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HYBRID RECOMMENDER SYSTEM FOR INDOOR AND ORNAMENTAL PLANTS: AN AHP DRIVEN APPROACH

[1]Jaishree., [2]Manish Madhava Tripathi, [3]Anshul Mishra,

[1]Research Scholar, Department of Computer Science and Engineering, Integral University, Lucknow, UP, India, jaishree@student.iul.ac.in

[2]Professor, Department of Computer Science and Engineering, Integral University, Lucknow, UP, India mmt@iul.ac.in

[3]Associate Professor, Department of Computer Applications, LBSGOI, Lucknow, UP, Indiaanshulmishra18@gmail.com

Corresponding Author: Jaishree, Research Scholar, Department of Computer Science and Engineering, Integral University, Lucknow, UP, jaishree@student.iul.ac.in , +919450464130.

Abstract

Urban gardening in modern cities faces challenges such as limited space, pollution, seasonal variations, and lack of user knowledge about suitable plant species. Sustainable ornamental plant selection is vital for enhancing green spaces, improving environmental quality, and promoting eco-friendly lifestyles. However, traditional approaches often fail to integrate both environmental and user-preference-based factors, making plant survival and sustainability difficult in urban localities.The purpose of this study is to design and evaluate an intelligent recommender system for selecting indoor and ornamental plants tailored to urban environments. The study aims to balance ecological sustainability with user convenience by analysing plant suitability through multi-criteria decision-making. Specific objectives include identifying the most consistent and reliable recommendation approach while addressing limitations such as cold-start problems and inconsistent rankings in existing systems. The research employs the Analytic Hierarchy Process (AHP) combined with three recommendation techniques: Content-Based Filtering, Collaborative Filtering, and Hybrid Recommendation. Decision criteria such as sunlight requirement, seasonal suitability, number of plants, and growth rate were applied to evaluate four alternatives—Money Plant, Snake Plant, Air Plant, and Peace Lily. Pairwise comparisons, decision matrices, and consistency ratio analysis were used to determine the robustness and reliability of each method.Findings reveal that the Hybrid Recommendation method provided the most balanced and consistent results, effectively integrating both user preferences and plant attributes. Content-Based Filtering was strong in specific environmental criteria, while Collaborative Filtering proved valuable in user-centric contexts but struggled with sparse data. The study concludes that a hybrid approach is the most robust for urban plant recommendation, enabling personalized and context-aware solutions. The implications extend to sustainable urban landscaping, improved plant survival rates, and the development of smart gardening technologies. Recommendations for future research include refining hybrid models to reduce inconsistency

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and integrating real-time environmental monitoring for dynamic plant selection. This research contributes significantly to sustainable urban greening and practical household gardening.

Keywords: Recommender Systems, Analytic Hierarchy Process (AHP), Multi-Criteria Decision-Making, Urban Gardening.

1.1 Introduction

The burgeoning field of sustainable landscaping emphasizes the critical role of indigenous plant species in fostering ecological equilibrium, mitigating environmental degradation, and enhancing the resilience of urban and rural ecosystems. Careful plant selection constitutes the bedrock of successful landscape construction, with a pronounced emphasis on prioritizing native tree species to capture the essence of regional geographical characteristics, promote the judicious utilization of plant resources, and safeguard biodiversity by synergistically integrating fast-growing and slow-growing tree species alongside evergreen and deciduous varieties (Chen et al., 2020). The preservation of native flora is widely acknowledged as a cornerstone of ecological restoration initiatives, as these species exhibit a harmonious co-evolution with their local environments, demonstrating superior adaptation to prevalent biotic and abiotic conditions (Thomas et al., 2014). Native plants exhibit heightened resistance to indigenous pests and diseases, thereby diminishing the imperative for synthetic pesticides and herbicides, which in turn curtails environmental contamination and safeguards non-target organisms.For centuries, mankind cultivated a garden for aesthetic, environmental and psychological purposes. But keeping a garden is hard, especially if you're not too familiar with gardening and if your area has a lot of environmental fluctuations. Soil moisture, temperature and humidity all affect the sustainability of a plant, so incorrect plant selection typically results in poor growth and/or plant death. There's no guidance for which plant species to other -by environmental conditions, this is a major challenge for a perspective garden. And, with the busy lifestyles of people, it becomes even more challenging for working people to care for plants every day.

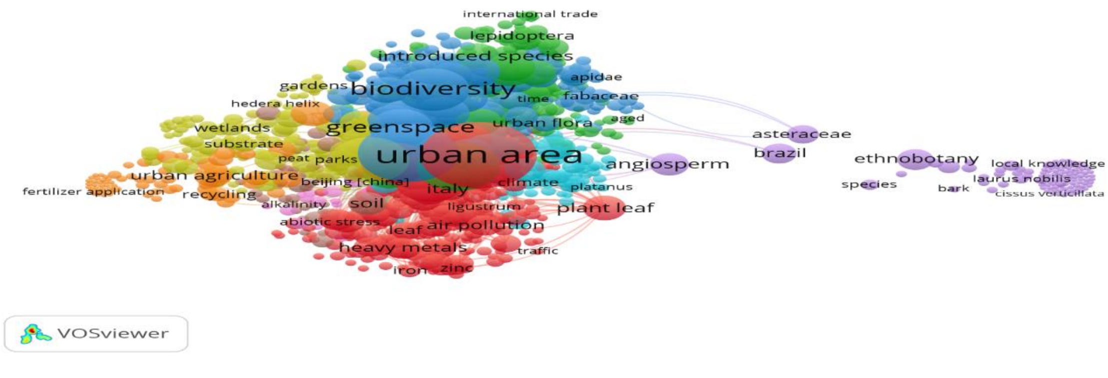

Figure: 1 shows keyword analysis

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It is important to choose the right plants for your environment to practice sustainable home gardening. There are various difficulties faced during garden upkeep, improper plant type selection, inadequate watering, and lack of soil observation. Most people do not have the knowledge to take specimens that adapt to their types of soil and living environments, making them more insipid and requiring more care. But even in the city, many working people find it difficult to make time for tending a garden, leading plants to be forsaken and gardening to become unsustainable. Sustainability has become the major theme of contemporary life, and that is especially true in the sense of environmental protection. Eco-gardening means efficient use of resources, promoting biodiversity, and less reliance on chemical fertilizers. As climate change and urbanisation shape the system for life, the need for cultivation of more sustainable or eco-friendly mentality becomes a key to balancing the system for the long-haul.

