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SkillConnect: A Multi-Criteria Recommendation System for On- Demand Home Services

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***Abstract*-- The growing on-demand home services sector often relies on basic filtering and rating mechanisms, ignoring critical factors for user satisfaction. To address this, we propose SkillConnect, a multi-criteria recommendation system that optimizes service selection using parameters like user preferences, location, price, and availability. SkillConnect utilizes a hybrid algorithm—combining collaborative and content-based filtering—alongside context-aware features to deliver accurate, personalized recommendations. Experimental analysis demonstrates that the system significantly improves user engagement, decision-making speed, and overall satisfaction. Future work will address remaining challenges such as data sparsity, scalability, and user trust through advanced algorithms.**

***Keywords*—SkillConnect; On-Demand Home Services; Recommendation System; Multi-Criteria Decision Making; Hybrid Filtering; Context-Aware Recommendation.**

I. INTRODUCTION

The digital technology's rapid progress has become a key factor in the 21st century in reshaping numerous service-based industries. The convenience and the need to save time have increased the development of on-demand home services platforms where users can access services such as plumbing, electrical domestic maintenance, or cleaning through digital applications. This transformation has been further affected by the change in lifestyle and urbanization globally where the users want quick, reliable and easy to reach services. Thus, service-based platforms have evolved from their manual forms of booking to the introduction of digital ecosystems designed to inform and interconnect service discovery and delivery processes.

The provision of household services has thus become an entirely different experience due to the extensive usage of digital platforms. The digital platforms provide for flexibility, ease of use, and real-time accessibility, eradicating the geographical nature of traditional service provision and potential communication delays. One of the most important advantages of such systems is their ability to deliver personalized recommendations based on user preferences and data.

Machine learning and data analytics provide a strong basis for analyzing user behavior and providing more targeted recommendations for services. In addition, such systems as tracking, feedback, and rating help to provide transparency, reliability, and quality of the service experience.

Recommendation systems are essential for boosting the efficiency and effectiveness of on-demand service platforms. The traditional system either develops a simple filter or averages the ratings and recommends on that basis, failing to consider several factors that influence a rating, such as the quality and cost of the service, distance from the location, and availability. To overcome this deficiency, multi-criteria decision making is incorporated in the modern system for recommending services, which takes into account a number of parameters and provides accurate and personalized recommendations. Hybrid recommendation techniques, including collaborative and content based recommendation systems, further increase prediction accuracy as well as optimize satisfaction. Besides helping the user to make the right decisions, the system also helps service providers gain more visibility and improve services.

Despite significant advantages of digital home service platforms, several challenges affect their overall effectiveness. Data sparsity, scalability, and trust between users and service providers remain key concerns. Also, there is a need for advanced system design and security mechanisms to control and manage reviews and detect fake reviews, fraudulent behavior, and data sparsity in the digital home service platform. Technologically, model improvements, as well as continued real-time data integration, are necessary to maintain the accuracy of recommendations. Recommendation systems based on multiple criteria, like SkillConnect, are therefore crucial to overcome aforementioned problems and deliver a good, efficient, and user-oriented solution for the modern home services on demand.

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Types of Recommendation Approaches

The SkillConnect system can be implemented using different recommendation techniques, depending on data availability and system requirements.

- *Content-Based Recommendation:* Suggests services based on user preferences and past selections. This approach analyzes the user's previous service history and identifies similar services that match their interests and requirements. It focuses on individual user behavior and generates personalized results without depending on other users' data. This method is useful when sufficient historical data about the user is available and helps in providing consistent and relevant recommendations.
- *Collaborative Filtering:* Recommends services based on similar users' choices and behavior. In this approach, the system compares user preferences with other users who have similar interests and suggests services that were selected by them. It works on the concept that users with similar behavior patterns are likely to prefer similar services. This technique improves recommendation accuracy by utilizing collective user data and helps in discovering new service providers that a user may not have considered before.
- *Hybrid Approach:* Combines both content-based and collaborative methods for better accuracy. This approach integrates the strengths of both techniques to overcome their individual limitations. By combining user preference analysis with collective user behavior, the system can generate more balanced and reliable recommendations. The hybrid model is widely used in modern recommendation systems because it improves performance and reduces the chances of incorrect suggestions.
- *Context-Aware Recommendation:* Considers additional factors such as location, time and availability to improve recommendations. This approach takes real- world conditions into account while generating results, ensuring that the recommendations are practical and relevant. For example, the system may suggest nearby service providers who are currently available at the requested time. Context-aware systems enhance user satisfaction by providing timely and situation-based recommendations.

