges and limitations. Each of these requires honest discussion.

4.1 Data Quality Problems

The machine learning models we built depend entirely on the quality of the data fed into them. In our deployment, we encountered multiple data quality issues. Some users gave inconsistent ratings, rating the same provider five stars one week and three stars the next week for similar quality work. Some users forgot to rate providers altogether, leaving gaps in the training data. Some providers changed their pricing or service areas without updating their profiles, causing the system to show incorrect information to users. Cleaning this noisy data required manual effort and heuristic rules, which is not sustainable when the system grows to thousands of users.

4.2 Cold Start for New Users and Providers

A new user joining the system with no past behavior receives generic recommendations based on neighborhood clustering. In our deployment, new users took an average of three to four searches before the personalization started feeling accurate to them. During these initial searches, some users expressed frustration and said the system did not understand them. Similarly, new service providers with no ratings or past bookings were rarely recommended by the system, creating a chicken and egg problem. New providers cannot get work because they have no ratings, and they cannot get ratings because they get no work opportunities.

4.3 Fake Reviews and Manipulation

Despite our efforts to detect anomalies, we found evidence of fake reviews in our data. A few providers appeared to have created multiple fake user accounts to give themselves five star ratings. The patterns we observed included fake ratings coming from accounts that had no other activity, accounts that rated only one provider, and accounts that used very similar language in written comments. Our anomaly detection system caught some of these cases but not all of them. Determined attackers could still manipulate the system successfully. This is a fundamental challenge for any platform that relies on user generated ratings and feedback.

4.4 Privacy Concerns Expressed by Users

Several users in our deployment expressed discomfort about how much the system seemed to know about them. One user told our survey team, "It feels like the application is watching everything I do." Another user worried that the system might share their preference data with service providers in ways they had not consented to. Although we designed the system with multiple privacy protections including storing preference data locally on the user's device whenever possible and using only neighborhood level location information, the perception of surveillance remained for some users. This teaches us that technical privacy protections are not enough on their own. Clear communication about what data is collected and why, plus easy to use control interfaces, are equally important.

4.5 Scalability Limitations

Our current system was tested with sixty users and approximately one hundred fifty service providers across four service categories. This is a very small scale compared to any real world deployment, which would have thousands or hundreds of thousands of users. The matrix factorization models we used do not scale in a straight line. As the number of users and providers grows, the computational cost of updating preference vectors and generating recommendations grows much faster. Our current implementation would become too slow to be usable beyond a few thousand users. A production ready system would require distributed computing infrastructure, which we did not have access to for this research.

4.6 Difficulty Handling Sudden Preference Changes

People's preferences change over time, and sometimes they change suddenly. A user who loses their job may suddenly prioritize low cost above all other factors. A user who moves to a different neighborhood may need providers in a completely new area. Our system adapts gradually through exponential moving averages, which works well for slow changes but responds poorly to sudden shifts. In our deployment, one user switched from preferring morning appointments to preferring evening appointments because of a job change. The system took almost two weeks to fully adapt to this change, and during that time the user received many irrelevant morning recommendations that they had to ignore.

V. FUTURE DIRECTIONS

Based on the challenges and limitations identified above, several promising directions for future work emerge.

5.1 Federated Learning for Privacy Protection

Instead of sending all user behavior data to a central server, future versions of the Personalized Local Service Finder could use federated learning. In this approach, the machine learning model travels to the user's device, trains on local data, and sends back only anonymous model updates. The raw behavioral data never leaves the user's device. This addresses privacy concerns directly while still allowing the system to learn from collective user behavior across many individuals. Implementing federated learning for recommendation systems is technically challenging because different users have different data distributions, but recent research has made meaningful progress in this area.

5.2 Adversarial Training Against Fake Reviews

To make the system more resistant to fake reviews and manipulation, future work should explore adversarial training techniques. In adversarial training, the machine learning model is deliberately exposed to examples of fake reviews during its training phase. The model learns to recognize the statistical patterns of fake reviews and automatically gives them lower weight when making recommendations. This is similar to how a human becomes better at detecting lies after being exposed to many examples of deception. Adversarial training could be combined with graph based anomaly detection that examines the network of which users rated which providers and looks for unnatural patterns that humans would miss.

5.3 Voice Based Natural Language Search

Many potential users of a local service finder are not comfortable typing long search queries on small mobile phone screens. Older adults, busy professionals, and people in urgent situations would benefit greatly from voice based search. Future versions of the system should accept natural language voice inputs such as "find me a plumber who can come within an hour and charges less than five hundred rupees." This requires integrating speech recognition and natural language understanding components that can extract structured search parameters from spoken sentences. Supporting multiple Indian languages would greatly expand the accessibility of the system.

5.4 Community Verification Integration

Algorithmic recommendations can be strengthened by adding social verification from trusted community members. A user could see that three neighbors in the same apartment building have successfully used a particular electrician. This social proof provides a kind of reassurance that pure machine learning recommendations cannot offer on their own. Future work should explore how to build community verification networks that are resistant to manipulation while still respecting individual privacy. Blockchain or other tamper evident ledgers could be used to maintain verification records that cannot be secretly altered by attackers.