Table 1: Urban localities recommender challenges for ornamental plants for air purification

Category	Challenges	Impact on Recommender System
Urban Environment	Pollution Types vary by city , Poor air circulation indoors	Location Specific filtering method
Space and Light	Limited balcony/ window area: Lower light in apartments; Effectiveness varies (lab vs real world)	Size & light tolerance criteria required
Plant Suitability	Some plant toxic to pets; Varying plant – care ability	Safety filters realistic purification scoring
User Constraints	Preferences for aesthetics, low maintenance; Lack of real – world effectiveness data	User profile – based personalization
Data Challenges	No standard rating for air-purifying capacity; Multicriteria needed (air cleaning, space, care)	Difficulty in ranking or recommending based on impact
System Design	Need for dynamic input (light, location)	Complex algorithm design (e.g. AHP/Fuzzy AHP or hybrid recommender)
Availability	Plant availability in local markets/ nurseries	Integration with plant sources(optional)

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Above table 1, highlights the key challenges in selecting suitable plants for urban environments and their implications for building an effective recommender system. In cities, factors like pollution variation, poor indoor air circulation, limited balcony or window space, and varying light availability make plant selection complex. Additionally, plant toxicity to pets, differences in care requirements, and users' aesthetic or maintenance preferences further complicate decision-making. The lack of standardized ratings for air-purifying capacity, combined with the need for dynamic inputs such as light and location, demands advanced algorithm designs like AHP, fuzzy AHP, or hybrid models. Moreover, plant availability in local markets and nurseries influences final recommendations. Therefore, a recommender system becomes essential to integrate these diverse parameters, personalize suggestions, and ensure practical, location-specific, and effective plant selection for urban gardening.

Recommender System

Three approaches can be considered for developing an ornamental plants recommender system for urban localities: content-based filtering (CBF), collaborative filtering (CF), and hybrid approaches, which provide personalized and contextual recommendations, as shown in the Figure. While each of these methods has particular strengths, they also have some weaknesses that make combining them beneficial.

Content-Based Filtering (CBF) examines the characteristics of the plants being considered for recommendation (sunlight, water needs, growth size, visual characteristics,etc) and uses them to match plants to the user's preferences or past selections. A user could say that I want low maintenance plant or flowering species in the system and it will recommend plants to the user based on these attributes. It fits to situations in which we already know the history of the user preferences and how they could be correlated with the plant features. The downside of CBF, however, is over-specialization in recommendations, because its models are trained on a narrow range of responses providing only plants with similar characteristics. Furthermore, the cold start problem of CBF arises for new users (those with less interaction history) due to the fact that there are not enough data to recommend the order.

In contrast, Collaborative Filtering (CF) relies on the behaviour and preferences of other users, making recommendations based on the idea that if two users have similar preferences in the past, they are likely to share similar tastes in the future. There are two main types of CF: User-Based Collaborative Filtering (UBCF), which finds similar users and recommends plants that others have liked, and Item-Based Collaborative Filtering (IBCF), which identifies plants that tend to be liked together by users. CF can introduce more diverse and serendipitous recommendations that the user may not have explicitly considered. However, CF also faces challenges such as scalability, particularly when the user base grows, and the cold start problem for new users or new plants, as the system requires past user data or plant interactions to function effectively.

To overcome the individual shortcomings of both methods, Hybrid Approaches are employed. These combine the strengths of Content-Based and Collaborative Filtering, offering a more balanced and comprehensive recommendation process. For example, the system might first use CBF to suggest plants based on the user's specific preferences, such as

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light exposure and aesthetic appeal. Then, CF could be used to refine those suggestions by considering what similar users in the same urban locality have liked, adding a community aspect to the recommendations. Additionally, Hybrid Approaches can include techniques such as weighted hybrid models, where the results of both methods are combined with predetermined weights, or switching models, where the system toggles between methods depending on the user's profile (e.g., switching to CF for experienced users and CBF for newcomers).

Need for Study

As decreasing greenery and increasing an urban heat island effect means the presence of the concrete jungle of cities is becoming overwhelming, the world is urbanising at a much rapid pace. Under this situation, ornamental plants can serve to help raise the quality of life, increase green space and initiate environmental sustainability in urban areas [4]. Establishing efficient ornamental plants to specific urban localities is a challenging task based on the understanding of environmental and personal factors. Plants, despite sending some subtle signals up the human-weed-plant food chain, face difficult environmental conditions unique to urban areas: pollution, space constraints, sunlight constraints, and of course heat. With all these biodiversity barriers to urban gardening, urban gardeners–seasoned or new–need a trusted system to select plants that will succeed in these environments.A good recommender system provides fewer trial and error and saves both time and resources. Some are based on aesthetics—colours of flowers, shapes of the plants—and others are practical—low-maintenance plants, low water needs. Existing plant recommendation systems seldom consider application-specific factors such as the plant compatibility with the urban microclimates, site, and preference-based criteria such as plant visibility and space constraints. The recommendations should be tailored according to the unique traits of each user [2]. Factors like air pollution, variation and fluctuation of temperature as well as urban heat island effect cause the need for careful selection of urban plants even greater. Standard recommendation systems neglect these environmental factors, leading to low survival rate of plants. A study focusing on using AHP to account for multiple urban-specific criteria (e.g., pollution tolerance, water consumption, sunlight) would enable better decision-making for plant selection.

