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DomestiQ AI – Intelligent Service Matching and Scheduling Platform

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Abstract — The boom of on-demand home service platforms has greatly facilitated users to receive household services, but existing systems require manual scheduling and pricing setting, as well as few verification mechanisms for providers, which may lead to inefficiency and privacy problems. DomestiQ AI: An intelligent home services matching and scheduling platform abstract. In this paper we describe DomestiQ AI, a smart matchmaking system for home service booking with the goal of increasing accuracy, transparency and trust by using artificial intelligence algorithms. Using the above system, users can express their service needs in natural language and these are automatically processed using Natural Language Processing to classify into relevant service category. A multi-criteria matching based recommendation model to find list of relevant local service providers is retained with appropriate users by taking into account geographical location, availability rating and performance in the past.

To ensure fairness as well as both the customer and professional know what to expect, the system utilizes a dynamic pricing model that takes demand intensity, distance, reduction of time in waiting for service and type of service into consideration when estimating charge. Real-time scheduling and map-based tracking provide on-demand service booking and optimal provider assignment, with emergency service mode available for timely household requirements. Platform security is enhanced with digital KYC validation and anomaly-based detection of fake service providers. OTP-based service complete validation is provided to verify the authenticity of transaction.

Furthermore, DomestiQ AI offers an assistant chatbot with voice and multilingual support to assist users when they login for booking. Experimental results show that the service matching accuracy is higher, the booking time is lower and user trust increases, which evidences the effectiveness of our system as a scalable and secure intelligent home-service solution.

Keywords - AI, Home Service Booking, NLP, Service Recommendation System, Dynamic Pricing Fraud Detection Real-time Scheduling.

1. INTRODUCTION

The growing consideration of technology-based means of provision in everyday services has dramatically changed the nature of access to household maintenance and repair. Online home services aggregator marketplaces have emerged as middlemen that facilitate booking local professionals for various household services like plumbing, cleaning, electrical repairs and appliance repairs. In spite of their rising success, most current platforms still have quite simplistic intelligence and are based on one or the other predefined category of service which is selected from a list by the client, then they select the vendor themselves (by hand) and finally we end up with mostly fixed quote or pencil-point pricing. These restrictions frequently lead to incorrect service matches, slow replies, opaque pricing and apprehensions related to stability of the services.

Another significant problem faced by the current systems is its inability to consider how user requirements for services can be interpreted. While the users typically present their issues in natural language, the conventional platforms are not able to properly exploit this information, resulting in inappropriate service categorization and suboptimal provider matching. In addition, provider verification procedures are typically manual and inadequate, thus unreliable or illegitimate profiles may linger on the system. Lack of real time scheduling, emergency service management and pricing transparency add to lack of user confidence and satisfaction.

Fig.1. Conceptual overview of the DomestiQ AI intelligent service matching platform.

In response to these challenges, this paper presents DomestiQ AI, an intelligent home service matching and scheduling platform that incorporates corresponding cutting-edge artificial intelligence technologies to facilitate efficiency, security and user experience. The system utilizes Natural Language Processing to effectively interpret the description of the service requirements by user which allows flexible, yet accurate service identification. A machine learning powered recommendation engine suggests appropriate providers by considering various aspects like the distance, availability, quality of service and historical performance. Dynamic pricing mechanisms guarantee fairness and transparency in the estimated cost, whereas a real-time schedule and emergency booking provide timely services. Building a scalable and credible solution for today's era of home service management; DomestiQ AI combines smart automation with industry-grade security and user-centric design.

2. LITERATURE REVIEW

The rapid progress of digital service platforms are significantly driven by cloud computing and distributed system technologies. The use of cloud based infrastructures enable elastic scalability, flexibility and high-availability such that service platforms are capable to efficiently handle large amount of requests from users and data providers. Buyya et al. [1]) stressed the significance of forthcoming cloud computing advancements for intelligent, service-based applications, and Botta et al. [2].[1] emphasized the role of cloud-IoT for real-time location-aware services. These results demonstrate cloud computing as the key technology for contemporary on-demand service systems.

