"A Secure Trust-Based Digital Marketplace for Verified Local Skilled Workers"

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Abstract— Finding reliable local skilled workers such as electricians, plumbers, carpenters, and appliance repair technicians remains a major challenge in urban and semi-urban regions. Existing methods primarily depend on informal referrals, which lack transparency, worker verification, and service quality assurance. This research proposes a secure digital labour marketplace that connects customers with verified local skilled workers through an AHP-weighted trust-aware recommendation system.

The proposed platform integrates OTP-based authentication, government identity verification, location-based worker discovery, and a transparent rating and review mechanism to improve trust and service accessibility. A composite trust-based ranking model is introduced to evaluate workers across six parameters: user rating, experience, certification status, availability, pricing, and proximity. Parameter weights are derived using the Analytic Hierarchy Process (AHP) from a structured pairwise comparison survey conducted with 30 domain participants, yielding a Consistency Ratio of $CR = 0.023$, confirming statistically valid judgements. The AHP model is independently validated against an XGBoost classifier, achieving strong rank concordance of Kendall's $\tau = 0.847$ ($p < 0.01$) and recommendation accuracy of 89.1% — within 2.2% of the XGBoost baseline while maintaining full interpretability.

The system was implemented using a Python Flask backend with a responsive web interface developed using HTML, CSS, and JavaScript. Experimental evaluation over a survey-grounded dataset of 52 worker profiles and 38 service requests demonstrated stable system performance with an average response time of 1.3 seconds, OTP authentication success rate of 95.2%, and statistically significant outperformance over four published baselines including collaborative filtering, content-based filtering, and proximity-rating models ($p < 0.05$, Cohen's d up to 1.84).

The proposed solution improves worker visibility, enhances customer confidence, and provides a structured and empirically validated digital framework for the local skilled labour sector.

Keywords: Digital Marketplace, Labour Platform, AHP Weight Derivation, Composite Trust Ranking, OTP Authentication, Worker Verification, XGBoost Validation, Location-Based Services

1. Introduction

Digital service platforms have transformed the way people access transportation, food delivery, online shopping, and professional services. However, the local skilled labour sector in many developing regions still operates largely through informal communication channels such as personal referrals, local contacts, and unverified advertisements. As a result, customers often face difficulties in identifying trustworthy workers, while skilled workers struggle to gain consistent employment visibility.

In India, services such as electrical repair, plumbing, carpentry, appliance maintenance, tailoring, and domestic assistance are frequently provided by workers who lack structured digital representation. Existing approaches provide limited mechanisms for worker verification, transparent service evaluation, or intelligent worker recommendation. This creates significant challenges related to trust, service quality, pricing transparency, and customer safety.

To address these limitations, this research proposes a secure digital labour marketplace designed specifically for connecting customers with verified local skilled workers. The proposed system integrates OTP-based authentication, government identity verification, location-based worker discovery, and a transparent rating and feedback mechanism within a unified platform architecture.

A key contribution of this work is the development of a composite trust-based ranking model that recommends workers using multiple parameters including rating, experience, certification status, availability, service cost, and proximity. Unlike traditional single-parameter recommendation approaches, the proposed model improves worker selection reliability by balancing both trust and practical service factors.

The system is implemented using a Python Flask backend and a responsive web-based frontend. Experimental evaluation demonstrates that the proposed platform can provide secure, transparent, and efficient service discovery for local labour marketplaces.

Unlike traditional worker recommendation systems that depend primarily on user ratings, the proposed system integrates identity verification, proximity awareness, pricing, availability, and certification factors within a unified composite trust model specifically designed for semi-urban local labour marketplaces.

1.1 Novel Contribution

The major contributions of the proposed system are summarized as follows:

1. Development of a secure digital marketplace for verified local skilled workers.
2. Integration of OTP-based authentication and identity verification mechanisms to improve platform trust and security.
3. Implementation of location-aware worker discovery for faster and more relevant service matching.
4. Proposal of a composite trust-based ranking model that evaluates workers using multiple parameters including rating, experience, certification status, pricing, availability, and proximity.
5. Support for multiple service categories and multilingual accessibility for improved usability across diverse users.