II. Methodology

A systematic review approach was adopted to design and gain a comprehensive understanding of the proposed SkillConnect system. Relevant academic literature was collected from well-known databases such as IEEE Xplore, Springer Link, and ScienceDirect. To ensure the inclusion of appropriate studies, the following keywords were used during the search process:

- "Recommendation System"
- "Multi-Criteria Decision Making"
- "Service Recommendation"
- "On-Demand Home Services"
- "Personalized Recommendation System"

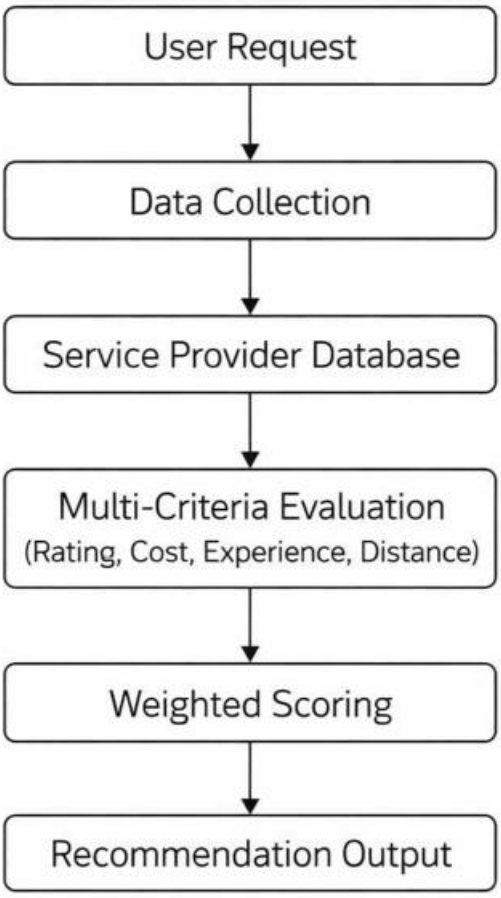

Figure 1: Simple Methodology of SkillConnect Recommendation System

The selection of research papers was carried out based on

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the following inclusion criteria:

- Peer-reviewed articles published between 2019 and 2025
- Studies primarily focused on "Recommendation System" and "Service-Based System"
- Articles providing detailed explanations of system architectures and associated challenges.

The exclusion criteria applied were as follows:

- Blog posts and other non-academic sources
- Duplicate or repetitive publications
- Studies that are purely theoretical without any practical implementation

Based on these criteria, several relevant research papers were shortlisted and examined in detail, with particular attention given to aspects such as system architectures and the challenges involved.

III. Architecture Of SkillConnect

In most scenarios, the architecture of the SkillConnect system follows a centralized approach. This allows the system to efficiently manage multiple users as well as service providers within a single framework. All relevant data is processed centrally to ensure accurate and reliable recommendations.

Step-by-step process

1. The user is required to enter the desired service, such as a plumber or an electrician.
2. The system then retrieves a list of available service providers from the database.
3. These service providers are evaluated based on multiple criteria.
4. A multi-criteria recommendation algorithm is applied by the system.
5. The weighted scoring method is used to assess each provider.
6. Finally, the most suitable service providers are recommended to the user.

The following diagram represents the complete workflow of the system, with particular emphasis on the multi-criteria recommendation algorithm.