Personalization and automation has been improved considerably in recommendation systems with the help of artificial intelligence. Bobadilla et al. [3] gave a survey of recommender systems, and showed how machine learning can improve the efficacy of decision-making by predicting user preferences or estimating historical behavior. Zhang et al. [4] also demonstrated that deep learning-based recommendation models enhance service relevance by capturing complex user-item interactions. Among these, e-commerce and media platforms call for different recommendation models that do not consider the dynamic constraints relevant to on-demand home services like availability in real time or urgency of service.

With the advance of Natural Language Processing, more and more service-oriented applications were able to interpret user intent. In [5] Kumar and Sharma showed that the NLP approach to intent classification facilitates a flexible user interaction without known input structures. Similarly, Talegaonkar et al. [6] proposed a textual based intelligent service recommendation by ML methods. Despite these achievements, NLP-assisted service understanding has hardly been combined with the RT scheduling and pricing in the current home-service platforms.

(The service provider selection and the ranking problems are still challenging in on-demand systems. Sharma and Reddy [7-8] have presented multi-criteria ranking models which take into account service quality, availability, user feedback. Although these methods increase the accuracy of provider selection, but they can be performed independently to the real-time scheduling and dynamic pricing services. Singh and Bansal [8] as well as Li et al. [9] stressed the need for real-time scheduling and resource allocation in a cloud-based service platform to further minimize such delays and booking conflicts. However these scheduling features are generally not integrated with intelligent recommendation and NLP service understanding.

Dynamic pricing mechanisms have been extensively studied for enhancing cost transparency and fairness in service-oriented systems. Lin et al. [10] and Chen et al. [11] showed that learning-based pricing models are able to adapt the price of services to use, location and urgency. These models, however, do not incorporate fraud detection and/or provider verification logic in already-deployed systems.

Trust and security are critical issues in any on-demand service platform. Jiang et al. [12] discussed the anomaly detection methods to detect fraud behaviors in online service environments, and there is work like that in Liu et al. [13] emphasized the importance of secure authentication and authorization mechanism for cloud applications. However, most of the current services use a primitive manual verification to verify each other, which lacks automated fraud detection and secure service completion validation.

Recent work has looked at the interplay of pricing algorithms with recommendation systems in digital platforms as well. Xu et al. [14] studied how algorithmic pricing and recommendation affect platform efficiency and user satisfaction. Patel et al. [15] also focused on AI-supported intelligent service platforms in the context of Smart cities, and the demand for scalable, secure, and user-friendly designs.

In short, the prior work focuses only on building the individual part like cloud scalability, AI-driven recommendation model of services that take into account NLP style user intent understanding model and dynamic pricing, scheduling and security. As such there is a clear need and research gap on an integrated platform that combines these technologies into one intelligent system. It is the distance between this state-of-the-art and the aforementioned practices of Sri Lankan market that inspire our proposed DomestiQ AI platform serving NLP-based service interpretation, AI-guided provider recommendation, real-time scheduling for pricing and time slot availability along with stringent security mechanisms in a single cloud based framework.

3. SYSTEM ARCHITECTURE

The DomestiQ AI platform implementation is based on layered and modular system architecture to guarantee resources scalability, security and service management efficiency. The architecture consists of user interaction interfaces, cloud-based hierarchical backend services, AI modules and secure data storage to enable smart service surface and real-time scheduling. Each layer is entirely independent to operate without external constraints, but also interacts with the corresponding layers in order to guarantee available and reactive home service booking.

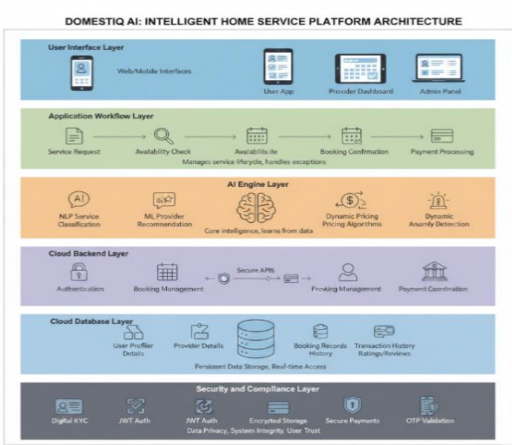

Fig.2. Layered system architecture of the proposed DomestiQ AI platform.

