STM JOURNALS

Journal of
Artificial Intelligence
Research & Advances

ISSN: 2395-6720
Volume 11, Issue 3, 2024
September–December
DOI Journal: 10.37591/JoAIRA

https://journals.stmjournals.com/joaira

Review JoAIRA

Elevating Seamless Housing Navigation with Precise Recommendations for Personalized Rental Experiences

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Abstract

The demand for rental housing has increased significantly in recent years, making more effective and individualized methods of housing navigation necessary. Renters become frustrated and ineffective when using traditional ways of researching rental houses since they frequently involve manual searches- es and little customization. By using sophisticated recommendation systems to deliver exact recommendations catered to user preferences, this research article suggests a novel way to improve house navigation. The proposed approach seeks to optimize rental property utilization, improve user satisfaction, and streamline the rental experience by merging machine learning algorithms with property data and user preferences. The primary objective is to introduce an advanced recommendation system that not only simplifies the process but also adapts to the dynamic preferences of users. By integrating a preference-based search technique with cutting-edge example-critiquing methodology, it aims to redefine the user experience in the realm of online property discovery. This forward-looking approach not only enhances efficiency but also sets a new standard for tailored and responsive solutions in the dynamic landscape of online property discovery. The paper investigates the difficulties in housing navigation, the possible advantages of personalized recommendations, and the technological issues involved in creating such systems through a thorough analysis of the body of existing material. It also addresses the privacy issues and ethical ramifications of individualized advice. The paper concludes with a framework for deploying accurate recommendation systems in the rental housing market, highlighting the significance of algorithmic fairness, user control, and transparency.

Keywords: Housing navigation, rental experience, recommendation systems, personalized recommendations, machine learning, user preferences, property data

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Received Date: May 18, 2024
Accepted Date: September 13, 2024
Published Date: October 07, 2024

Citation: Mohammad Shees, Md. Faisal Quaiyum, Saquib Hussain, Mantasha Perween, Hasan Nawaz, Sunil. Elevating Seamless Housing Navigation with Precise Recommendations for Personalized Rental Experiences. Journal of Artificial Intelligence Research & Advances. 2024; 11(3): 50–62p.

INTRODUCTION

Welcome to the future of hassle-free home-rental experiences in today's fast-paced world, finding a perfect rental home is a daunting task. This is where the proposed innovative home-rental recommendation system comes into play. To simplify and enhance your home-hunting journey, our system leverages advanced technologies and intelligent algorithms to match your ideal rental property. Say goodbye to hours spent sifting through countless listings and struggling to narrow down options. The proposed recommendation system redefines how anyone searches for a new place to call home. By seamlessly integrating cutting-edge data analysis, personalized preferences, and real-time market trends, we ensure that you are presented with rental options that perfectly align with your needs and aspirations. The rental housing market is dynamic, with tenants always looking for acceptable places to live and landlords trying to fill available spaces [1]. Renters typically find rental properties by utilizing techniques such as perusing online listing platforms, contacting real estate agents, or looking through classified advertisements. However, these approaches are frequently impersonal and ineffective, producing less-than-ideal results for landlords and tenants. The emergence of cutting-edge technologies and data analytics presents an opportunity to transform the home navigation process by offering individualized recommendations based on user preferences.

Imagine a platform that not only understands your preferences for location, budget, and amenities, but also factors in your lifestyle, commute, and even your favorite nearby spots. The proposed recommendation system goes beyond the basics of considering the holistic experience of living in a particular rental property. It considers factors such as safety, local services, community vibrations, and many more, creating a comprehensive picture to guide the decision-making process [2]. Powered by the latest advancements in artificial intelligence and machine learning, our home-rental recommendation system continuously learns and adapts based on interactions. The more you engage with the system, the smarter it becomes to understand your evolving preferences, refine its suggestions, and present you with options that are increasingly tailored to your unique tastes. Whether you are a young professional seeking a vibrant urban atmosphere, a family looking for a spacious suburban home, or anyone in between, our home rental recommendation system is your trusted partner in finding the perfect rental property. Experience the future of home-hunting today, where technology and comfort unite to simplify the process, ensuring that you discover not just a place to stay but a place that truly feels like home.

LITERATURE SURVEY

In the past, tenants found rental properties using online listing platforms, real estate agencies, and classified ads. Renters become frustrated and inefficient as a result of these tactics, which frequently include manual searches and a lack of customization. The process of navigating the property market is full of obstacles such as an abundance of information, a lack of transparency, and the complexity of locating properties that suit certain preferences. It can be difficult for renters to locate properties that meet their requirements, which may result in less-than-ideal results and discontent. Several industries have effectively applied personalized recommendation systems, such as social networking, e-commerce, and entertainment. By using machine learning algorithms to assess user preferences and make personalized recommendations, these systems increase user satisfaction and engagement levels.

Xian et al. [3] proposed their study about a house rental recommendation algorithm based on deep learning by combining a text convolutional Neural Network with a content-based recommendation algorithm. Their goal is to extract useful information quickly and effectively from redundant and complicated data. They lack the accuracy of recommendation results; in addition, they do not provide recommendations based on users’ past views and interests. Our system uses these approaches to achieve better results.