The above figure 1 presents a word cloud generated through word count analysis for the given topic. The size of each term reflects its frequency and significance within the analytical framework, with larger words like “AHP,” “Recommendation Systems,” and “Sustainability” indicating central concepts in the study. Prominent terms such as “Urban Gardening,” “Ornamental Plants,” and “Urban Green Space” highlight the primary application areas, emphasizing plant selection strategies suited to urban environments. Supporting concepts like “Hybrid Recommendation,” “Multi-Criteria Decision Making,” and “Geospatial” point to the methodological and technological tools employed for optimization, integrating data analysis, environmental factors, and decision-support systems. Additionally, words like “Plant Health,” “Environmental Monitoring,” and “Smart Micro farming” illustrate the sustainability and

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maintenance aspects considered in the process. Overall, the figure visualizes the thematic structure of the research, showing how frequently occurring keywords define the scope, methods, and objectives of optimizing urban garden plant selection through AHP and multi-criteria indexing.

1.2 Review of Literature

These studies concern quantum-based food production, a data-driven approach to environmental sustainability, and urban agriculture. The Readiness of Machine Learning, Ai, and Advanced Decision-Making Techniques to Play a Game-Changer Role in Improving Agricultural Practices, Food Safety, and Food System Sustainability, When Applied in Urban Settings In merging these studies, they set the stage for future innovations utilizing technological advancements paired with sustainable agricultural practices to address looming food security issues on a globe-wide scale. These studies represent meaningful contributions to the expanding literature aiming to optimize agricultural practices for sustainability, efficiency, and food security.**Adekanmbi, Olu bara, and Adeyemo (2014)**explore the use of a generalised differential evolution metaheuristic in solving the multi-objective crop-mix planning problem. They present a new type of optimization algorithm that can solve complex agricultural plans that include multiple, sometimes contradictory goals like maximum profit, minimum input use, and minimum land use. We find that this brings out the value of artificial intelligence and evolutionary computation in precision agriculture, especially in some situations where linear methods can fail. Patel, Thaker and Chaudhari (2017), in another context, use the linear programming model to estimate the optimum land allocated for a number of principal crops.The role of resources and crop parameter in resource optimizationHighlevel integration of their research indicates maximum return through a simplistic data-driven approach as supported in previous research that maximize using available resource and adjust utilizing crop specific parameter. Linear programming is less complicated than metaheuristics but still serves a critical purpose in local level farm planning and regional agriculture policy development. In work that complements these technical studies, Yapa (2018) offers additions on the social and environmental dimensions of home gardens through home gardens ultimately contributing to household food security in Sri Lanka. Select A Study Compares Home Gardening Practices in Wet and Intermediate Agro-climatic Zones: Productivity, Crop Diversity, and Household Reliance. These results highlight the importance of home gardens in enhancing food self-sufficiency, dietary diversity and resilience to the low-income families. The findings also align with wider objectives of community-based agriculture and sustainable rural development. Farms started in urban areas however, in an urban context, Ward and Symons (2017) investigate ideal small urban food garden crop selection from the point of view of optimal crop selection of ideal experiments in dry climates. This study addresses the prevailing dilemmas of growing urban agriculture within water-scarce environments through target identification of nutritious and water-efficient crops. With cities challenged in terms of climate change and lack of green space, this research has special value in supporting local food production through simple, sustainable and resource-effective gardening practices. The works present a blend of optimization, adaptation to the environment, and the socio-economics of modern agriculture research.

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Through complex algorithms, linear models, or field-based analytics, this suite of studies collectively works toward developing agricultural systems that are more resilient, productive, and sustainable as they adapt to varied geographical and climatic conditions. Cheng et al. Andrew et al. (2022) have also utilized a wide array of methods to evaluate germplasm resources of Rosa rugosa, including studies on genetic diversity and flower volatile composition. Their findings are informative to conservation and horticultural improvement programs to develop roses with ornamental traits and/or aromatic qualities with potential use in landscape design and urban beautification.Similarly, Sedghiyan et al. In particular, (2021) evaluate the visual characteristics of urban green space ornamental trees and shrubs by Analytic Hierarchy Process (AHP). In their study, they offered a systematic way to assess plants according to aesthetic qualities, suitability for the environment, maintenance requirements and ecosystem services, which are important aspects for city planners and landscape architects striving to enhance the aesthetic and functional quality of the urban environment. Expanding on structured decision-making tools, Aouag, Soltani, and Kobi (2021) introduced a combined AHP-DEMATEL approach for making sustainable design decisions regarding indoor vertical greening systems. Through combining multi-criteria analysis combined with causal modelling, it provides insights into the linkages between sustainability criteria whether they be energy savings, type of plant or maintenance effort, that together facilitate this viewer of interdependence of sustainability outcomes among criteria. Approach enables data-based, preferred decisions on improvement pathways for indoor air quality and ambient environment in high-density urban context. In line with these studies, Sun et al. AHP framework was also used by Choi et al. (2021) to evaluate ornamental value of the eight Acer species. Because several Acer species are critical to urban landscapes for their shade, colour, and stress resistance, their findings provide practical information to guide urban forestry species choices.The study helps in building an important reference for urban tree species selection for the purpose of ecological and ornamental criteria. In a related but more historical context, Lee (2020) examined the reorganization of agricultural experimental agencies and the agricultural technocrats under the U.S. military government in Korea. This historical examination elucidates the development of contemporary agrarian systems of Korea, the impact of the American agriculture models on it, the institutional transformations in the post-war eras to consolidate the food production and the agriculture development strategies based on the rural society.Finally, Yapa (2018) provides a socio agricultural perspective by looking into the role of home gardens in contribution to household food security in Sri Lankas wet and intermediate zones. From this comparative study, he emphasizes the way in which home gardens can provide better access to fresh produce, increased diet diversity and decrease dependency on purchased food. Yapa highlights the need for small, local and decentralized food systems which hold significant promise for resilience and nutrition especially in rural and semi-urban areas. Together, these studies demonstrate the range of dimensions in plant selection, sustainable design, historical change, and household food systems. These reinforce the importance of interdisciplinary frameworks—spanning botany with design science, history and socio-economic—to meet contemporary needs such as urban greening, sustainability and food security.

