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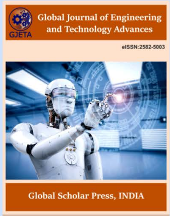

(Research Article)

Recommendations in augmented reality-based furniture shopping application

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Abstract

In today's e-commerce landscape, technological innovations are reshaping traditional shopping experiences. Augmented Reality (AR) has emerged as a pivotal tool, offering immersive solutions for online furniture shopping. By enabling users to visualize furniture in their own spaces, AR mitigates uncertainties and enhances decision-making. Integrated with personalized recommendation systems, AR transforms the shopping process into a tailored experience, considering user preferences and room characteristics. Through testing, to evaluate the effectiveness in enhancing user satisfaction and streamlining the shopping journey. These findings underscore the transformative potential of AR and personalized recommendations, paving the way for future advancements in e-commerce and consumer experience optimization.

Keywords: Augmented Reality; Space Compatibility; Color Compatibility; Personalized Recommendations

1 Introduction

In recent years, technological advancements have reshaped the landscape of the e-commerce market, revolutionizing the way consumers interact with products and services. Among these innovations, Augmented Reality (AR) stands out as a transformative tool, offering immersive experiences that bridge the gap between the digital and physical worlds. In the realm of furniture shopping, AR technology has emerged as a game-changer, offering unparalleled benefits to both consumers and retailers alike.

Augmented Reality (AR) redefines the traditional shopping experience by empowering users to visualize furniture in their own living spaces before making a purchase. By simply leveraging their smartphones or devices, consumers can overlay virtual furniture onto their real-world environments, allowing them to assess factors such as size, style, and compatibility with existing decor. This immersive visualization capability not only enhances the decision-making process but also mitigates the uncertainty and risk associated with traditional online furniture shopping.

Moreover, the integration of AR technology in e-commerce platforms introduces the concept of a Smart Catalog, where user preferences and behavior are seamlessly integrated into the shopping experience. The system tailors recommendations based on user demographics, preferences, and past interactions. This personalized approach not only saves users valuable time but also enhances their satisfaction by presenting them with relevant and curated options tailored to their tastes and needs.

Furthermore, the advent of personalized recommendation systems extends beyond user preferences to encompass the unique characteristics of their living spaces. By analyzing images provided by users, these systems can extract key features like the room colors, enabling the generation of recommendations that complements with the existing

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aesthetics of their homes. This contextual understanding not only enriches the shopping experience but also fosters a deeper sense of connection between consumers and the products they envision in their spaces.

This paper delves into the innovative realm of intelligent furniture shopping applications, exploring the multifaceted benefits and functionalities offered by AR technology and personalized recommendation systems. Through comprehensive testing and analysis, assessing the efficacy of these systems in enhancing user satisfaction, streamlining the shopping process, and driving engagement. By shedding light on the transformative potential of AR and personalized recommendations in the furniture industry, this research aims to pave the way for future advancements and innovations in e-commerce and consumer experience optimization.

2 Related Work

2.1 "The design and implementation of an interactive mobile Augmented Reality application for an improved furniture shopping experience"[3]

The research paper proposes an AR-based mobile application to revolutionize furniture shopping. By leveraging AR technology, users can virtually visualize furniture items from different stores in their own homes before purchasing. The paper follows the waterfall software engineering model, detailing requirements gathering, design, implementation, and testing. Future work includes integrating AI-based shopping assistants and ML-based recommender systems to further enhance the user experience.

2.2 "A Mobile Application and Web Recommendation System for Assisting Indoor Decoration"[6]

The research paper introduces a framework comprising mobile and web applications to aid users in selecting decoration products such as furniture, paint, and carpet. The system analyzes the color content of the environment and user-specified criteria to provide recommendations. Preliminary results using scalar quantization and linear matching for color analysis and recommendation are presented. This paper aims to address the growing interest in mobile applications and the need for efficient decoration assistance in the furniture industry.