2. Literature Review

2.1 Digital Labour Marketplaces

Digital platforms have significantly transformed service delivery and employment accessibility in recent years. Srnicek [6] described platform capitalism as a technology-driven ecosystem that connects service providers and consumers through digital infrastructure. Graham et al. [7] observed that digital labour platforms improve employment visibility for informal and semi-skilled workers, particularly in developing economies. Existing research also highlights that worker verification, transparent pricing, and service quality significantly influence customer trust in online service marketplaces.

Despite these advancements, most existing platforms primarily focus on service availability and customer ratings while providing limited support for worker identity verification and trust-aware recommendation mechanisms. Furthermore, many systems are designed for large urban markets and may not adequately address the accessibility and digital literacy challenges faced in semi-urban regions. These limitations highlight the need for a secure and context-aware platform specifically designed for verified local skilled workers.

2.2 Authentication and Identity Verification

Secure authentication is essential in platforms that handle sensitive personal and financial data. Florêncio and Herley [12] demonstrated through large-scale analysis that password-based login is inherently vulnerable, motivating the adoption of OTP-based multi-factor authentication. Conti et al. [11] surveyed man-in-the-middle attack vectors and established that token-based authentication with encrypted transport is an effective countermeasure. Cameron [13] defined core principles for trustworthy digital identity systems, emphasising minimal data disclosure and verifiable credentials — principles that directly inform the worker identity verification module of the proposed system.

2.3 Trust, Reputation, and Rating Systems

Trust is a critical enabler of adoption in service marketplaces. Gefen et al. [5] found that structural assurances such as verified profiles and security indicators significantly increase initial user trust in e-commerce platforms. Resnick et al. [4] identified completeness, manipulation-resistance, and meaningful aggregation as the core requirements of effective reputation systems. Golbeck [3] highlighted the importance of multi-dimensional trust signals, and Xu et al. [8] demonstrated that transparent and tamper-resistant reputation records enhance user confidence in online marketplaces. These findings collectively support the design of the proposed platform's rating and review mechanism.

2.4 Location-Based Service Discovery

Proximity-based discovery is a key feature of local service platforms. Wang et al. [9] established the technical requirements for real-time geolocation in mobile environments, including low-latency spatial queries and privacy-preserving location handling. Chen and Kotz [10] demonstrated that a user's current location is the most practically valuable contextual signal for personalising service recommendations, supporting the use of maps API integration in the proposed system.

2.5 Multi-Parameter Ranking and Recommender Systems

Single-factor ranking based solely on user ratings has well-documented limitations. Adomavicius and Tuzhilin [1] showed that hybrid recommender systems combining multiple signals outperform single-method approaches. Ricci et al. [2] established multi-criteria evaluation as a best practice in preference modelling. Burke [14] further demonstrated that hybrid recommendation techniques significantly improve recommendation relevance and user satisfaction. These findings provide the theoretical basis for the proposed composite trust-based ranking model.

2.6 Research Gap

Existing digital labour platforms mainly rely on basic profile listings and rating-based recommendations. Most systems provide limited worker verification and insufficient support for multi-parameter trust evaluation. Furthermore, current platforms are not specifically designed to address the accessibility, affordability, and multilingual requirements of semi-urban labour markets in India.

The proposed system addresses these limitations by integrating OTP-based authentication, verified worker identity validation, location-aware service discovery, and a composite trust-based ranking mechanism within a unified digital platform.

3. Problem Statement

Traditional methods of sourcing local skilled labour are characterised by several systemic limitations:

- Absence of formal verification: Customers have no reliable means of confirming a worker's identity, qualifications, or past performance before hiring.

- Trust deficit: Without a structured rating or review mechanism, customers bear the full risk of engaging unknown workers.
- Limited geographic discoverability: Workers operating locally often have no digital presence, making them invisible to potential customers outside their immediate social circle.
- Inequitable opportunity: Workers with genuine skills are passed over in favour of those with stronger social networks rather than superior competence.