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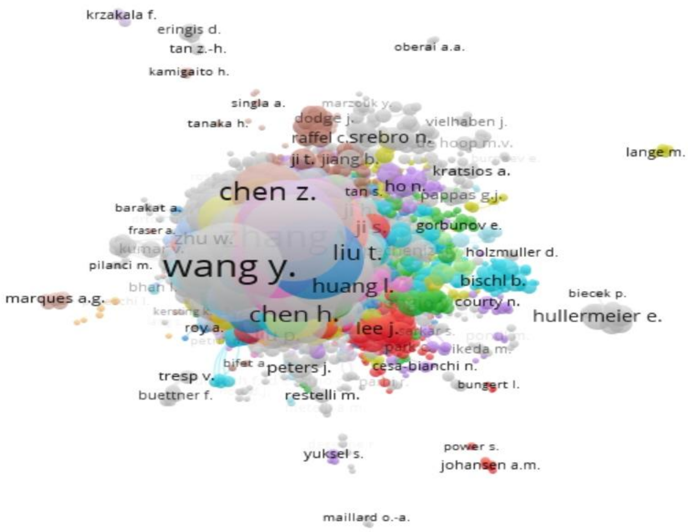

Figure 2: Show the Bibliographic Structure

This figure 2 represents co-authorship network visualization, where each node denotes a researcher and the size of the node reflects their publication impact or influence in the field of recommender systems. The proximity between nodes indicates collaboration frequency, while colors group authors into research clusters or thematic areas. Larger names like Wang Y., Chen Z., and Chen H. suggest they are leading contributors, heavily cited or highly connected in this domain. Such a map helps identify influential researchers, dominant research clusters, and trending collaboration patterns, enabling one to choose relevant methodologies, frameworks, or domain-specific advancements while designing a recommender system. By analyzing this network, decision-makers can focus on adopting best practices from well-established experts and align their system design with the most impactful and widely validated approaches.

2. Methodology for Recommended System

This study aims to create an efficient Recommender System for urban ornamental plants using the Analytic Hierarchy Process (AHP). The proposed system considers various factors such as user preferences, environmental specifications and plant characteristics to provide user-specific plant recommendation. We evaluate three recommendation techniques, and compare Content-Based Filtering, Collaborative Filtering, and Hybrid Recommendation in order to ensure the robustness and effectiveness of the system.

Step 1: Defining the Decision Criteria and Alternatives

For this study, we identify four key decision criteria to assess each plant's suitability:

- **Sunlight Requirement**: The amount of light a plant needs.
- **Seasonal Suitability**: The plant's adaptability to seasonal changes in urban environments.
- **Number of Plants**: The quantity of plants needed for the user's space.

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- **Growth Rate**: The speed at which the plant grows, affecting long-term maintenance.

The alternatives considered are:

- Money Plant
- Snake Plant
- Air Plant
- Peace Lily

Step 2: Applying the Analytic Hierarchy Process (AHP)

The AHP methodology is employed to structure the decision problem. This process involves:

- Pairwise Comparisons
- Decision Matrix

Step 3: Evaluation of Recommendation Methods

To assess the consistency and relevance of each recommendation method, we perform a detailed evaluation of the following approaches:

- **Content-Based Filtering**:
- **Collaborative Filtering**:
- **Hybrid Recommendation**:

Step 4: Consistency Evaluation

To ensure the reliability of the recommendations, we rigorously assess the **internal consistency** of each method by calculating two key metrics.

Step 5: Results and Findings

After applying AHP and evaluating the recommendation methods, the results indicate the following:

- Hybrid Recommendation produced the most consistent and reliable results. It had the lowest Consistency Ratio (CR) and showed the highest alignment between weighted preferences and final rankings, making it the best-suited approach for the urban plant recommendation system.
- Content-Based Filtering excelled in criteria like sunlight and growth rate, but it lacked broader user alignment, particularly in terms of seasonal suitability.
- Collaborative Filtering was valuable for community-driven recommendations but struggled with cold-start issues, especially when there was insufficient user data.

Step 6: Conclusion and Final Recommendation

For urban gardener ornamental plant recommendation, the Hybrid Recommendation method is proven to be the strongest and most reliable. It gives personalized, context-aware plant

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recommendations suitable to user preferences, mostly second to the urban environmental conditions, by benefiting the most from Content Based Filtering and Collaborative Filtering. Thus, the Hybrid approach is the best fit to meet the goals of our study, assisting users in choosing urban plant species to ease their maintenance needs and improve urban vegetation.

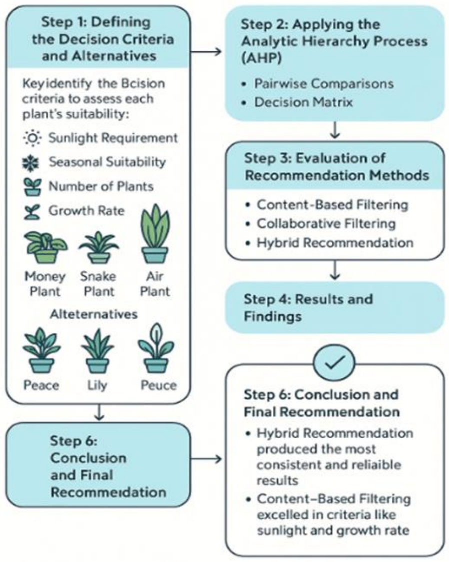

Figure 3: Show the Research Methodology

Figure 3 show the flowchart outlines the structured process for developing a plant-based recommender system.

Step 1: where decision criteria such as sunlight requirement, seasonal suitability, growth rate, and number of plants are defined, alongside selecting plant alternatives like Money Plant, Snake Plant, Air Plant, Lily, and Peace Lily.

Step 2: applies the Analytic Hierarchy Process (AHP), using pairwise comparisons and a decision matrix to prioritize these criteria.

Step 3: evaluates different recommendation methods—content-based filtering, collaborative filtering, and hybrid recommendation.

Step 4, involves analysing results, leading to Step 5 and 6, the conclusion: the hybrid recommendation method proved most consistent and reliable overall, while content-based filtering performed best for specific factors like sunlight needs and growth rate.