2.3 "An Intelligent Recommendation System Model based on Style for Virtual Home Furnishing in Three-dimensional Scene" [7]

The research paper presents a model aimed at enhancing the virtual home furnishing experience in online furniture shopping. The system utilizes style-based recommendations to help users find furniture based on personalized preferences. It consists of four modules: user information mining, furniture merchandise processing, recommendation computation, and result display. By incorporating users' browsing behaviors and physiological perceptions, the system creates unified style virtual home furnishing scenes to improve turnover rates and network marketing of furniture products in e-commerce.

2.4 "Art Rich: Place Your AR Artwork"[1]

The research paper introduces Art Rich, an artwork augmentation service designed to aid users in selecting artworks for their personal space without physically visiting art fairs or galleries. The service recommends artworks based on the color scheme of users' rooms, utilizing the k-means algorithm to extract primary colors. Users can visualize and determine the size of artworks using augmented reality (AR) measurements, facilitating convenient online art selection and purchase. This service caters to the needs of the MZ generation, providing a platform for artists to showcase their works and exhibition history. With the global art market rapidly growing, there is a need for AR artwork visualization solutions to revitalize the market and enhance accessibility for both artists and consumers. Inspired by the success of IKEA Place in visualizing furniture in homes, Art Rich seeks to connect AR with the art market, enabling users to virtually place artworks in their spaces and fostering a seamless art-buying experience.

3 Research Gap

Based on a thorough analysis of the current literature about AR and recommender systems, it is found that despite the extensive research in the field, there is a lack of exploration in terms of combining the two technologies. Existing literature surveys within the realm of furniture recommender systems reveal notable gaps in three key areas.

Firstly, while many systems focus on recommending furniture based on style, size, and material, there's a distinct lack of emphasis on color aspects in recommendations. Color plays a pivotal role in interior design and furniture selection, yet its incorporation into these systems remains limited, as demonstrated by the absence of color-based recommendation mechanisms in papers such as [7] and [1].

Secondly, despite the significance of user feedback in enhancing recommendation accuracy, several systems fail to adequately leverage or incorporate this valuable input, resulting in a lack of adaptability and personalization. The paper [3] discusses user feedback systems, the extent to which this feedback is utilized to enhance recommendations is unclear, Additionally, personalized fuzzy recommendation systems, as discussed in [5] offer a promising avenue for incorporating user preferences and feedback into the recommendation process but require further investigation and refinement for optimal performance in the furniture domain.

Lastly, comprehensive testing and validation of these systems, especially concerning the accuracy of recommendations in real-world settings or through augmented reality experiences, are notably scarce in the literature, as evidenced by the limited discussion on testing and validation methodologies in papers such as [6] and [1]. Closing these gaps holds the potential to significantly enhance the effectiveness and user satisfaction of furniture recommender systems by ensuring they account for color preferences, leverage user feedback for personalization, and undergo rigorous testing in practical scenarios.

4 Methodology: Craft Comfort

The methodology employed in this study integrates insights from previous research. The proposed system shown in Fig 1, combines content-based and collaborative filtering techniques to develop a hybrid recommender system. Leveraging the AR feature for visualizing furniture, the system offers users an immersive experience to preview how selected items fit within their living spaces. Additionally, a second recommender utilizes user-provided images of their rooms, alongside dimensions of available space and desired furniture types, to generate personalized recommendations within the AR view. The methodology emphasizes the practical implementation of AR technology and user-centric design principles to create a seamless and intuitive furniture shopping experience.

Users begin by signing up and creating a profile within the application. During this process, demographic information such as name, email, age, sex, number of family members, employment status, and income are collected. This information is stored in a user database to personalize the shopping experience and tailor recommendations based on user preferences and characteristics.

Upon logging in, users are presented with a home page featuring a catalog of furniture items. These items are curated and recommended using a hybrid recommender system, which combines content-based and collaborative filtering techniques.