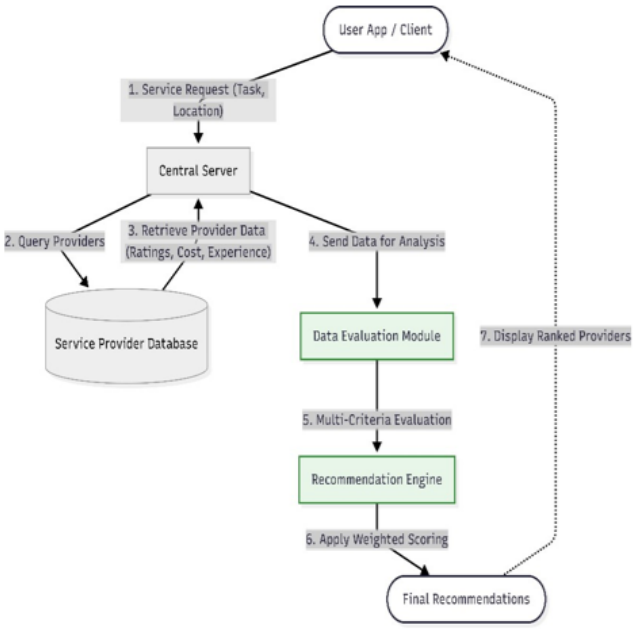

Figure 2: Centralized rchitecture of the SkillConnect Recommendation System

3.1 Data Collection and Distribution

The process begins within the central system, where data related to all registered service providers is stored. This data typically includes ratings, service cost, level of experience, and other relevant attributes. When a user requests a service, this information is retrieved and prepared for further evaluation.

3.2 Multi-Criteria Evaluation

Unlike traditional systems that rely solely on ratings to select a service provider, SkillConnect evaluates providers based on multiple criteria. For instance, professionals such as plumbers, electricians, or technicians are assessed using criteria specific to their respective skills and expertise.This approach enables a more balanced and accurate selection process, rather than relying on a single evaluation factor.

3.3 Data Processing and Scoring

After collecting and evaluating the data, the system implements a weighted scoring mechanism. Each criterion is assigned a weight based on its relative importance. Using these weights, a final score is calculated for every service provider. The processed data and computed scores are then utilized by the system to generate appropriate recommendations.

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Recommendation Generation using Weighted Scoring

The system uses the evaluated data to produce final recommendations for users.

- *Evaluation Layer:* In this layer, the weighted scoring mechanism is applied. Each parameter— such as rating, price, experience, and distance— contributes to the overall score according to its assigned weight.
- *Result Generation:* Based on the calculated scores, the system ranks the service providers and recommends the most suitable options to the user, prioritizing those with higher scores.

Summary of components in the architecture

TABLE I.
Architecture Components and Their Roles.

Component	Function in the Diagram
Central Server	Manages overall operations, processes user requests and controls the recommendation flow.
User	Provides service requirements and interacts with the system.
Service Provider (i)	Represents professionals (plumber, electrician, etc.) offering services.
Database	Stores details of service providers such as ratings, price, experience and location.
Data Evaluation Module	Analyzes multiple criteria for each service provider.
Recommendation Engine	Applies weighted scoring algorithm to generate final recommendations.

IV. Key Challenges In SkillConnect

The SkillConnect system faces several key challenges that are not commonly encountered in traditional service selection approaches. These challenges arise due to the system's reliance on multiple parameters and dynamic data handling.

4.1 Data Variability

In real-world scenarios, the data associated with service providers can vary considerably. Factors such as ratings, pricing, and level of experience differ from one provider to another. Managing and balancing these variations can be challenging, as they may affect the overall accuracy of the service selection process.

4.2 Processing Overhead

The system is required to continuously process data due to the involvement of multiple parameters in the selection process. Evaluating service providers based on criteria such as rating, price, distance, and experience increases computational complexity, which can lead to higher processing overhead within the system.

4.3 Trust and Security Issues

Maintaining trust among users and service providers is a critical concern. Since the selection process relies heavily on system-generated recommendations, it is essential to ensure that these recommendations are reliable, transparent and secure.

4.4 Scalability

As the number of users and service providers increases, the volume of data also grows significantly. Variations in user preferences and provider attributes can further add to system complexity. Therefore, the system must be designed to efficiently handle this growth while maintaining smooth and reliable performance.