Mehmet et al. [4] implemented recommendation systems in the Turkish real estate market. For recommendations, they use two approaches of collaborative filtering: item-based collaborative filtering and alternating least squares (ALS). For both methods, they calculated F1-score values, compared their results, and found that item-based gave better results for their system, and content-based filtering was used. Thus, the diversification technique in the system is low. Our project provides user-specific, popularity-based, and diverse diversification techniques for a smooth user experience.

Shristi et al. [5] stated that the evolving landscape of online property searches poses a challenge for renters seeking accommodation that aligns with their preferences. Navigating through various online platforms can be time-consuming, exacerbated by the disparity between renters' expressed preferences and their actual requirements. This study introduced an innovative recommendation system to simplify the search for rental properties. Our approach integrates a preference-based search technique with an example-critiquing methodology. Instead of traditional database queries, renters are prompted to articulate their preferences, allowing the system to construct a personalized preference model. This model is then utilized to generate a curated list of rental properties that best match the user's unique criteria, offering a more efficient and tailored solution to the challenges of online accommodation search.

Satapathy et al. [6] implemented a recommender system for rental properties. They used collaborative filtering, which eased the tenants to find their preference-based properties, and augmented reality, which allows users to visually explore rental options in a more immersive and interactive manner. This study emphasizes the potential of this hybrid approach to revolutionize the rental industry by combining intelligent recommendations with augmented reality (AR) visualization to enhance the user experience. One prominent issue is the potential for inaccurate or biased recommendations, leading to suboptimal user experiences. In addition, AR visualization may face hurdles related to user adoption and seamless integration. In our home-rental application, we aim to address these challenges by implementing advanced algorithms for more accurate and unbiased recommendations.

Aamir et al. [7] proposed a state-of-the-art recommender system state-of-the-art approach that plays a pivotal role in modern online platforms, offering users personalized recommendations to navigate vast collections of items. This technology has been emphasized in numerous studies. The ease of Internet usage has resulted in a surge in online transactions, making the Web a predominant source for buying and selling products. One significant issue identified in the literature is the overwhelming abundance of choices and the lack of a centralized platform that provides comprehensive information for online consumers. To address this challenge, we propose a home-rental recommendation system that aims to streamline the decision-making process for individuals seeking rental properties. By leveraging advanced algorithms and user preferences, the system offers tailored recommendations for rental homes by considering factors such as location, amenities, pricing, and user reviews.

Ayush et al. [8] reviewed various research papers in the field of recommendation systems and identified three major categories: content-based, collaborative filtering, and hybrid systems. They also found that most deep learning technology is used in the entertainment industry, such as in movies and music recommendations. Thus, they examined whether the progress made in different areas, such as real estate datasets, analgesic author-article datasets, online retail shopping datasets, and other datasets that include rich metadata about users and items in addition to user-item interaction, thereby proving the recommendation system in their respective fields.

Burke et al. [9] conducted experiments on various types of recommendation systems, revealing that each technique has advantages and disadvantages. The findings suggest that implementing a hybrid recommender system can enhance performance. The experiments demonstrated that collaborative filtering outperformed the standalone knowledge-based component. In addition, semantic evaluations from the knowledge-based portion improved user preference prediction beyond numerical ratings.

Mubarak et al. [10] implemented a map-based recommendation system and a house price prediction model for real estate. They utilized sophisticated techniques such as TuriCreate, K-means clustering, TensorFlow, and Keras API to develop their recommendation system. This system incorporates content-, collaborative-, and location-based filtering methods to ensure precise property suggestions. Multiple linear regression and Keras regression techniques were compared to select the most accurate model for price prediction. Their system lacked seamless integration and scalability. Our system overcomes this problem by seamlessly integrating diverse methods, ensuring superior user experience and accurate predictions.

Amika et al. [11] implemented an online rental system called LeKeDe to facilitate efficient communication between users and product owners. They utilized Google Firebase and JavaScript for their development, emphasizing security and privacy in user data storage. However, their system lacked location-based filtering and recommendation systems. In contrast, our system addresses this drawback by incorporating location-wise filtering and recommendation features, thereby enhancing the user experience and satisfaction.

Ning X. et al. [12] surveyed and found that neighborhood-based recommendation is a popular method for item recommendation, offering advantages such as explanations, computational efficiency, stability, and serendipitous recommendations. It is crucial to choose between user- and item-based methods, with item-based approaches being preferred for commercial systems. Different components of a neighborhood-based method can influence the quality of the system. When performance issues arise, techniques, such as dimensionality reduction or graphs, can be explored to address sparsity and limited coverage.

RECOMMENDATION SYSTEM

Recommendation systems employ an automated information-filtering mechanism to suggest items based on user preferences. The focus is on identifying and providing information that users are likely to obtain valuable or interesting information. It helps consumers by providing pertinent information and filtering data sources [13].

Recommender systems can be broadly classified into three main types as shown in Figure 1: content-based systems, collaborative systems, and hybrid systems. A content-based system suggests items based on the characteristics and features of the items themselves, making predictions by analyzing the content and metadata associated with each item. Collaborative systems that rely on user interactions and preferences to make suggestions. It identifies patterns by analyzing the behavior and preferences of similar users to recommend items that the current user may like. A hybrid recommendation system combines content-based and collaborative approaches to provide more accurate and diverse suggestions [14].