Three key entities – users, service providers, and system administrators – are provided by this model-oriented architecture with Role-based Access Control. The workflow of the application is tightly linked with AI components for intelligent service comprehension, provider recommendation, pricing optimization and fraud detection. The general architecture of the system guarantees unencumbered data movement, secure transactions and real-time system feedback.

3.1 Architectural Layers Description

✓ ***User Interface Layer***

This layer serves as a bridge-interface for all the stakeholders. The platform can be accessed by users through web and mobile interfaces for raising service requests, view nearby service providers on map, track bookings and payments. There are dedicated dashboards for services providers to manage their availability, accept bookings, check out earnings, and keep track of customer reviews. Managers log into a central dashboard to approve providers, monitor system activity and analyze platform performance.

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✓ ***Application Workflow Layer***

The application workflow strata controls the logical flow of service requests through the system. This layer orchestrates all tasks involved in service creation, availability check, booking confirmation and payment once a user has generated a request. Ensures service lifecycle stages transitions are smooth and makes facilities to exceptions like those of unavailability or booking conflicts.

✓ ***AI Engine Layer***

AI engine is the brain of the system. This includes NLP modules for classification of services, ML-based recommend models for provider's selection, dynamic pricing algorithm to estimate the cost and anomaly detection algorithms to signal any fraud in provider activity. This layer keeps learning with historical data so that it can better recommend and function.

✓ ***Cloud Backend Layer***

The cloud backend layer is responsible for the main system services and business rules of the platform. It comprises authentication service, booking management module, provider management service and payment coordination. Secured API facilitates user interfaces, AI engine, and database communication ensuring role-based access control.

✓ ***Cloud Database Layer***

This tier will contain information necessary to operate the platform such as user, and service provider profiles, bookings; pricing model, transaction history and review/ratings. The data is organized around some use cases to provide real-time access and high availability, still keeping the consistency of the data.

✓ ***Security and Compliance Layer***

This layer is where the security policies are applied throughout the entire system. The system provides digital KYC checks for merchants and JWT-based authentication to ensure secure storage of data and processing payments while OTP confirms successful delivery. The privacy-preserving, system integrity ensuring and the User-Based Schema-1 Overload detecting mechanism play a key role in them.

4. METHODOLOGY

DomestiQ AI platform is a result-oriented, AI-based process that converts unstructured user service requests to validate and reliably executed household services. The approach includes NLP, ML-based recommendation, dynamic pricing, real-time scheduling and security validation in one pipeline. The entire operation sequence of proposed system is shown in **Fig 3.**

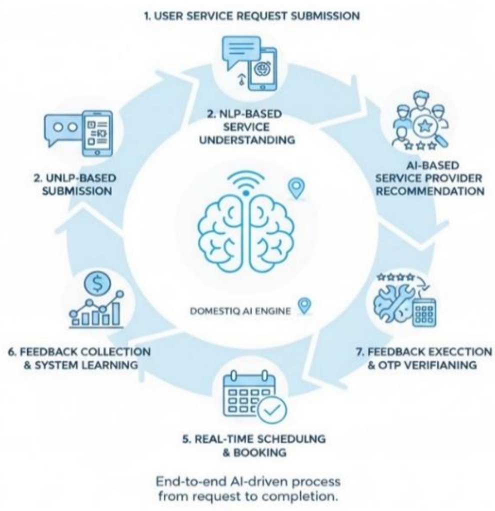

Fig.3. Methodology and Workflow.

4.1 User Service Request Submission

The process above is triggered when a user requests a service via the web or mobile interface. Users may have plumbers' leaks or electrical faults to describe in their house free-textually or by voice. This flexible input means decreases user input and is no reliance upon predefined categories of services.