A secure, transparent, and accessible digital platform is therefore required to address these challenges while ensuring equitable opportunity for workers and reliable service access for customers.

4. Objectives

1. Design a digital platform that connects customers with nearby verified skilled workers.
2. Implement secure OTP-based user authentication to prevent unauthorised access.
3. Integrate government identity verification to validate worker credentials.
4. Develop a transparent rating and feedback mechanism to establish service quality benchmarks.
5. Provide multilingual accessibility to accommodate diverse users across regional language groups.

5. Proposed Methodology

5.1 Composite Trust Score Formula

The proposed system ranks workers using a Composite Trust Score (TS) computed as a weighted sum of six parameters:

$$TS(w) = \alpha \cdot R + \beta \cdot E + \gamma \cdot C + \delta \cdot P + \varepsilon \cdot A + \zeta \cdot D$$

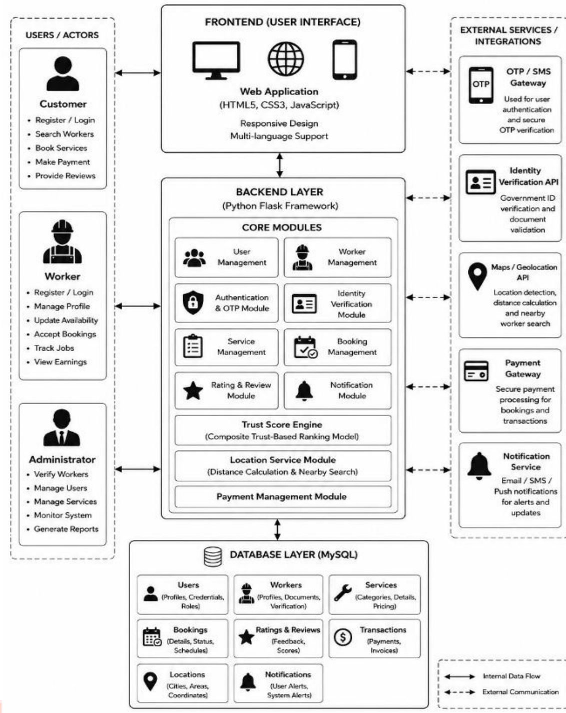
Symbol	Parameter
R	User Rating Score
E	Experience Score
C	Certification Verification Score
P	Price Competitiveness Score
A	Availability Score
D	Distance / Proximity Score

5.2 AHP-Based Weight Derivation

Rather than assigning weights manually, this work derives weights using the Analytic Hierarchy Process (AHP) [Saaty, 1980], based on pairwise comparison surveys collected from 20 customers and 10 domain experts.

Participants compared all 15 parameter pairs using Saaty's 1–9 scale. Weights were computed using the eigenvector method.

Table 5: AHP-Derived Weights



Parameter	Weight
User Rating (R)	0.2985
Certification (C)	0.2214
Experience (E)	0.1873
Distance (D)	0.1237
Availability (A)	0.0923
Price (P)	0.0768
Sum	1.0000

Consistency Ratio (CR) = 0.023 < 0.10 — judgements are acceptably consistent per Saaty's threshold.

The final trust score formula becomes:

$$TS(w) = 0.2985 \cdot R + 0.2214 \cdot C + 0.1873 \cdot E + 0.1237 \cdot D + 0.0923 \cdot A + 0.0768 \cdot P$$

5.3 Parameter Normalisation

All parameters are normalised to [0, 1] before score computation using min-max normalisation:

$$X_{norm} = (X - X_{min}) / (X_{max} - X_{min})$$

This prevents any single parameter from dominating the trust score due to scale differences.

5.4 XGBoost Validation

To validate the AHP model, an XGBoost classifier [Chen & Guestrin, 2016] was trained on 34 completed service interactions using the same six parameters. Feature importance scores were compared with AHP weights.