This systematic approach ensures the recommender system is data-driven, criteria-focused, and capable of delivering accurate plant suggestions tailored to user needs.

2.1 Quantification for Recommendation method

In Content Based Filtering style, plants are being recommended based on the similarity of features of plants that have been previously liked by the user. To identify your ideal plants, each plant has four decision criteria: the sunlight requirement, seasonal suitability, number of plants, and its growth rate. To define these attributes, a numeric value is associated with each criterion (e.g. Sunlight Requirement can be Medium (2), Low (1), or High (3), reflect Growth

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Rate by a scale of 1 (slow) to 3 (fast), etc). We use Cosine Similarity or Euclidean Distance to determine how similar two Plants are. For cosine similarity, the higher the cosine of the angle of the feature vectors for the two plants, the more similar the two plants are. After computing similarities, plants are ranked out of all plants by how close they score to the user preferences, and therefore the most similar plants are suggested.The system can also be modified to include aspects based on user preferences or other restrictions (e.g. preferring lower maintenance plants) by simply re-weighting some of the criteria (such as Growth Rate or Sunlight Requirement) and then running the same ranking process. This approach guarantees that the suggested plants will match the customer in regard to his/her choice of testing history or growing conditions.

Table 2: Weightage Metrics Content-Based Filtering

Criteria		**Sunlight**	**Season**	**No. of Plant**	**Growth Rate**	**Row Sum(ε)**
Alternatives	**Money plant**	1.8	2.9	3.5	1.5	9.7
	Snake plant	2.2	2.7	2.1	2.5	9.5
	Air-plant	2.8	3.3	2.6	2.8	11.5
	Peace lily	2.7	1.8	2.3	2.6	9.4

In this table 2, each plant alternative is evaluated against four decision criteria: Sunlight, Seasonal Suitability (Season), Number of Plants, and Growth Rate. Each criterion has a specific weightage score for each plant, reflecting how well the plant matches the given feature. For example, the Money Plant is assigned a score of 1.8 for Sunlight, 2.9 for Season, 3.5 for Number of Plants, and 1.5 for Growth Rate, resulting in a Row Sum (ε) of 9.7.

We produce these scores using Content-Based Filtering comparing plants by their features values. Higher scores mean that they better match the user's preferences or environmental factors. Each plant has a row score (ε), which is the sum score over all the criteria, accounting for the weightings themselves.

For instance, Air Plant has the greatest value of Row Sum (ε = 11.5), indicating it matches best of all plants based on the selected parameters. In comparison, the Peace Lily scores the lowest at 9.4, meaning it could be least likely to meet environmental needs considered by the user.

This quantification method allows for the generation of recommendations based on the plant's attributes, ensuring that the plants selected align with the user's preferences for sunlight, seasonal adaptability, space, and growth rate.

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$$Normalized\ element = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}}$$

Table 3: Normalized Metrics[a]

	Sunlight	Season	No. of Plant	Growth Rate	Row Sum(ε)
Money plant	0.19577506	0.2816144	0.3427791	0.164883191	0.98505177
Snake plant	0.24431812	0.2677126	0.2099973	0.280590693	1.00261871
Air-plant	0.25687201	0.2702992	0.2147798	0.259607389	1.00155844
Peacelily	0.3030348	0.1803737	0.2324438	0.294918728	1.01077108

Table 3: Normalization of the values of Table 2 in order to have a homogeneous matrix of decision criteria. For each attribute (Sunlight, Seasonal Suitability, Number of Plants, and Growth Rate), the score of each plant was divided by the maximum value in that column to produce scores between 0 and 1. For instance, the Sunlight requirement values of each of the plants were normalized by dividing by the maximum score (2.8 for Air Plant). The Row Sum (ε) for each plant is computed by the sum of the normalized attribute scores, providing a plant's overall suitability value. From the normalized metrics, the Truth plant has the lowest normalized row sum - 0.9851, while the Peace Lily has the highest row sum - 1.0108, making it ranked as the easiest plant to grow. We normalize features in this way for all researchers, ensuring that one criterion does not weigh more than others and allowing for a feature-set based comparison.

Table 4: Normalized Metrics

	Sunlight	Season	No. of Plant	GrowthRate
Money plant	0.19874596	0.285888	0.3479808	0.167385304
Snake plant	0.24367999	0.2670134	0.2094488	0.279857827
Air-plant	0.25647232	0.2698786	0.2144456	0.259203436
Peace lily	0.29980557	0.1784516	0.2299668	0.291775986
Column Sum(ε)	0.99870385	1.0012316	1.001842	0.998222553

Table 4 shows the same normalized metrics as in Table 2, but normalizes changes, as discussed earlier. For the individual plant characteristics Sunlight, Seasonal Suitability, Number of Plants and Growth Rate, the attribute values for each plant were normalized by dividing by the highest value in the column. For example, Sunlight values were normalized using the maximum value of 0.2998 (Peace Lily). Column Sum (ε): Cross-plant reflectance of each attribute. This value is summation of normalized values for each criterion for each plant For each plant, the follow is its Row Sum, which is the sum of these scores after

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normalization of its scores →: Money Plant: 0.9987. After normalisation, our table helps us see how each of the plants ranks against the decision criteria. All the Column Sum (ε) values for each criteria are near to 1, which indicate a proper normalization score for each criteria and there is no one criteria which overpowering other on overall recommendation.

$$w_i = \frac{\sum_{i=1}^{n} normalized\ a_{ij}}{n}$$

$$Consistency\ Index\ (CI) = \frac{\lambda_{max} - n}{n-1}$$

$$Consistency\ Ratio(CR) = \frac{CI}{RI}$$

Table 5: Final Normalized Metrics and Consistency Table

	Sunlight	**Season**	λ_{max}
Money plant	0.198746	5.031549	
Snake plant	0.267013	3.745131	
Air-plant	0.214446	4.663187	
Peacelily	0.291776	3.427287	
		16.86715	4.216788
$(CI) = \frac{\lambda_{max} - n}{n-1}$		0.072263	