Collaborative filtering using automated recommender systems first appeared in the 1990s. Among these were Merry Andrew for jokes, BellCore Videos Recommender for flicks, and Ringo for music. Amazon is arguably the most well-known company that uses recommender systems to encourage user purchases [15]. Amazon recommends products for the user to think about purchasing based on their past purchases, browsing history, the item they are currently viewing, and other user behaviors. Cooperative filtering has been pushed aside by recommender technology in favor of content-based, Bayesian logical, and case-based reasoning techniques. With the introduction of the Netflix Prize, a $1 million reward for research that might increase the accuracy of Netflix's movie recommendations by 100%, interest in recommender system analysis has grown.

Model and Filtering Used in the Proposed Recommender System

Content-Based Filtering

Content-based filtering is a fundamental recommendation technique that relies on the analysis of item attributes or features to generate personalized recommendations for users. This approach profiles users based on their past interactions or preferences and matches them with items possessing similar attributes. In the context of home-rental recommendation systems, content-based filtering extracts relevant features from property listings such as location, price, amenities, and property type. These features are then utilized to compute the similarity scores between properties and recommend those that closely align with the user's preferences [16]. Content-based filtering offers advantages such as transparency because recommendations are based on explicit features, and the ability to handle the cold-start problem by relying solely on item attributes. Nonetheless, its effectiveness relies heavily on the quality of the feature representation and the diversity of available items, which may pose challenges in scenarios with sparse or limited data.

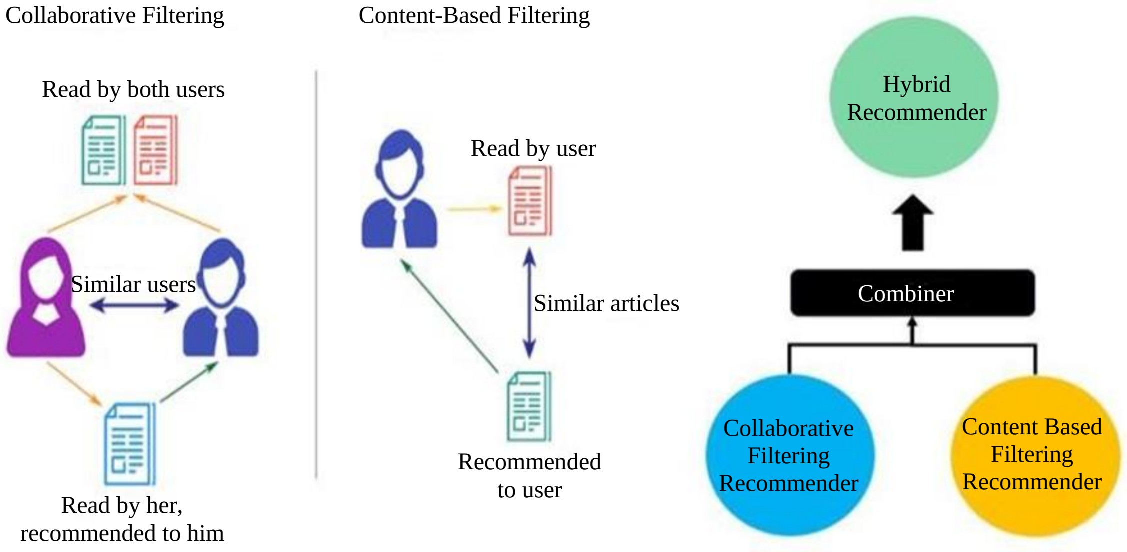

Figure 1. Recommender system types.

K-Nearest Neighbors (KNN) Model

The KNN algorithm is a versatile and intuitive method commonly used in recommendation systems owing to its simplicity and effectiveness in generating personalized recommendations. Operating on the principle of similarity, KNN identifies a set of nearest neighbors for a given query instance based on a chosen distance metric, typically the Euclidean or cosine distance [17]. By considering the ratings or attributes of these neighbors, KNN predicts the target rating or relevance of items for the user. One of the notable strengths of KNN is its ability to handle both numerical and categorical data seamlessly, making it suitable for various types of recommendation tasks. However, challenges such as the determination of an optimal value for K and the computational overhead associated with large datasets necessitate careful parameter tuning and optimization to achieve optimal performance.

METHODOLOGY

Data Collection

Data Collection is the initial stage in creating a recommendation system for housing navigation. This entails compiling data on user preferences, rental properties, and rental transactions. Online listing services, property management programs, and user reviews are examples of data sources.

Selection of Algorithms

After gathering data, the next stage is to choose suitable algorithms to produce customized recommendations. Collaborative filtering, content-based filtering, and hybrid techniques are examples of the most frequently used algorithms. The choice of the algorithm is influenced by variables such as user engagement, scalability, and data sparsity.

Model Development

After choosing the algorithm, the next stage is to create a model that produces customized recommendations. This entails preparing the data, training the model, and utilizing methods, such as cross-validation and hyperparameter tuning, to maximize its performance.