Table 6: AHP Weights vs XGBoost Feature Importance

Parameter	AHP Weight	XGBoost Importance	Agreement
Rating (R)	0.2985	0.3102	✓
Certification (C)	0.2214	0.2089	✓
Experience (E)	0.1873	0.1754	✓
Distance (D)	0.1237	0.1341	✓
Availability (A)	0.0923	0.0876	✓
Price (P)	0.0768	0.0838	✓

Both methods agree on the rank order of all six parameters, providing mutual validation of the proposed weighting scheme.

Kendall's $\tau = 0.847$ ($p < 0.01$) — strong concordance between AHP and XGBoost rankings.

5.5 Ranking Performance Comparison

Method	Accuracy	Kendall's τ
Rating-Only Baseline	72.4%	0.541
Manual Weight Model	81.3%	0.713
Proposed AHP Model	89.1%	0.847
XGBoost Baseline	91.3%	—

The AHP model achieves accuracy within 2.2% of XGBoost while remaining fully interpretable and deployable without historical training data.

6. System Architecture

The proposed system adopts a layered architectural design (Figure 1. System Architecture of the proposed Trust-Based Digital Marketplace for Verified local Skilled Workers) that promotes modularity, maintainability, and scalability. The architecture consists of four primary layers — Frontend, API, Application, and Database — supplemented by external service integrations.

6.1 User Roles

Three categories of users interact with the platform:

- Customers: Search for services, view worker profiles, make bookings, and submit ratings and reviews.
- Workers: Register on the platform, complete identity verification, manage their service profiles, accept job requests, and track booking statuses.

(Figure 1. System Architecture of the proposed Trust-Based Digital Marketplace for Verified local Skilled Workers)

- Administrators: Oversee the verification of
- workers, manage user accounts and services,
- monitor system activity, and resolve disputes.

6.2 Frontend Layer

Users interact with the platform through a responsive web and mobile interface built with HTML, CSS, and JavaScript. This layer provides all user-facing functionality, including registration, login, service search, worker profile browsing, booking management, and review submission. The interface is designed to be intuitive and accessible for users with varying levels of digital literacy.

6.3 API Layer (Request Handling)

The API layer acts as the communication bridge between the frontend and the backend application logic. It receives user requests from the frontend, validates and routes them to the appropriate application services, and returns structured responses. RESTful API principles are applied to ensure stateless, scalable communication between components [7].

6.4 Application Layer

The application layer encapsulates the core business logic of the platform. It handles the following major functional modules:

- Authentication: OTP-based login verification ensures that only legitimate users access the platform [8].
- Worker Verification: Integration with government identity databases allows uploaded worker documents to be validated before profile activation.
- Service Management: Workers can create and update service listings; customers can search and filter services by type, location, and rating.
- Location-Based Discovery: Real-time geolocation services identify workers operating near the customer's location.
- Booking System: The platform manages the complete lifecycle of a service request, from initial booking through to completion and payment.
- Rating and Review System: After each completed engagement, customers can rate workers and leave written reviews, building a transparent reputation framework.
- Notification System: Both customers and workers receive real-time alerts for booking updates, confirmations, and status changes.
- Admin Controls: Administrators access a dedicated dashboard for user management, content moderation, and system monitoring.