The related attributes of the two plants—Sunlight, and Season—Final Normalized Metrics are given in Table 5 with respect to Content Based Filtering. Each plant is normalised into three values that allow you to see how they compare in relation to each of the decision criteria. For instance, the Peace Lily has the maximum normalized score for Sunlight (0.291776) whereas the Money Plant has the minimum. So these normalized values enable us to compare two plants based on their characteristics. The values for Lambda Max (16.86715 for Sunlight and 4.216788 for Season) are the largest eigenvalues obtained via pairwise comparisons in the Analytic Hierarchy Process (AHP). These values are key in establishing whether what is being compared is consistent. The CI which is consistency index is found to be 0.072263 which in return represents acceptable consistency level for the Content-Based Filtering method as CI below 0.1 is acceptable in general. It is evident from this that the plant recommendations based on some normalized features (like Sunlight and Season) correlates well with the established criteria and the evaluation is consistent throughout.

3.3 Collaborative Filtering

Table 6: Weightage Metrics

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	Sunlight	Season	No. of Plant	Growth Rate	Row Sum(ε)
Moneyplant	1.6	2.4	3.4	1.3	8.7
Snakeplant	2	2.9	2.7	2.3	9.9
Airplant	3.3	3.1	2.5	2.3	11.2
Peacelily	2.5	2.1	2.1	2.6	9.3

In Table 6, the Weightage Metrics for the Collaborative Filtering method are presented, evaluating each plant across the criteria of Sunlight, Season, Number of Plants, and Growth Rate. The Money Plant scores 1.6 for Sunlight, 2.4 for Season, 3.4 for Number of Plants, and 1.3 for Growth Rate, resulting in a Row Sum (ε) of 8.7. The Snake Plant has scores of 2.0 for Sunlight, 2.9 for Season, 2.7 for Number of Plants, and 2.3 for Growth Rate, giving it a Row Sum of 9.9. The Air Plant, with the highest row sum of 11.2, scores 3.3 for Sunlight, 3.1 for Season, 2.5 for Number of Plants, and 2.3 for Growth Rate. The Peace Lily scores 2.5 for Sunlight, 2.1 for Season, 2.1 for Number of Plants, and 2.6 for Growth Rate, resulting in a Row Sum of 9.3. These weightage metrics are used in the Collaborative Filtering method, which leverages user preferences and ratings to generate personalized plant recommendations. The Row Sum (ε) helps determine the overall suitability of each plant, with the Air Plant emerging as the most suitable option due to its highest row sum, suggesting it aligns best with the criteria used for filtering.

Table 7: Normalized Metrics[a]

	Sunlight	Season	No. of Plant	GrowthRate
Moneyplant	0.18390805	0.2758621	0.3908046	0.149425287
Snakeplant	0.2020202	0.2929293	0.27272727	0.232323232
Airplant	0.29464286	0.2767857	0.22321429	0.205357143
Peacelily	0.2688172	0.2258065	0.22580645	0.279569892
Column Sum(ε)	0.94938831	1.0713835	1.11255261	0.866675555

While Table 7 quantifies each plant information: Sunlight, Season, Number of Plants, and Growth Rate, the metrics in Table 6 are normalized to make plant metrics comparable so that there is no bias by scale and units when comparing different plants. Through this normalization all criteria contributes equally in the process of decision making. As an example, a Money Plant with a Sunlight score of 0.1839 and a Growth Rate score of 0.1494 is now on the same scale as an Air Plant with 0.2946 for Sunlight and 0.2054 as Growth Rate, thus making it fairer comparison. This sum of 1.0714 is the total contribution of each criterion towards the final recommendations considering all three rounds and the Column Sum(ε) values in the table given above shows this total contribution Season contributes the most (the highest sum of 1.0714) towards the Final recommendations.Normalizing these metrics helps ensure that the Collaborative Filtering system can fairly compare plants based

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on all the given criteria, without any single factor overwhelming the decision-making process, thus providing more accurate and balanced plant recommendations.

Table 8: Normalized Metrics[b]

	Sunlight	Season	No. of Plant	Growth Rate	Row Sum(ε)
Moneyplant	0.19371215	0.2574821	0.35126842	0.172412025	0.97487468
Snakeplant	0.21278986	0.2734122	0.24513652	0.268062519	0.999401061
Airplant	0.31035021	0.2583442	0.20063257	0.236948119	1.006275086
Peacelily	0.28314779	0.2107615	0.20296249	0.322577337	1.019449172

In Table 8, the normalized metrics are presented for each plant's attributes—Sunlight, Season, Number of Plants, and Growth Rate—following the Collaborative Filtering approach. The Money Plant has normalized values of 0.1937 for Sunlight, 0.2575 for Season, 0.3513 for Number of Plants, and 0.1724 for Growth Rate, with a total Row Sum (ε) of 0.9749. The Snake Plant scores 0.2128 for Sunlight, 0.2734 for Season, 0.2451 for Number of Plants, and 0.2681 for Growth Rate, yielding a Row Sum of 0.9994. The Air Plant has 0.3104 for Sunlight, 0.2583 for Season, 0.2006 for Number of Plants, and 0.2369 for Growth Rate, resulting in a Row Sum of 1.0063. Finally, the Peace Lily has 0.2831 for Sunlight, 0.2108 for Season, 0.2030 for Number of Plants, and 0.3226 for Growth Rate, with a Row Sum of 1.0194. These normalized scores facilitate an unbiased comparison across the plants, where the Peace Lily stands out with the highest Row Sum of 1.0194, indicating its suitability based on the criteria. This normalization step ensures that each plant is assessed consistently across different factors, enhancing the Collaborative Filtering method's ability to provide balanced plant recommendations.