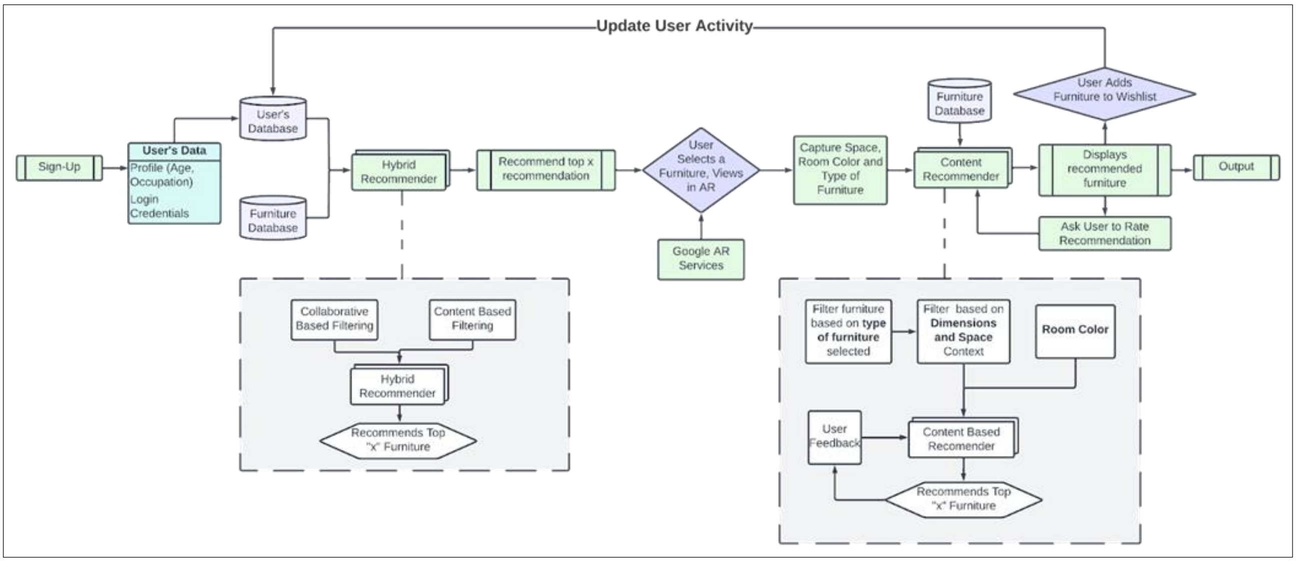

Figure 1 System Design

4.1 Hybrid Recommender

4.1.1 Content Recommender

The content recommender utilizes a comprehensive furniture dataset containing attributes such as product ID, category, color, material, dimensions (length, breadth, height), and price. Categorical data is encoded to numerical representations, and the entire dataset is normalized to ensure uniformity in feature scales. To determine similarity between furniture items, various metrics were explored, including Cosine Similarity, Euclidean Distance, Pearson Correlation Coefficient, Manhattan Distance, and Jaccard Distance.

Cosine Similarity is chosen for its suitability in high-dimensional sparse data, such as binary feature vectors, commonly found in furniture datasets. This metric measures the cosine of the angle between two vectors, focusing solely on the direction rather than the magnitude of the vectors. This property makes Cosine Similarity robust to varying vector lengths and an ideal choice for comparing furniture items based on their features.

$$cosine\ similarity = \frac{a \cdot b}{||a||\ ||b||} \qquad (1.1)$$

The get_content_recommendations function is then implemented, which takes as input the furniture clicked or wishlisted by the user. Using the Cosine Similarity calculated between the user-selected furniture and all items in the database, the function recommends the top N furniture items with the highest similarity scores.

4.1.2 Collaborative Filtering

The dataset includes user demographics collected during sign-in, along with user activity such as wishlisted and added-to-cart items. After preprocessing, which includes one-hot encoding and normalization, the dataset is ready for similarity analysis.

Cosine Similarity is utilized to measure the similarity between users based on their demographic information and activity. Cosine Similarity is well-suited for collaborative filtering, as it captures the similarity between users' preferences and behaviors.