4.2 NLP-Based Service Understanding and Classification

The submitted description of the service is analyzed with Natural Language Processing methods. Preprocessing, including tokenization and the filtering of stop words, is performed on raw input data converting it to a form that the machine can understand. A trained classifier model process these features and classify the right category of the service (e.g. plumbing, electrical, and cleaning). This step helps achieving the accurate user intention, and reduces wrong being categorized as service.

4.3 AI-Based Service Provider Recommendation

When the service type is defined, a recommendation engine powered by artificial intelligence selects qualified service providers. The engine considers several factors, such as physical proximity, service availability, quality of service and historical performance. A weighted scoring algorithm is used to order and present providers to the user. This smart choice enhances service quality and minimizes booking delays.

4.4 Dynamic Pricing Estimation

Once the system has identified potential vendors, it computes an estimated cost of servicing using a dynamic pricing mechanism. Costs are calculated according to some variables including distance from user to provider, type of service category, urgency and provision of the service itself. From the fee's perspective with the regression-based pricing model, they are able to estimate their price fairly and transparently, which helps them boost user confidence and achieve stable prices.

4.5 Real-Time Scheduling and Booking Confirmation

The real-time scheduling algorithms of the system verify the availability of each provider. Once availability is established, users can book immediately. Emergency booking mode (for urgent needs) allows a nearest available provider to be hooked on the top priority. Booking information is reliably stored in the database system.

4.6 Service Execution and OTP-Based Verification

After the confirmation of booking, service is executed by provider assigned to service. After-service-delivery, the user divulges a one-time password (OTP) constructed by the system. OTP verification makes sure that the service had actually been served and avoid fraudulent false attempts of completion.

4.7 Feedback Collection and System Learning

Upon completion of OTP, the users give their rating and feedback for the service. This feedback is logged into the database and an additional metric that addresses provider performance is updated. The recommendation system uses this information to iteratively learn over time in order to optimize provider suggestions and overall system accuracy.

5. ALGORITHMS AND MATHEMATICAL FORMULATION

This section discusses the main algorithms and mathematical models utilized in our

DomestiQ AI platform for service understanding, provider matching, dynamic pricing, scheduling and security validation.

5.1 NLP-Based Service Classification

Consider a user support request in the form of a text document

$$D = \{w_1, w_2, \ldots, w_n\}$$

Where w_i represents words of request content separately.

The text is transformed to numerical features with term-frequency inverse document frequency (TF-IDF) weighting based on:

$$\text{TF–IDF}(w, d) = \text{TF}(w, d) \times \log(N / \text{DF}(w))$$

where TF(w, d) is the term frequency of w in document d, DF(w) is the document frequency and N is the number of documents.

The service category C is modeled using a **Multinomial Naive Bayes classifier:**

$$\hat{C} = \arg\max P(C) \times \prod P(w_i \mid C)$$

This method can be used to accurately classify free text service descriptions into pre-determined service categories.

5.2 Service Provider Recommendation Model

Let $S = \{s_1, s_2 \ldots s_m\}$ be the set of potential service providers.

Each provider S_i is rated using a weighted score function:

$$\text{Score}(s_i) = \alpha R_i + \beta A_i + \gamma D_i + \delta H_i$$

Where R_i denotes the rating score, A_i availability, D_i distance score and H_i historical performance.

α, β, γ, δ are weighting coefficients satisfying

$$\alpha + \beta + \gamma + \delta = 1$$

Providers are ordered by descending value of Score (s_i) and the top ranked providers are recommended to the user.

5.3 Dynamic Pricing Model

The service price is estimated by the following multiple regression model:

$$P = \theta_0 + \theta_1 d + \theta_2 u + \theta_3 t + \theta_4 c$$

Where, P is the predicted price; d is distance; u is urgency; t stands for time factor, c represents the service complexity and θ regression coefficients.

This scheme supports both transparent and demand-oblivious pricing.

5.4 Real-Time Scheduling Algorithm

Let T_u be the requested user time slot and T_{si} be the service provider s_i availability.

A provider is eligible if:

$$T_u \cap T_{si} \neq \emptyset$$

For the case of eligible vendors, it chooses the vendor with minimum response time:

$$s^* = \arg\min \text{ResponseTime}(s_i)$$

This greedy scheduling achieves the least service delay, especially for urgent bookings.