Assessment Criteria

Finally, relevant metrics, including accuracy, precision, recall, and F1 score, were used to assess the effectiveness of the recommendation system. These metrics aid in evaluating how well the system provides users with customized recommendations.

PROPOSED SYSTEM

Current systems require a significant amount of paperwork and human data entry to record the details of multiple actions of a user. Because the system is now operated manually, which results in extraordinarily high response times and fewer cure transactions because of the possibility of papers being lost or damaged, it needs to be reorganized with greater benefits and flexibility [18]. The proposed research implemented a system that, once a user searches for a property, suggests the top ten rental properties in the user's neighborhood. The system’s user interface is designed on ‘Figma’ and uses Android Studio 2023 as its Integrated Development Environment (IDE). The official IDE for creating Android apps is Android Studio. Utilizing powerful code editor and developer tools from IntelliJ IDEA, Android Studio offers extra features that boost its productivity when making Android apps. For the frontend and backend development implementation, the system utilized the Dart programming language in ‘Flutter’ and the Firebase database is used for data storage purposes.

System Architecture

The system architecture defines the structure and interactions of the components in a complex system, including hardware and software. It determines how these components communicate and work together to achieve the system's goals. Architects make decisions based on constraints and trade-offs to meet requirements while considering scalability and maintainability. Over time, the architecture evolves to adapt to changing needs and technologies, ensuring that the system remains effective and efficient.

As shown in Figure 2, the user and admin both interact with a user interface that is designed with ‘Figma’ and implemented using Dart language, those commands are sent to the server side which has three different functions. Log-in with phone number, a search engine where search engine works on content-based recommendation system having KNN model and the other is interaction with database deployed on the cloud.

Data Flow Diagram

A data flow diagram (DFD) is a visual representation of how data flows through a system and how it is processed. It comprises processes, data stores, data flows, and external entities. DFDs are categorized into different types based on their level of detail. Figure 3 shows that Level 1 DFD decomposes a single process from the Context Diagram into more detailed sub-processes. Each subprocess represents a specific function or transformation performed within the system. Level 1 DFDs provide a more granular view of the processes and interactions of the system.

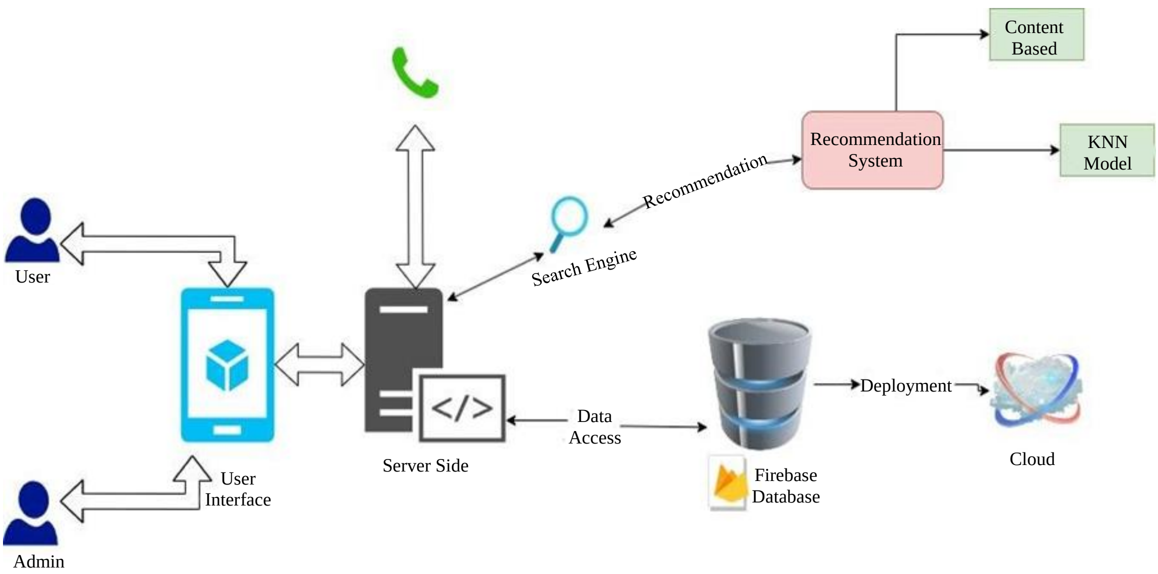

Figure 2. System architecture.

Journal of Artificial Intelligence Research & Advances
Volume 11, Issue 3
ISSN: 2395-6720