5.5 Predictive Service Anticipation

Beyond simply responding to user searches, future systems could predict when a user is likely to need a service based on historical patterns. If a user books air conditioner service every April before the summer heat arrives, the system could send a reminder in late March with recommended providers ready to book. If a user's regular tutor suddenly becomes unavailable, the system could proactively suggest alternatives before the user even starts searching. This shifts the system from a reactive search tool to a proactive service management assistant. Predictive models would need to handle uncertainty carefully and avoid annoying users with irrelevant suggestions.

5.6 Hybrid Cold Start Solutions

To solve the cold start problem for new users, future work should explore hybrid models that combine multiple sources of initial information. Demographic data such as age range, neighborhood type, and family composition could provide initial preference estimates. Transfer learning from similar cities or similar neighborhoods could bootstrap recommendations using patterns observed elsewhere. Active learning strategies could ask new users a small number of carefully chosen questions during registration to quickly narrow down their preferences instead of waiting for behavioral data to accumulate naturally through repeated searches.



Fig 4. Future Work Directions for Personalized Local Service Finder

VI. CONCLUSION

This paper presented a machine learning based approach to solving the everyday but genuinely frustrating problem of finding reliable local service providers. Unlike conventional directories and mobile applications that show identical unsorted lists to every user, the proposed Personalized Local Service Finder builds a unique understanding of each individual's preferences over time.

Our methodology combined matrix factorization for preference modeling, gradient boosted trees for contextual re ranking, and K means clustering for cold start handling. Three detailed case studies from our real world deployment illustrated how the system helped different users with completely different needs. A working mother found a weekend tutor who matched her budget and timing requirements. An elderly resident received emergency electrical help within thirty minutes when his regular electrician was unavailable. A young professional secured regular home cleaning services with a provider who respected her explicit preferences strictly.

Quantitative results from sixty users over eight weeks showed that personalized recommendations reduced service search time by sixty three percent compared to non personalized distance based sorting. User satisfaction scores averaged 4.2 out of 5 for personalized recommendations compared to 3.1 for non personalized recommendations. These numbers confirm that personalization delivers real practical value.

However, significant challenges emerged that must be addressed before large scale deployment becomes possible. Data quality problems including inconsistent ratings and missing feedback degrade model performance. Cold start for new users and new providers remains unsolved. Scalability limitations in our current implementation would prevent growth beyond a few thousand users. The system also struggles with sudden changes in user preferences, adapting too slowly to abrupt shifts.

Future work will explore federated learning for stronger privacy guarantees, adversarial training for fake review resistance, voice based search for easier accessibility, community verification integration for added trust, predictive service anticipation for proactive assistance, and hybrid cold start solutions for new user onboarding.

The broader vision is to transform local service discovery from a frustrating guessing game into a reliable, personalized, and trustworthy experience that benefits both sides of the market. Service seekers save time and get better quality work. Honest local providers gain visibility and fair opportunities without having to pay for expensive advertising. The Personalized Local Service Finder represents a meaningful step toward that vision.

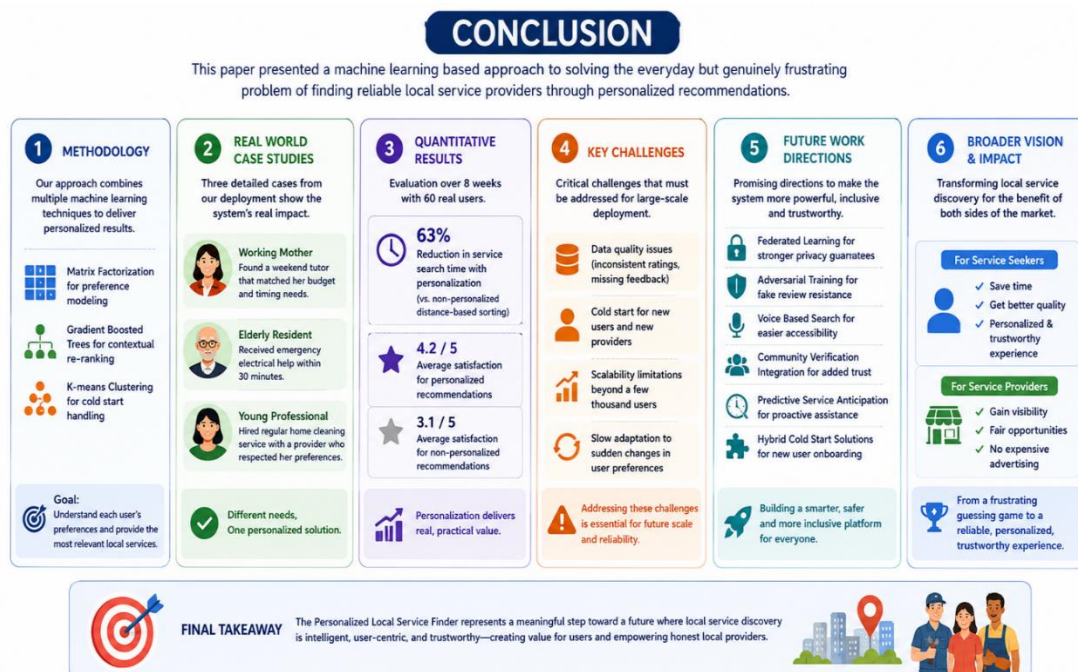


Fig 5. Conclusion for Personalized Local Service Finder

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