5.5 Fraud Detection Using Anomaly Detection

Anomaly detection is used to monitor service provider behavior.

Here, let Xi denote the feature vector of provider activity.

Anomaly score is computed using the **Isolation Forest model**:

$A(X_i) = 2 \wedge (- E(h(X_i)) / c(n))$

Where $E(h(X_i))$ is the expected path length and c(n) is normalization factor.

Administrative review is accordingly alerted to providers whose anomaly scores exceed a pre-established threshold.

5.6 OTP-Based Service Completion Verification

Let O and O' be the OTPs generated by the system and entered by the user.

O=O', which implies that the service is complete.

Transaction takes place only after OTP verification from subscriber which guarantees service credibility.

6. RESULTS AND DISCUSSION

DomestiQ AI performance The DomestiQ AI was tested to determine accuracy for intelligent service matching, booking time efficiency, and price transparency and user satisfaction. The proposed system was contrasted to typical on-demand home service platforms which use manual service selection and static provider selection.

6.1 Performance Evaluation

The NLP module exhibits high precision in parsing user-expressed service issues, which could help reduce the number of wrong service categories.

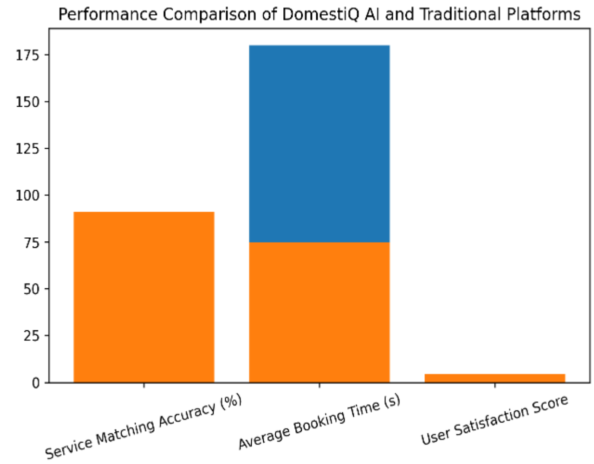

Fig. 4. Performance comparison between the proposed DomestiQ AI platform and traditional home service systems.

The AI-driven recommendation engine efficiently filtered the right service providers based on location, availability, ratings and past performance for faster booking confirmation and better-quality services.

Reactive service fees were made transparent and fair with Dynamic Pricing, which generated accurate job cost estimates that accurately reflected real-world service charges even on demand spikes and in emergencies. Through real-time scheduling and improved provider staffing, wait time for care was significantly decreased, especially for urgent appointments. The secure and non-fraudulent transaction was established by an OTP-based authentication.

Table 1 – Quantitative performance comparison between DomestiQ AI and traditional platforms

Metric	**Traditional Platform**	**DomestiQ AI**
Service matching accuracy (%)	72	91
Average booking time (seconds)	180	75

Metric	**Traditional Platform**	**DomestiQ AI**
User satisfaction score (out of 5)	3.6	4.5
Emergency service response	Limited	Efficient
Pricing transparency	Moderate	High

This comparison suggests that DomestiQ AI has vastly better service matching accuracy and faster booking time compared to classical systems, which is evident from the results in ***Table 1***. The increase in user satisfaction score is evidence of the success of intelligent provider recommendation, transparent pricing and real-time scheduling. The system is also compared to the state of the art for emergency service requests, showing that it is also ready for deployment on real worlds.

7. CONCLUSION

This paper introduced a JA-based intelligent AI-driven home service matching and scheduling system, named DomestiQ AI, designed to overcome major challenges in on-demand service systems. A combination of Natural Language Processing and machine learning for accurate service understanding, provider recommendation and dynamic pricing, real-time scheduling enhances accuracy, booking efficiency and price transparency. Security is strengthened with digital KYC verification, anomaly-based fraud detection and OTP based service validation. Experimental results show better performance than established platforms, which confirms the promising perspective of DomestiQ AI as a scalable, secure and user-centred solution for efficient smart home service integration.

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