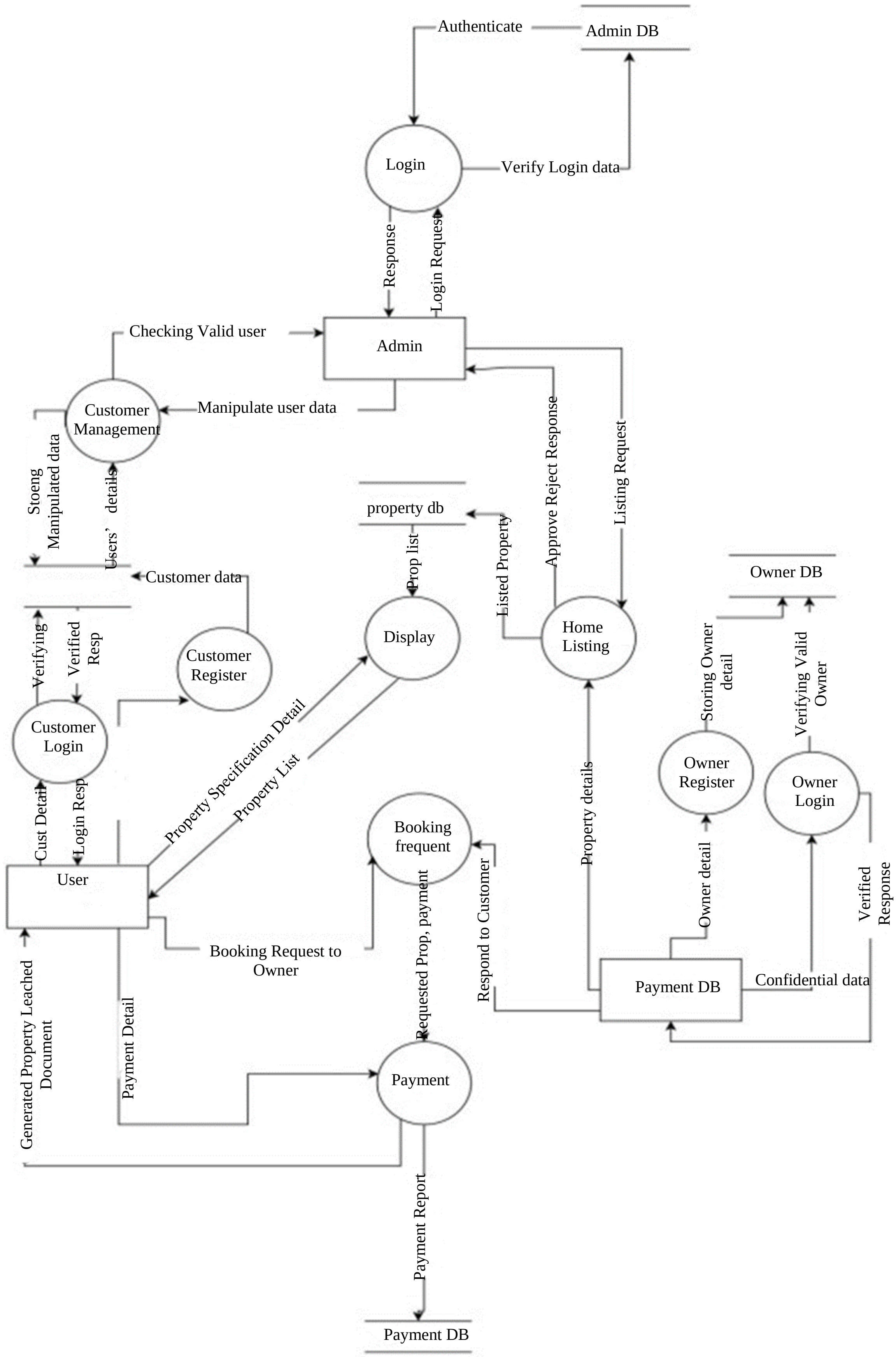

Figure 3. Level 1 DFD of proposed system.

Use Case Diagram

A use case diagram visually represents the interactions between actors (users or external systems) and the system itself. In the context of a home-rental recommendation system, a simplified use case diagram illustrating the main interactions and functionalities is shown in Figure 4.

In this use case diagram, various actors interact within the home-rental system. Users, represented by the "User" role, engage in activities such as searching for properties based on preferences, viewing detailed property information, and saving properties for future consideration. Property owners or managers, depicted as "Owner," have the capability to manage their listings by adding, updating, or removing properties. The "Recommendation Engine" plays a crucial role by suggesting properties to users based on their preferences, historical interactions, and market trends. In addition, it continuously refines its recommendations through user feedback and behavior analysis. The "Admin" role oversees the platform's integrity by reviewing posted properties. Together, these roles and functionalities create a dynamic and user-friendly ecosystem for property searches, management, and personalized recommendations within the home-rental system.

Figure 4. Use case diagram of the proposed system.

IMPLEMENTATION DESIGN

The proposed platform employs collaborative filtering, which is a recommendation system technique, to provide personalized property suggestions based on user interactions and preferences. By analyzing past rental history, property preferences, and user ratings, collaborative filtering tailors' recommendations for each user's unique taste. This streamlines the rental property search process, offering users accurate and personalized suggestions. Below, it shows a graphical user interface (GUI) showcasing its intuitive recommendation system, which allows users to explore rental options effortlessly.

Log-in/Sign-up Page

Figure 5 shows the log-in/sign-up GUIs of the home-rental recommendation system, which presents an intuitive interface with fields for entering credentials and a prominent call-to-action button for both new users to sign-up and existing users to log-in. It prioritizes simplicity and ease of use, ensuring smooth navigation for users seeking personalized rental recommendations.