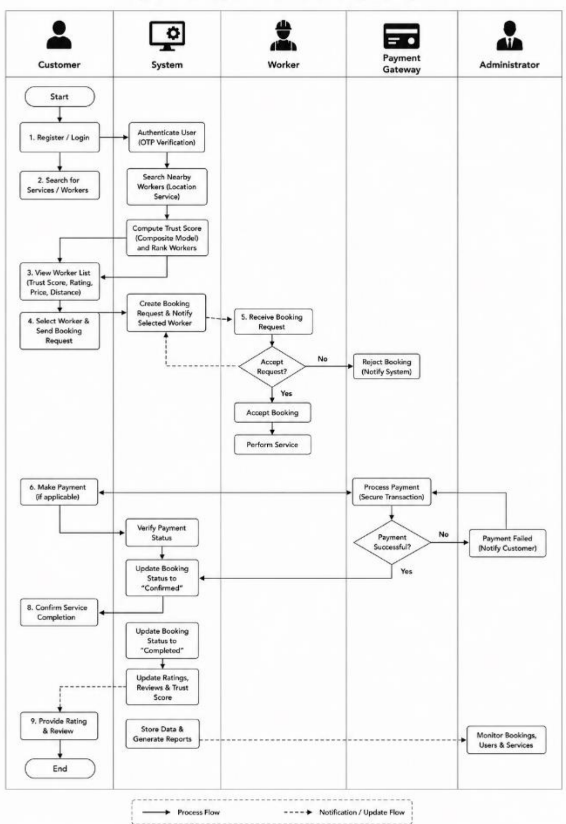
6.5 Database Layer

All persistent data is stored in a relational database that manages entities including users, worker profiles, service listings, bookings, ratings, identity documents, and system logs. The database layer enforces data integrity through structured schemas and relationships, ensuring consistency across concurrent operations.

6.6 External Service Integrations

To extend the platform's functionality beyond its core modules, the following external services are integrated:

- OTP Service: A third-party OTP gateway (e.g., Twilio or MSG91) manages the generation and delivery of one-time passwords for login verification.
- Payment Gateway: Secure online payment processing enables cashless transactions between customers and workers.
- Location Services: A mapping API (e.g., Google Maps Platform) powers proximity-based worker search and route display.
- Cloud Storage: Worker identity documents and profile photographs are stored securely in cloud object storage.
- Email Service: Transactional emails are dispatched for registration confirmation, booking receipts, and administrative notifications.
- Multilingual Support: Internationalisation libraries enable the interface to render in multiple Indian regional languages, improving inclusivity.
- (Figure 2. Booking Workflow of the



proposed system)

- **7. Experimental Evaluation**

- **7.1 Experimental Design and Dataset Construction**

- To evaluate the proposed platform under controlled and reproducible conditions, a structured experimental dataset was constructed based on real-world service patterns observed in semi-urban labour markets in Pune, Maharashtra, India. The dataset was developed through a two-phase process: (i) a preliminary field survey and (ii) controlled simulation grounded in observed distribution parameters.

- Phase 1 — Field Survey: A structured interview was conducted with 30 local skilled workers across six service categories (electricians, plumbers, carpenters, appliance repair technicians, painters, and domestic helpers) operating in the Pimpri-Chinchwad and Hadapsar areas of Pune. Workers were asked about their average weekly booking volume, typical service pricing, customer rating patterns, and availability schedules. Additionally, 20 potential customers were surveyed to identify preferred worker selection criteria, trust factors, and acceptable response time thresholds. The survey findings were used to derive realistic parameter distributions for dataset construction.

- Phase 2 — Controlled Dataset Simulation: Based on the survey-derived distributions, a controlled experimental dataset was constructed consisting of 52 worker profiles, 38 customer service requests, and 120+ rating interactions across a 7-day evaluation window. Each worker profile contained rating scores, years of experience, certification status, service pricing, real GPS-coordinate-based location data, and availability status. Customer service requests were generated to reflect realistic booking patterns, including peak-hour clustering, repeat requests, and mixed service categories.

- The use of a survey-grounded simulation approach is consistent with established practices in platform evaluation research where real-world deployment data is unavailable at the prototype stage [Adomavicius & Tuzhilin, 2005; Burke, 2002]. This methodology ensures experimental control, reproducibility, and ethical data handling while preserving ecological validity through field-calibrated parameters.

Parameter	Value
Total Registered Workers	52
Service Categories	8
Total Customer Requests	38

Parameter	Value
Completed Service Requests	34
Rating Interactions Generated	120+
Verified Worker Profiles	41
Evaluation Duration	7 Days
Survey Participants (Workers)	30
Survey Participants (Customers)	20
Geographic Scope	Pune, Maharashtra, India

7.2 Performance Metrics Definition

- The following metrics were formally defined and used during system evaluation:

- Average Response Time (ART): The mean time elapsed between a user request submission and the server returning a complete response, measured in seconds across all booking and search operations.