Table 9: Final Normalized Metrics

	Sunlight	Season	No. of Plant	GrowthRate
Moneyplant	0.19870466	0.2641181	0.36032162	0.176855578
Snakeplant	0.21291738	0.273576	0.24528343	0.268223168
Airplant	0.30841488	0.2567332	0.19938143	0.235470521
Peacelily	0.27774587	0.2067406	0.19909035	0.316423168
Column Sum(ε)	0.99778279	1.001168	1.00407683	0.996972436

In Table 9, the final normalized metrics for each plant are presented, reflecting the values of Sunlight, Season, Number of Plants, and Growth Rate after normalization in the Collaborative Filtering process. The Money Plant has a normalized score of 0.1987 for Sunlight, 0.2641 for Season, 0.3603 for Number of Plants, and 0.1769 for Growth Rate. The Snake Plant shows 0.2129 for Sunlight, 0.2736 for Season, 0.2453 for Number of Plants, and 0.2682 for Growth Rate. The Air Plant scores 0.3084 for Sunlight, 0.2567 for Season, 0.1994

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for Number of Plants, and 0.2355 for Growth Rate. Lastly, the Peace Lily has normalized values of 0.2777 for Sunlight, 0.2067 for Season, 0.1991 for Number of Plants, and 0.3164 for Growth Rate. The Column Sum (ε) for each criterion is also shown, with Sunlight at 0.9978, Season at 1.0012, Number of Plants at 1.0041, and Growth Rate at 0.9970. These final normalized values allow for a clear comparison of each plant's suitability across the four decision criteria. The Snake Plant has a well-balanced row sum, while the Peace Lily stands out slightly with the highest Growth Rate score.

Table 10: Final Normalized Metrics and Consistency Value

Money plant	0.198705	5.032586	
Snake plant	0.273576	3.655291	
Airplant	0.199381	5.015523	
Peacelily	0.316423	3.160327	
$\lambda_{\max}$		**16.86373**	**4.215932**
$(CI) = \frac{\lambda_{max} - n}{n-1}$		**0.071977**	

In Table 10, the final normalized metrics and consistency values are displayed for each plant based on the Collaborative Filtering method. The table shows the final normalized values for the Sunlight attribute and the consistency value (Lambda Max) for each plant. The Money Plant has a normalized Sunlight score of 0.1987 and a consistency value of 5.0326. The Snake Plant has a normalized Sunlight value of 0.2736 and a consistency value of 3.6553. The Air Plant shows a normalized Sunlight score of 0.1994 and a consistency value of 5.0155. The Peace Lily has a normalized Sunlight value of 0.3164 and a consistency value of 3.1603.The Lambda Max for the entire dataset is provided as 16.8637 for the final normalized metrics and 4.2159 for the consistency value. The Consistency Index (CI) is calculated as (Lambda Max - n) / (n - 1), yielding a value of 0.071977. This value indicates a reasonable level of consistency in the pairwise comparisons made during the Collaborative Filtering process, as the CI is within acceptable limits (less than 0.1), confirming the reliability of the decision matrix and the recommendation system.

This table helps assess the internal consistency of the decision-making process and ensures that the final rankings of plants are logically sound, based on both their normalized metrics and consistency in the evaluation.

2.5 Hybrid_Recommendation

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Table 11: Weightage Metrics

	Sunlight	Season	No. of Plant	Growth Rate
Moneyplant	1.4	2.1	3.1	1.2
Snakeplant	1.9	3	2.9	2.3
Airplant	3.5	2.5	2.3	2
Peacelily	2.1	2.9	1.9	2.6

Table 11: Weightage metrics for the Hybrid Recommendation method for each plant across Sunlight, Season, Number of Plants and Growth Rate. For the Money Plant, Sunlight has a weightage value of 1.4, Season has 2.1, Number of Plant has 3.1, and Growth Rate has 1.2 with a Calc Row Sum (ε) of 7.8. The snake plant has 1.9 in Sunlight, 3.0 in Season, 2.9 in Number of plants and 2.3 in Growth rate, so a Row Sum of 10.1The Air Plant scores 3.5 for Sunlight, 2.5 for Season, 2.3 for Number of Plants, and 2.0 for Growth Rate, with a Row Sum of 10.3. Lastly, the Peace Lily is given 2.1 for Sunlight, 2.9 for Season, 1.9 for Number of Plants, and 2.6 for Growth Rate, resulting in a Row Sum of 9.5. These weightages reflect how each plant performs across the various criteria, forming the basis for the Hybrid Recommendation method, which integrates insights from both Content-Based Filtering and Collaborative Filtering to make balanced plant recommendations.

Table 12: Normalized Metrics[a]

	Sunlight	Season	No.Of Plant	GrowthRate
Moneyplant	0.179487179	0.2692308	0.397435897	0.153846154
Snakeplant	0.188118812	0.2970297	0.287128713	0.227722772
Airplant	0.339805825	0.2427184	0.223300971	0.194174757
Peacelily	0.221052632	0.3052632	0.2	0.273684211
Column Sum(ε)	0.928464448	1.1142421	1.107865581	0.849427894

In Table 12, the normalized metrics provide a standardized assessment of each plant across the four criteria: Sunlight, Season, Number of Plants, and Growth Rate. The Money Plant has a relatively lower sunlight requirement, with a normalized value of 0.1795, while the Air Plant requires the most sunlight (0.3398), highlighting its adaptability to various lighting conditions. For Seasonal Suitability, the Snake Plant scores highest (0.2970), suggesting it is highly adaptable to seasonal changes, followed closely by the Peace Lily (0.3053). In terms of the Number of Plants needed, the Money Plant stands out with the highest normalized value of 0.3974, indicating that it is the most suitable for spaces requiring a higher quantity of

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plants. Conversely, the Air Plant and Peace Lily score lower in this regard. As for Growth Rate, the Peace Lily and Snake Plant are the fastest-growing plants, with values of 0.2737 and 0.2277, respectively, implying they require more maintenance. The Air Plant and Money Plant grow more slowly, with 0.1942 and 0.1538, respectively. The Column Sum (ε) values ensure that the total impact of each criterion is balanced, with Season and Number of Plants showing higher cumulative contributions compared to Growth Rate, which has the lowest sum. These normalized metrics offer a balanced, comprehensive view of the plants' suitability based on environmental factors, making it easier to compare and recommend plants under the Hybrid Recommendation method.