V. Application Domains

The analysis of the recommendation system suggests that the SkillConnect model can be effectively applied across multiple domains. Its flexibility and adaptability allow it to support a wide range of service-based applications. The major domains in which the system can be utilized are as follows:

- *Home Maintenance Services:* The system can be used to recommend various home maintenance services, such as plumbers, electricians, and carpenters, based on user requirements and preferences.

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- *Repair and Installation Services:* SkillConnect can assist in selecting suitable technicians for the repair and installation of different appliances in an efficient and reliable manner.
- *Cleaning and Housekeeping Services:* The system can recommend cleaning and housekeeping services by considering factors such as cost, availability, and service ratings.
- *Local Professional Services:* SkillConnect can also be applied to services such as tutors, beauticians, and fitness trainers, enabling users to easily access and choose appropriate professionals.
- *Smart Service Platforms:* By integrating with mobile and web-based applications, the system enhances accessibility and allows users to conveniently access services in a seamless manner.

Among the domains listed above, home maintenance and repair services emerge as the most significant application area. This is primarily due to the high demand for such services and the increasing need for efficient and reliable service selection.

Comparative Insights

Several common observations can be derived from the analysis of the reviewed research papers.

- Traditional service systems primarily rely on simple rating-based approaches, which are often insufficient for effective and informed decision-making.
- Variability in data and differences in the characteristics of service providers are recurring challenges that affect the accuracy of recommendations.
- The use of multiple evaluation criteria is widely recognized as essential for improving recommendation quality; however, it also introduces additional complexity into the system.
- Many studies highlight the importance of incorporating robust trust and verification mechanisms, although these aspects are still evolving and not fully implemented in most systems.
- Despite advancements in recommendation algorithms, the overall development of service recommendation systems is still at a relatively early stage.
- These observations highlight a clear gap between existing recommendation systems and the growing need for more effective, efficient, and user-friendly solutions such as SkillConnect.

SkillConnect introduces a multi-criteria recommendation approach with centralized architecture to provide reliable, transparent, and efficient service provider recommendations in the home service domain.

VI. Literature Review Summary

Ref	Author & Year	Key Contribution
[1]	Jinfeng Xu, Zheyu Chen, Shuo Yang, Jinze Li, Wei Wang, Xiping Hu, Steven Hoi, Edith Ngai (2025)	This paper provides a comprehensive survey of multimodal recommender systems and explains how different data types such as text, image, video, and user interaction improve recommendation accuracy. The study discusses feature extraction, encoder design, multimodal fusion techniques, and loss optimization methods. It also highlights major challenges like data sparsity, scalability, and real-time processing, and suggests future research directions for building intelligent and personalized recommendation platforms similar to SkillConnect.
[2]	Chengkai Huang, Hongtao Huang, Tong Yu, Kaige Xie, Junda Wu, Shuai Zhang, Julian McAuley, Dietmar Jannach, Lina Yao (2025)	This research introduces foundation model-powered recommender systems and explains how large-scale AI models can enhance recommendation accuracy and decision-making. The paper categorizes recommender systems into feature-based, generative, and agent-based approaches and analyzes their performance in real-world applications. It also identifies open challenges such as system complexity, data privacy, and computational cost, providing a strong foundation for developing intelligent service matching systems like SkillConnect..