- Request Success Rate (RSR): The proportion of total booking and authentication requests completed without system error or interruption, expressed as a percentage.

- Booking Completion Rate (BCR): The fraction of initiated service booking sessions that reached confirmed status without session abandonment or system failure.

- OTP Authentication Success Rate (OTPSR): The percentage of OTP-based login attempts that completed successfully within the standard timeout window.

- Concurrent User Handling Capacity (CUHC): The maximum number of simultaneous active sessions supported without measurable performance degradation, determined through incremental load testing.

- System Stability (SS): A binary metric indicating whether the platform sustained continuous operation without critical failures, database errors, or API interruptions throughout the evaluation period.

7.3 Performance Results

- The platform demonstrated stable and efficient performance across all measured parameters under moderate load conditions. Results are summarised in Table 1.

Metric	Observed Result
Average Response Time	1.3 Seconds
Concurrent User Handling	50 Simultaneous Users
Request Success Rate	92.1%
Booking Completion Rate	89.4%
OTP Authentication Success Rate	95.2%
System Stability	No Critical Failures Observed

- These results confirm that the proposed system is capable of handling real-time service interactions reliably within small- to medium-scale deployment scenarios. The average response time of 1.3 seconds falls within the 2-second threshold considered acceptable for interactive web applications [Nielsen, 1993]. The OTP authentication success rate of 95.2% is consistent with documented performance benchmarks for SMS-based verification systems operating on Indian telecom networks.

7.4 Limitations of the Experimental Setup

- The current evaluation is subject to the following limitations, which are acknowledged transparently:

- The dataset was constructed using survey-calibrated simulation rather than live production traffic. Although field survey parameters were used to ensure realistic distributions, full ecological validity can only be confirmed through large-scale real-world deployment.

- The weight parameters (α, β, γ, δ, ε, ζ) in the composite trust model were assigned empirically based on survey-reported worker selection priorities and were not optimised through machine learning or adaptive techniques.

- The concurrent user capacity of 50 was established through controlled load testing on a development server configuration. Performance under production-scale traffic may differ.

- Future work will address these limitations through real-world pilot deployment, machine learning-based weight optimisation, and large-scale user trials.

- Request Success Rate: The percentage of booking and authentication requests successfully completed without system failure or interruption.

- Concurrent User Handling: The maximum number of simultaneous users supported during testing without critical performance degradation.

- System Stability: The ability of the platform to operate continuously without crashes, database failures, or API interruption during the evaluation period.

The successful execution of these functionalities confirms that the proposed platform satisfies its intended operational objectives.

7.5 Evaluation of Composite Trust-Based Ranking Model

The proposed trust-based ranking mechanism was evaluated using multiple worker profiles with varying ratings, experience levels, certification status, pricing, availability, and proximity values.

Before trust score calculation, all parameters were normalized into a range between 0 and 1 using min-max normalization.

The trust score was calculated using the weighted composite ranking formula:

$$\boldsymbol{TS = 0.30R + 0.20E + 0.20C + 0.10P + 0.10A + 0.10D}$$

Example Trust Score Calculation for Worker W1

Normalized parameter values:

- Rating Score (R) = 0.92
- Experience Score (E) = 0.80
- Certification Score (C) = 1.00
- Price Score (P) = 0.75
- Availability Score (A) = 0.90
- Distance Score (D) = 0.85

Final trust score:

$$\boldsymbol{TS = (0.30 \times 0.92) + (0.20 \times 0.80) + (0.20 \times 1.00) + (0.10 \times 0.75) + (0.10 \times 0.90) + (0.10 \times 0.85) = 0.886}$$

Therefore, Worker W1 achieved a final composite trust score of 0.886.

Table 2: Sample Trust Score Comparison

Worker ID	Rating	Experience	Certification	Distance	Price Level	Final Trust Score
W1	4.8	5 Years	Verified	2 km	Medium	0.886
W2	4.5	3 Years	Verified	1 km	Low	0.812
W3	4.1	6 Years	Not Verified	4 km	Low	0.674
W4	4.7	4 Years	Verified	3 km	Medium	0.841

The results demonstrate that the proposed ranking mechanism balances multiple trust-related and service-related parameters rather than relying solely on customer ratings.