The get_collaborative_recommendations function is then implemented, which takes a user ID as input. It identifies the top 5 users most similar to the input user based on cosine similarity. The function then aggregates the items liked, wishlisted, and added to cart by these similar users into a frequency table. The frequency table is sorted to determine the most occurring furniture items, and the top N items are recommended to the input user.

Denoted as T, each entry Tij represents the count of furniture item j for user i among those top N similar users.

$$T_{ij} = \sum_{k=1}^{N} \quad I_{ijk} \qquad (1.2)$$

4.1.3 Hybrid Recommender

The hybrid recommender module integrates both Content-Based and Collaborative Filtering approaches. The function takes input as the user's wishlist, which consists of furniture items, and the user ID. For each furniture item in the wishlist, the module calls the get_content_recommendations function to retrieve content-based recommendations. Next, the module calls the get_collaborative_recommendations function to obtain collaborative filtering recommendations for the user.

Subsequently, the hybrid recommender calculates a weighted sum for each furniture item in the recommender array. The hybrid score for each item is computed as a weighted sum of its content-based score (CBS) and collaborative score (CFS). The weight distribution for the hybrid score is determined based on trials and findings, considering the sparse nature of the user rating database and the need to leverage user-item interactions effectively. A higher weight of 0.7 is assigned to the collaborative score to accommodate the sparse data, while a lower weight of 0.3 is allocated to the content-based score. This weightage balance optimizes recommendation accuracy while addressing database constraints.

By combining the strengths of both Content-Based and Collaborative Filtering approaches, the hybrid recommender module provides users with personalized and diverse furniture recommendations tailored to their preferences and behavior patterns.

$Combined\ Recommendation = \sum_{i=1}^{n} \quad w_i \cdot R_i$ (1.3)

4.2 Augmented Reality

The system integrates Google AR services to enable users to visualize furniture items in their physical space. Upon selecting a furniture item from the home page, users engage with the Augmented Reality (AR) viewer to virtually place the chosen piece within their environment. The system enhances the user's ability to accurately envision how the furniture will appear and fit within their space. By leveraging AR technology, the system provides users with an immersive and interactive shopping experience, allowing them to make more informed decisions about furniture purchases by visualizing how items will look in their actual living spaces. This feature enhances user engagement and satisfaction, ultimately improving the overall furniture shopping experience.

4.3 Color-based Recommender

The color-based recommender system integrates advanced image processing and color analysis techniques to provide personalized furniture recommendations based on user color preferences. This section outlines the key components and methodologies employed in the system.

4.3.1 Color Quantization using Modified Median Cut Quantization (MMCQ) Algorithm

Color quantization is essential for reducing the color space of input images while preserving visual quality. The Modified Median Cut Quantization (MMCQ) algorithm efficiently partitions the color space into a reduced palette of representative colors. The algorithm follows these steps:

Step 1: Initialize the Histogram: A histogram is created to count the frequency of each color in the input image. The histogram is indexed by color index, calculated using the getColorIndex formula:

$getColorIndex(r, g, b) = (r \ll (2 \times sigbits)) + (g \ll sigbits) + b$ (2.1)

Step 2: Create Initial VBox: The algorithm identifies the minimum and maximum values of the RGB components across all pixels in the image to create the initial VBox (color space box). The volume of each VBox is computed to determine the number of colors it encompasses:

$Volume = (r_2 - r_1 + 1) \times (g_2 - g_1 + 1) \times (b_2 - b_1 + 1)$ (2.2)

Step 3: Splitting the VBox: The algorithm selects the longest dimension of the VBox for splitting and computes partial sum arrays along the selected axis to determine the cut planes.

Step 4: Perform Median Cut: Iteratively, the algorithm finds the best cut plane based on partial sums and lookahead sums. It splits the VBox into two sub-VBoxes along the selected axis using the cut plane.