Home Page

The home page GUI is shown in Figure 6 of the home-rental recommendation system that greets users with a visually appealing layout, showcasing featured properties, search functionality, and personalized recommendations based on their preferences and browsing history. It integrates intuitive filters and sorting options for users to refine their search criteria swiftly, thereby enhancing their overall experience in finding the ideal rental property.

Property Search and Results

The Property Search page GUI in the home-rental recommendation system shown in Figure 7 leverages collaborative filtering, enabling users to search for properties based on area pin codes. It features an intuitive interface with a pin code input field, providing tailored recommendations by analyzing user preferences and historical data. Users can quickly find relevant rental options within their desired locations, thereby enhancing the efficiency of their property searches.

Profile Management (User Account/Business Account)

As shown in Figure 8, the profile management interface in the home-rental recommendation system provides users with a centralized hub for viewing and editing their personal information. It features an intuitive design that allows users to update contact details, set notification preferences, and track rental history.

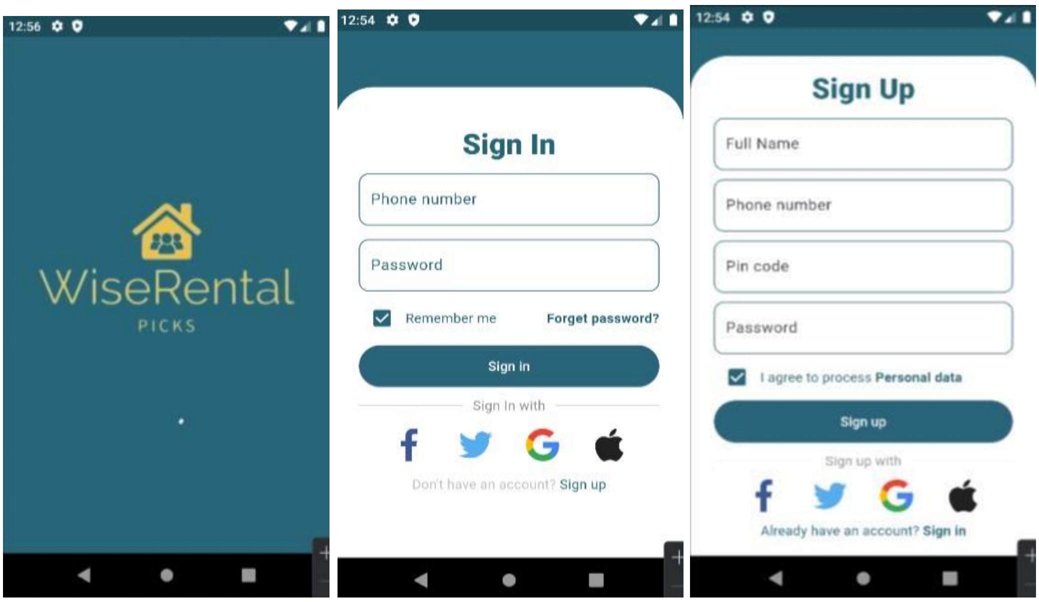

Figure 5. Splash screen, sign-in, and sign-up screen.

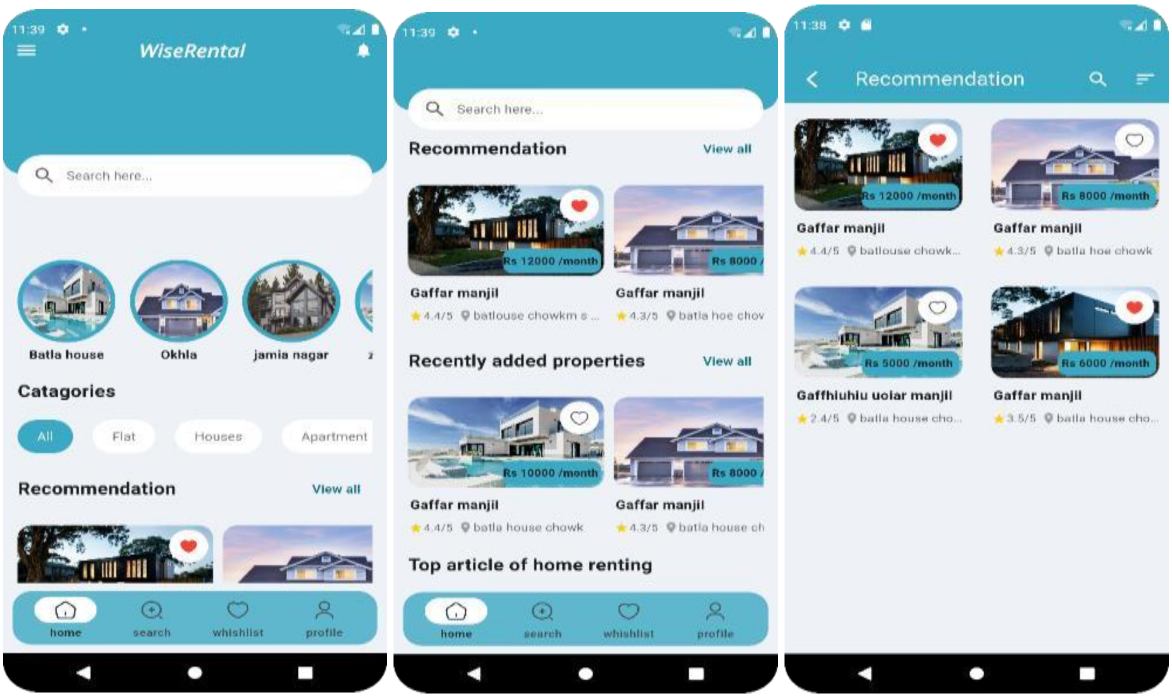

Figure 6. Home Page of the Proposed System.