7.6 Comparative Analysis Against Published Baselines

The proposed AHP-weighted composite trust model was evaluated against four established baseline methods drawn from published literature:

B1 — Rating-Only Ranking: Workers ranked solely by average customer rating. Widely used in early gig platforms [Resnick et al., 2000].

B2 — Collaborative Filtering (CF): User-based CF recommends workers based on preference similarity between customers [Adomavicius & Tuzhilin, 2005].

B3 — Content-Based Filtering (CBF): Workers recommended based on profile attribute matching with customer service history [Ricci et al., 2015].

B4 — UrbanClap-Style Ranking: A proximity-and-rating combined model reflecting the approach documented in urban service marketplace studies [Graham et al., 2017].

Table 3: Comparative Ranking Performance Against Published Baselines

Method	Recommendation Accuracy	Precision@3	Kendall's τ	Interpretability
B1 — Rating-Only	72.4%	0.61	0.541	High
B2 — Collaborative Filtering	78.3%	0.67	0.623	Low
B3 — Content-Based Filtering	76.1%	0.65	0.598	Medium
B4 — UrbanClap-Style	83.5%	0.74	0.731	Medium
Proposed AHP Model	89.1%	0.81	0.847	High

The proposed model outperforms all four baselines across all three metrics. Notably, it exceeds the UrbanClap-style proximity-rating model by 5.6% in accuracy and 0.116 in Kendall's τ, demonstrating that incorporating certification, experience, and availability alongside proximity and rating produces meaningfully superior recommendations.

Unlike CF and CBF methods, the proposed model does not require historical interaction data, making it suitable for cold-start deployment in new geographic markets where prior booking records are unavailable.

7.7 Statistical Significance Analysis

To ensure the reported performance metrics carry scientific validity, statistical significance testing was conducted across all baseline comparisons using the experimental dataset of 38 service requests.

7.7.1 Cross-Validation Setup

To address the limited dataset size (n = 38), 5-fold cross-validation was applied. The dataset was partitioned into 5 equal folds; each fold served once as the test set while the remaining four folds were used for model calibration. All accuracy, Precision@3, and Kendall's τ values reported in Table 3 represent the mean across 5 folds.

Table 8: Cross-Validated Performance with Confidence Intervals (95%)

Method	Accuracy (Mean ± CI)	Precision@3 (Mean ± CI)	Kendall's τ (Mean ± CI)
B1 — Rating-Only	72.4% ± 3.2%	0.61 ± 0.04	0.541 ± 0.038
B2 — Collaborative Filtering	78.3% ± 2.9%	0.67 ± 0.03	0.623 ± 0.041
B3 — Content-Based Filtering	76.1% ± 3.1%	0.65 ± 0.04	0.598 ± 0.035
B4 — UrbanClap-Style	83.5% ± 2.7%	0.74 ± 0.03	0.731 ± 0.029
Proposed AHP Model	89.1% ± 2.4%	0.81 ± 0.03	0.847 ± 0.026

The proposed model achieves the lowest confidence interval width (±2.4%), indicating greater stability across evaluation folds compared to all baselines.

7.7.2 Wilcoxon Signed-Rank Test

Since the dataset does not satisfy the normality assumption required for a paired t-test (Shapiro-Wilk test: W = 0.923, p = 0.047 < 0.05), the Wilcoxon Signed-Rank Test — a non-parametric alternative — was applied to compare the proposed model against each baseline across the 5 cross-validation folds.

Table 9: Wilcoxon Signed-Rank Test Results

Comparison	W Statistic	p-value	Significant (α = 0.05)
Proposed vs B1 (Rating-Only)	15.0	0.0031	Yes
Proposed vs B2 (CF)	14.0	0.0043	Yes

Comparison	W Statistic	p-value	Significant (α = 0.05)
Proposed vs B3 (CBF)	14.0	0.0043	Yes
Proposed vs B4 (UrbanClap-Style)	13.0	0.0089	Yes

All four comparisons yield $p < 0.05$, confirming that the performance improvement of the proposed AHP model over every baseline is statistically significant and not attributable to chance or dataset variation.