Step 5: Update Histogram and Repeat: The histogram is updated based on the pixel counts in each sub-VBox, and the splitting process is repeated recursively until the desired number of colors is achieved.

4.3.2 Color Mapping and Nearest Color Calculation

After color quantization, a reduced palette of representative colors is obtained. For each pixel color in the original image, the nearest color in the palette is determined using the Euclidean distance formula. The process involves:

Nearest Color Calculation: The nearest color to each pixel color is found by calculating the Euclidean distance between the pixel color and colors in the palette:

$Nearest\ Color = argmin_{palette\ colors}\sqrt{(r - r_i)^2 + (g - g_i)^2 + (b - b_i)^2}$ (2.3)

Mapping: Each pixel color is mapped to its nearest color in the palette.

4.3.3 Recommending Colors that Complement Existing Colors

The system recommends colors that complement existing colors in the user's space. It employs Euclidean distance calculation and color clustering techniques to determine color similarity and dissimilarity. The process includes:

Euclidean Distance Calculation: The squared Euclidean distance between two colors is calculated using the get_distance function, considering their RGB values:

$$d = \sqrt{(r_2 - r_1)^2 + (g_2 - g_1)^2 + (b_2 - b_1)^2} \qquad (2.4)$$

Color Clustering: Colors are clustered based on their similarity in the RGB color space, utilizing a rule-based approach. Each input color is assigned to its corresponding cluster.

Sorting: The distances between input colors and colors within the same cluster are sorted to find the closest colors. The sorted distances aid in selecting the two closest colors from each cluster, excluding the input color itself.

Overall, the color-based recommender system suggests colors that are visually similar to the user's preferences while ensuring contrast and harmony within the space.

4.4 User Feedback

The system places significant emphasis on actively engaging users to provide ratings for recommended furniture items showcased within the AR scene. These ratings serve as vital feedback mechanisms, playing a pivotal role in refining future recommendations and enhancing the overall user experience.

By encouraging users to share their thoughts and opinions through ratings, the system gathers valuable insights into user preferences and satisfaction levels. This iterative feedback loop enables continual improvement of recommendation accuracy and ensures that the system adapts to evolving user needs effectively.

Furthermore, by leveraging user feedback, This can help fine-tune recommendation algorithms, optimize the selection of furniture items, and tailor suggestions more precisely to individual preferences. Ultimately, this user-centric approach fosters a collaborative environment where users actively contribute to the enhancement of the AR-based furniture shopping application, resulting in a more satisfying and personalized experience for all users.

5 Results

Comparing user satisfaction ratings across different age groups and genders is highly relevant as it provides valuable insights into the diverse preferences, behaviors, and needs of various demographic segments. Understanding how age and gender influence user satisfaction with the recommender system allows us to tailor and optimize the system to better meet the specific requirements of different user groups.

Firstly, age-related factors such as life stage, preferences, and technological proficiency can significantly impact how users interact with and perceive the recommender system. For example, younger users prioritize novelty and trendiness in their recommendations, while older users value practicality and reliability. By analyzing satisfaction ratings across age groups, A pattern was identified and preferences unique to each demographic segment, enabling us to fine-tune our algorithms and recommendations accordingly.

Similarly, gender differences in preferences, tastes, and shopping behaviors can also influence user satisfaction with the recommender system. For instance, studies have shown that males and females often have distinct preferences in product categories, styles, and aesthetics. By comparing satisfaction ratings between genders, the results suggest gender-specific preferences and tailor our recommendations to better align with the interests and expectations of male, female, and other gender-identifying users.

Moreover, understanding how age and gender intersect with other demographic variables, such as income, occupation, and geographic location, can provide deeper insights into user behavior and satisfaction levels. For instance, users from different age groups and genders may have varying levels of disposable income, which can impact their purchasing decisions and satisfaction with recommended products.