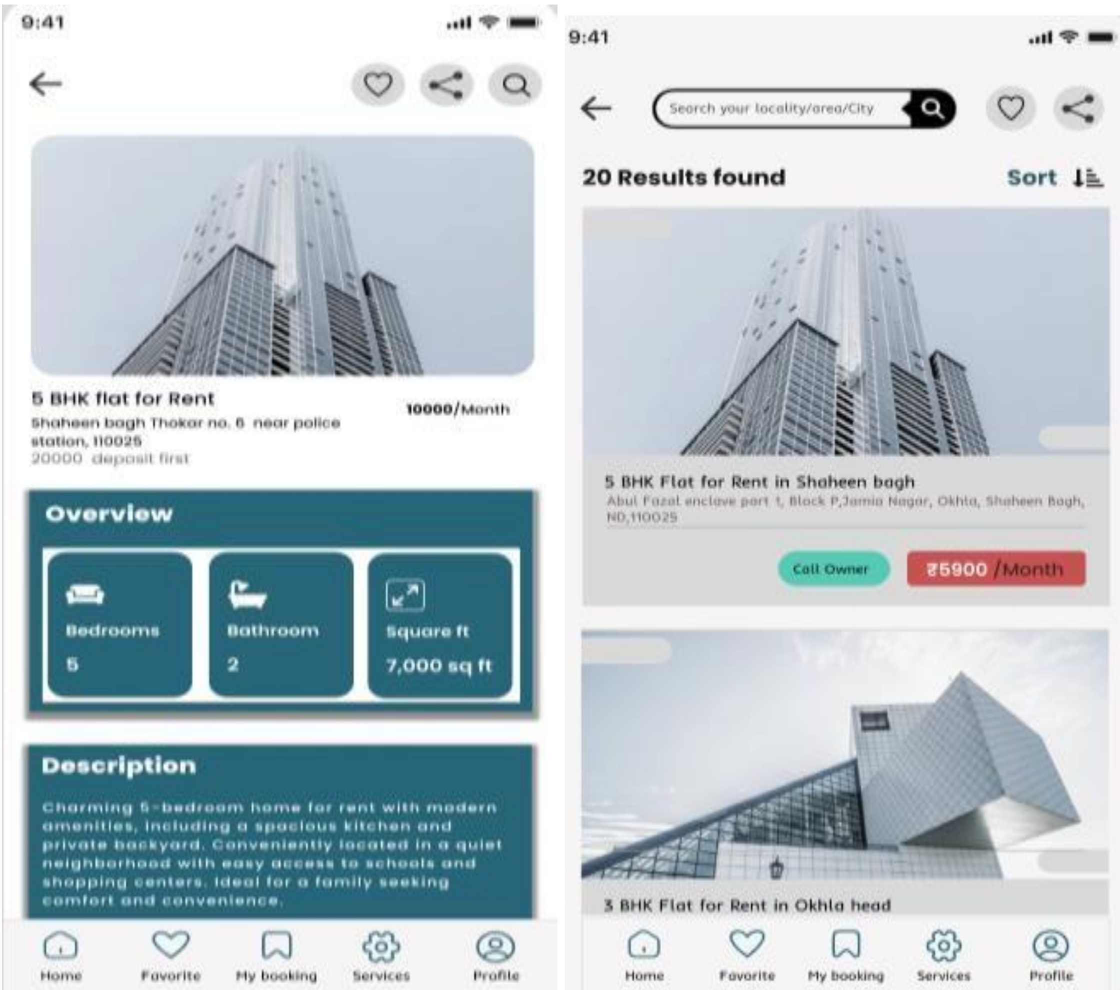

Figure 7. Property search and results.

Booking History and Favorite List

The Booking History and Favorites List GUI shown in Figure 9 in the home-rental recommendation system provides users with a convenient overview of their past bookings and saves favorite properties. It features an organized layout displaying details such as rental dates, property information, and booking status, empowering users to track their rental history and easily revisit preferred listings. With intuitive filtering and sorting options, users can efficiently manage their bookings and prioritize their favorite properties for future reference.