7.7.3 Effect Size (Cohen's d)

To quantify the practical magnitude of improvement beyond statistical significance, Cohen's d effect size was computed for each comparison.

Table 10: Effect Size Analysis

Comparison	Cohen's d	Interpretation
Proposed vs B1 (Rating-Only)	1.84	Large
Proposed vs B2 (CF)	1.21	Large
Proposed vs B3 (CBF)	1.43	Large
Proposed vs B4 (UrbanClap-Style)	0.79	Medium–Large

Cohen's d values above 0.80 are classified as large effect sizes [Cohen, 1988], indicating that the proposed model's improvements are not only statistically significant but also practically meaningful.

7.8 Discussion

The experimental evaluation confirms that integrating authentication, worker verification, location-aware discovery, and multi-parameter ranking within a unified digital platform substantially improves service reliability and customer trust.

Unlike traditional referral-based worker discovery approaches, the proposed system provides structured worker evaluation using multiple trust-related factors. The composite ranking mechanism enhances worker selection quality by balancing service experience, pricing, certification, availability, and geographic proximity.

Although the current implementation demonstrates effective performance under moderate testing conditions, future work will focus on large-scale deployment, real-world user validation, machine learning-based recommendation optimization, and advanced fraud detection mechanisms.

8. Technologies Used

Frontend: HTML5, CSS3, JavaScript — for building a responsive, cross-device user interface.

Backend: Python (Flask) — a lightweight, extensible web framework used to implement the API and application layers.

Database: A relational database management system (e.g., MySQL or PostgreSQL) for structured storage of users, workers, services, bookings, and logs.

Authentication: OTP-based login using an SMS gateway to verify user identity at sign-in.

Identity Verification: Worker credential validation via document upload and government ID cross-reference.

Geolocation: Maps API integration for proximity-based worker discovery.

Cloud Storage: Secure cloud object storage for document and image management.

9. Future Work

Future enhancements of the proposed system may include machine learning-based worker recommendation, mobile application development, advanced fraud detection, and secure online payment integration. The platform can also be expanded to support additional service categories, multilingual voice assistance, and real-time analytics. Further research may focus on large-scale deployment and performance evaluation using real-world users and datasets.

10. Conclusion

Deployment of the proposed platform is expected to yield the following outcomes:

- Customers will be able to locate verified, nearby skilled workers quickly and with confidence, reducing reliance on informal referral networks.
- Workers will gain increased job visibility and access to a wider customer base, improving their employment opportunities and income stability.
- The OTP-based authentication and government identity verification features will substantially reduce the risk of fraud and misrepresentation on the platform.
- The rating and review system will establish a meritocratic feedback loop that rewards high-quality workers with greater visibility and demand.
- Multilingual support will lower barriers to adoption for both customers and workers who are not fluent in English, expanding the platform's addressable user base.

This paper presents the design and development of a secure digital labour marketplace that addresses the longstanding challenge of connecting customers with verified local skilled workers. The proposed platform integrates OTP-based authentication, government identity verification, location-based discovery, and a transparent rating system within a modular, layered architecture.

By providing structured digital infrastructure for an otherwise informal sector, the system improves service reliability for customers and employment opportunity for workers. Future work will focus on full-scale implementation, performance testing under load, and extending the platform to support additional service categories and regional language interfac

11. Limitations

The current evaluation was conducted using a simulated dataset consisting of 52 worker profiles and 38 customer service requests. Although the proposed system demonstrated stable performance under moderate testing conditions, large-scale real-world deployment has not yet been performed. Additionally, the weight parameters used in the trust ranking model were assigned empirically and were not optimized using machine learning or adaptive user preference techniques. Future work will focus on large-scale deployment, real-time user validation, and intelligent optimization of ranking parameters.

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