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[3]	Shaina Raza, Mizanur Rahman, Safiullah Kamawal, Armin Toroghi, Ananya Raval, Farshad Navah, Amirmohammad Kazemeini (2024)	This paper presents a comprehensive review of recommender systems from theoretical concepts to industrial applications. It explains collaborative filtering, content-based filtering, and hybrid models in detail and evaluates their strengths and limitations. The study also discusses performance evaluation metrics, datasets, and real- world deployment challenges, making it useful for designing scalable and efficient service recommendation platforms like SkillConnect.
[4]	Yashar Deldjoo, Zhankui He, Julian McAuley, Anton Korikov, Scott Sanner, Arnau Ramisa, René Vidal, Maheswaran Sathiamoorthy, Atoosa Kasirzadeh, Silvia Milano (2024)	This research explores generative AI-based recommender systems and the integration of large language models in recommendation tasks. The paper discusses how generative models improve personalization, user interaction, and recommendation quality. It also highlights challenges such as model bias, transparency, and scalability, providing insights into future intelligent recommendation systems that can be applied in SkillConnect.
[5]	Pablo Mateos, Alejandro Bellogín (2025)	This paper focuses on context-aware recommender systems and explains how contextual information such as location, time, and user behavior improves recommendation performance. The study presents a systematic literature review and identifies future research opportunities in adaptive and real-time recommendation systems relevant to SkillConnect service matching.
[6]	Yousef H. Alfaifi (2024)	This research explains recommender system applications, data sources, and evaluation challenges in different domains. The paper highlights system design, performance measurement, and implementation issues, which help in understanding how to develop efficient and scalable recommendation platforms like SkillConnect.
[7]	Yiquan An, Yingxin Tan, Xi Sun, Giovannipaolo Ferrari (2024)	This study discusses technical and social challenges in recommender systems, including privacy, fairness, and ethical issues. It emphasizes the importance of trustworthy and transparent recommendation systems, which is essential for building reliable platforms such as SkillConnect.
[8]	Shafiq Shehmir, Reda Kashef (2025)	This paper presents the integration of large language models in recommender systems and explains how LLMs improve content understanding, personalization, and recommendation accuracy. It also discusses benchmarking techniques, evaluation methods, and implementation challenges in modern recommendation systems.
[9]	Alfred Krzywicki, Mark Bain, Wayne Wobcke (2025)	This research focuses on natural language processing-based recommender systems and hybrid recommendation approaches. The study explains how textual data and user reviews can enhance recommendation quality and improve decision-making in digital service platforms.
[10]	Jianghao Lin, Jiaqi Liu, Jiachen Zhu, Yunjia Xi, Chengkai Liu, Yangtian Zhang, Yong Yu, Weinan Zhang (2024)	This paper introduces diffusion model-based recommender systems and explains modern AI- based recommendation approaches. It highlights system performance, training strategies, and real-world application benefits for intelligent recommendation platforms.

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[11]	Siddhanth Darshan Jain Gouder Nagpal (2025)	This research focuses on reinforcement learning-based recommender systems and explains how dynamic decision- making improves recommendation quality. It highlights adaptive learning and user preference modeling, which is useful for service recommendation platforms like SkillConnect.
[12]	Alejo Lopez-Avila, Jinhua Du (2025)	This study explains the role of large language models in multimodal recommender systems and presents a taxonomy of LLM-based recommendation frameworks. It highlights scalability, performance, and future research challenges in intelligent recommendation systems.

VII. Future Research Directions

The reviewed research studies highlight several promising directions for enhancing the SkillConnect system in the future. These areas of improvement focus on increasing system accuracy, reliability, and overall user experience.

1. AI-based Recommendation Enhancement: The use of artificial intelligence and machine learning techniques can enable the development of more efficient algorithms, leading to more accurate and personalized service recommendations.

2. Improved Trust and Verification Mechanisms: Strengthening verification processes for both service providers and users can enhance system reliability and build greater trust among stakeholders.

3. Dynamic Weight Adjustment: Future systems can incorporate mechanisms to dynamically adjust the importance of different criteria based on user behavior and preferences, resulting in more adaptive recommendations.

4. Integration with Blockchain Technology: The adoption of blockchain technology can improve transparency and ensure the security of transactions as well as service provider information.

5. Real-Time Recommendation and Tracking: Implementing real-time tracking of service providers can improve responsiveness and significantly enhance the overall user experience.

6. Personalized Recommendation Systems: Developing more advanced personalization techniques based on individual user behavior and preferences can further improve the relevance of recommendations.

VIII. Conclusion

This study reviewed various research works to understand the current advancements in recommendation systems for on-demand home services. The proposed SkillConnect system offers an effective solution by incorporating a multi-criteria decision-making approach, rather than relying solely on basic rating-based methods.

However, the study also identified several limitations, including data variability, processing complexity, scalability concerns, and trust-related issues. These challenges need to be addressed to ensure the development of a more efficient and reliable system.- Further research is required to explore the use of advanced technologies that can enhance the performance and effectiveness of recommendation systems like SkillConnect. Such improvements will contribute to building more accurate, scalable, and user-centric service recommendation platforms.

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