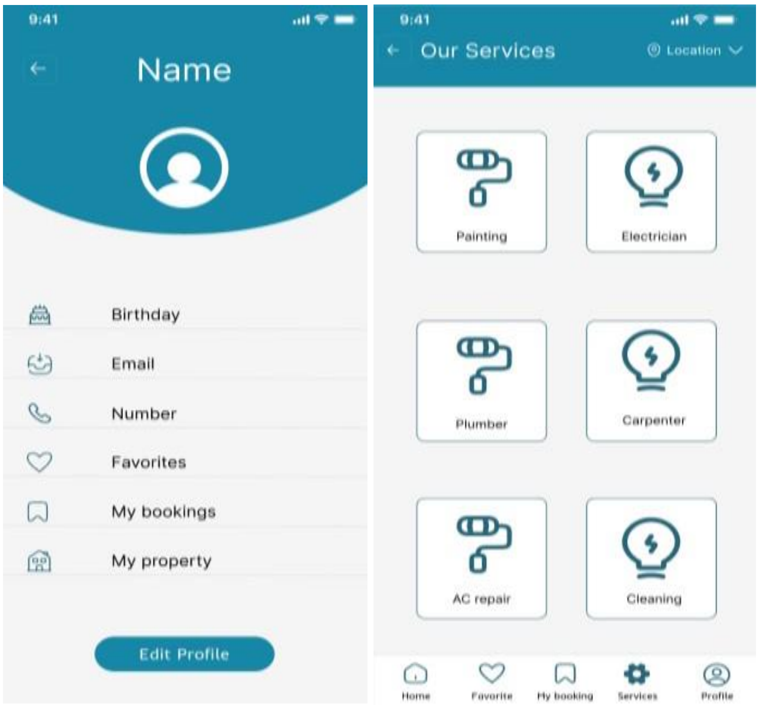

Figure 8. Profiles and Services of the Proposed System.

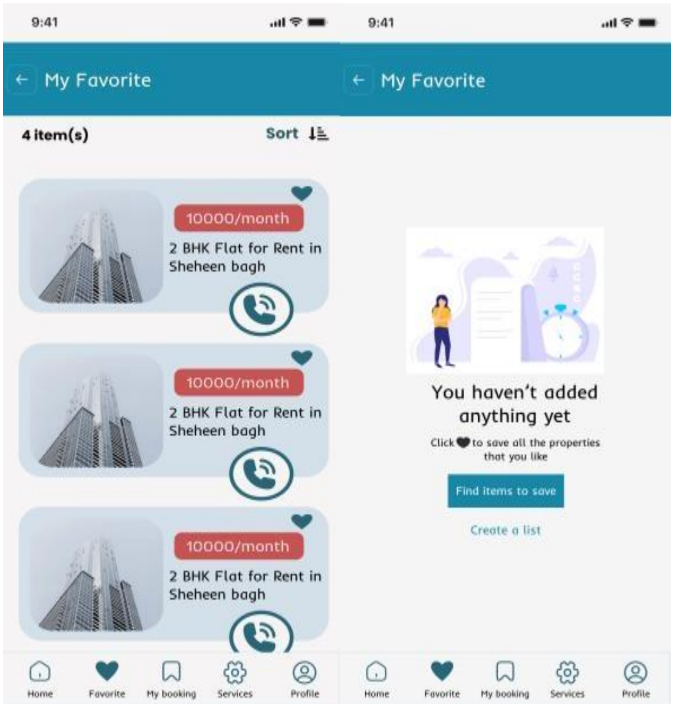

Figure 9. Booking History and Favorite List.

Table 1. Comparative Evaluation of Previous Research.

Product Name	Issues Occurred	Solution by Proposed System
Trulia Rentals	No option for property reviews and ratings, making it challenging to assess property quality.	Reviews and ratings are provided in our system.
Zillow Rentals	Some listings may be outdated or inaccurate, leading to wasted time for users.	Accuracy and updated listings are achieved using collaborative filtering and the options provided to the user end to post their property for rent, which expands the dataset of the property listing.
PadMapper	Lack of advanced search filters.	Area pin code, Price Range and property ratings are some advanced filtering used in our recommender system.
HotPads	No option to post own property for rent.	We provide options to post your property for rent.

RESULT ANALYSIS

Table 1 presents a comparison of the proposed system with previous research. All the works are presented here, along with our improved solution. The core component of our system is a recommendation system that offers an innovative approach compared with existing methods. Compared to current algorithms, the system performs better with larger datasets.

CONCLUSION AND FUTURE WORK

In conclusion, this study suggests a new way to improve housing navigation by employing sophisticated recommendation systems to deliver accurate suggestions for customized rental experiences. The proposed method seeks to improve user pleasure, expedite the rental process, and maximize property utilization by fusing machine learning algorithms with user preferences and property data. Personalized recommendation systems can revolutionize the rental housing market by enhancing user experience, efficiency, and transparency. Renters can locate properties that fit their unique requirements more readily, and landlords can draw appropriate tenants more successfully. The implementation of content-based, collaborative filtering, and KNN algorithms ensures personalized and accurate property suggestions, further enriching the platform's utility. Through the development of comprehensive use cases and DFDs with a focus on stakeholder needs, functional and non-functional requirements, and system efficiency, the rental system is poised to revolutionize the rental market, offering convenience, reliability, and value to all involved parties. By adhering to best practices and prioritizing user experience, security, and scalability, our system is positioned to revolutionize the rental industry by offering unparalleled convenience, transparency, and satisfaction to all parties involved. To address the implementation issues and moral dilemmas surrounding personalized recommendation systems in the rental housing market, more studies are required in the future. To fully exploit the potential of recommendation systems in this sector, future research should concentrate on enhancing algorithmic fairness, user acceptance, and data quality.

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