By comparing satisfaction ratings across age and gender demographics, to identify potential disparities or areas for improvement in the recommender system. This information enables us to develop targeted strategies to enhance user satisfaction, improve recommendation accuracy, and ultimately drive engagement and loyalty among users from diverse demographic backgrounds. Additionally, it underscores the importance of inclusivity and diversity in the design and optimization of recommender systems to ensure they effectively meet the needs and preferences of all users.

The performance evaluation of our recommender system involved soliciting ratings from users to gauge their satisfaction with the recommendations provided. Each user was asked to rate the system on a scale of 1 to 5, where 1 indicated dissatisfaction and 5 indicated complete satisfaction.

Ratings from a sample of users spanning different demographics, including age groups and genders were gathered. The average rating, x, calculated from these ratings provided a comprehensive measure of user satisfaction with the recommendations generated by the system. Our system achieved an average rating of 4.7, indicating satisfactory results overall.

Upon further analysis, the findings show variations in user satisfaction across different demographic groups. For instance, among gender demographics, male users provided an average rating of 4.5, while female users rated the system slightly higher at 4.8. Users identifying with other genders gave the highest average rating of 5. This disparity suggests potential differences in preferences or experiences influencing satisfaction levels.

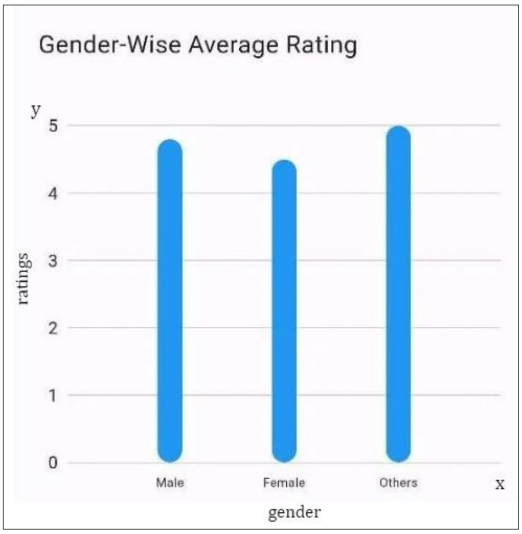

Figure 2 Analysis of User Ratings Based on Gender

Similarly, when considering age demographics, users aged 10 to 30 provided an average rating of 4.2, indicating a relatively high level of satisfaction. Users aged 30 to 60 rated the system even higher, with an average rating of 4.7. However, users aged 60 and above gave a slightly lower average rating of 3.7. These variations highlight the importance of considering age-related factors in tailoring the recommender system to better meet the diverse needs and preferences of different age groups.

Figure 3 Analysis of User Ratings Based on Age

6 Conclusion and Future Scope

In conclusion, the incorporation of color-based recommendation algorithms into the furniture recommender system has demonstrated significant potential, enriching user engagement and fostering personalized decision-making processes. Looking ahead, several avenues for future development present themselves

6.1 Enhanced Augmented Reality (AR) Integration:

Future iterations of the system could focus on refining AR capabilities by integrating features capable of extracting precise dimensions of spaces. By enabling users to accurately visualize how furniture fits into their specific room dimensions, the virtual try-out experience can be significantly enhanced.

6.2 Consideration of Other Room Aspects

There is scope for expanding recommendation algorithms to encompass additional room aspects such as lighting conditions, existing aesthetics, and spatial layout. This holistic approach ensures that recommended furniture pieces not only fit dimensionally but also harmonize with the overall ambiance of the room, enhancing user satisfaction.

6.3 More Enhanced Interior Design Assistance

The system could further enhance interior design assistance by incorporating a broader range of factors into the recommendation process. This includes considering how recommended furniture pieces can optimize room space, altering perceptions of size and luxury based on user preferences and room characteristics. By providing comprehensive interior design guidance, the system can better meet the evolving needs and preferences of users in the realm of furniture shopping and home decor.

Compliance with ethical standards

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Furthermore, our thanks are due to the individuals and organizations that provided inspiration through their innovative advancements in augmented reality, recommendation systems, and user-centric design, which have served as benchmarks for our aspirations.

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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