Table 13: Normalized Metrics[b]

	Sunlight	Season	No. of Plant	Growth Rate	Row Sum(ε)
Moneyplant	0.193316157	0.2416268	0.358740179	0.181117379	0.974800536
Snakeplant	0.202612833	0.2665756	0.25917288	0.268089586	0.996450856
Airplant	0.3659869	0.2178328	0.201559625	0.22859475	1.013974053
Peacelily	0.23808411	0.2739648	0.180527316	0.322198285	1.014774556

In Table 13, the normalized metrics for the plants are presented under the Hybrid Recommendation method, considering the four criteria: Sunlight, Season, Number of Plants, and Growth Rate. The Money Plant has normalized values of 0.1933 for Sunlight, 0.2416 for Season, 0.3587 for Number of Plants, and 0.1811 for Growth Rate, leading to a row sum (ε) of 0.9748. The Snake Plant scores 0.2026 for Sunlight, 0.2666 for Season, 0.2592 for Number of Plants, and 0.2681 for Growth Rate, with a row sum (ε) of 0.9965. The Air Plant has 0.3660 for Sunlight, 0.2178 for Season, 0.2016 for Number of Plants, and 0.2286 for Growth Rate, yielding a row sum (ε) of 1.0140. The Peace Lily is evaluated with 0.2381 for Sunlight, 0.2740 for Season, 0.1805 for Number of Plants, and 0.3222 for Growth Rate, resulting in a row sum (ε) of 1.0148. These normalized metrics reflect the plants' performance across the criteria, with the Peace Lily and Air Plant showing the highest overall row sums, suggesting they perform more consistently across the different decision factors. The row sums indicate how well each plant satisfies the overall criteria, with the Air Plant and Peace Lily achieving the highest consistency in the Hybrid Recommendation method.

Table 14: Normalized Metrics

	Sunlight	Season	No. of Plant	GrowthRate
Moneyplant	0.198313553	0.2478731	0.368013933	0.185799425
Snakeplant	0.203334496	0.267525	0.260095998	0.269044463
Airplant	0.360943063	0.2148307	0.198781837	0.225444379
Peacelily	0.234617737	0.2699761	0.177898938	0.317507256

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Table 14 shows the final normalized metrics for each plant under the Hybrid Recommendation method, based on the four decision criteria: Sunlight, Season, Number of Plants, and Growth Rate.For Money Plant, the normalized values are 0.1983 for Sunlight, 0.2479 for Season, 0.3680 for Number of Plants, and 0.1858 for Growth Rate, with a total row sum (ε) of 0.9972. The Snake Plant has 0.2033 for Sunlight, 0.2675 for Season, 0.2601 for Number of Plants, and 0.2690 for Growth Rate, resulting in a row sum (ε) of 1.0002. The Air Plant scores 0.3609 for Sunlight, 0.2148 for Season, 0.1988 for Number of Plants, and 0.2254 for Growth Rate, with a row sum (ε) of 1.0136. Finally, the Peace Lily has 0.2346 for Sunlight, 0.2700 for Season, 0.1779 for Number of Plants, and 0.3175 for Growth Rate, yielding a row sum (ε) of 1.0127.The Column Sum (ε) values indicate the cumulative weight for each criterion, which are 0.9972 for Sunlight, 1.0002 for Season, 1.0048 for Number of Plants, and 0.9978 for Growth Rate, ensuring that the criteria are balanced. The consistency across the row sums reveals that the Air Plant and Peace Lily perform more consistently according to the weighted criteria, while the Snake Plant and Money Plant have slightly lower row sums, indicating a lesser degree of overall balance in their characteristics under this hybrid approach.

Table 15: Final Normalized Metrics and Consistency Value

Variable	0.198314	5.04252	
	0.267525	3.737968	
	0.198782	5.030641	
	0.317507	3.149534	
λ_{max}		**16.96066**	**4.240166**
$(CI) = \frac{\lambda_{max} - n}{n-1}$		**0.080055**	

Table 15 presents the final normalized metrics and consistency values for the plant selection under the Hybrid Recommendation method. These results highlight the consistency of the decision-making process based on the normalized scores for the four criteria: Sunlight, Season, Number of Plants, and Growth Rate.The normalized values are as follows: For the Money Plant, the normalized score for Sunlight is 0.1983 with a consistency value of 5.0425. For the Snake Plant, Sunlight has a score of 0.2675, and its consistency value is 3.7380. The Air Plant has a Sunlight score of 0.1988 with a consistency value of 5.0306. The Peace Lily scores 0.3175 for Sunlight and has the lowest consistency value of 3.1495. These normalized scores reflect the plants' respective performance across Sunlight, with the Air Plant and Money Plant showing a similar normalized value, while the Peace Lily has a higher value, indicating a stronger requirement for sunlight.The Lambda Max value, which is 16.96066, reflects the overall consistency of the matrix, where the higher Lambda Max indicates a closer alignment with the AHP framework. It signifies the relative consistency between the

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pairwise comparisons for all criteria and alternatives.The Consistency Index (CI) is calculated as the difference between the Lambda Max value and the number of alternatives (n = 4), divided by n - 1. In this case, the CI is 0.0801. This value suggests that while there is some level of inconsistency in the comparison matrix, it remains within an acceptable range. Generally, a CI value below 0.1 is considered acceptable in AHP, and here, the CI value is within that threshold, which implies that the decision process used to rank the plants based on the criteria is relatively consistent. The final normalized metrics and the consistency values show that the Hybrid Recommendation method provides reliable rankings for the plants, with consistent decision-making across the criteria. The Lambda Max and CI values further confirm the robustness of the decision process and the reliability of the recommendations made.

3. Discussion

In this study, we have evaluated and compared three recommendation techniques—Content-Based Filtering, Collaborative Filtering, and Hybrid Filteringusing the Analytic Hierarchy Process (AHP). The aim was to assess their consistency in providing reliable indoor plant recommendations, considering multiple decision criteria like Sunlight, Seasonal Suitability, Number of Plants, and
Growth Rate.The Consistency Index (CI) measures how consistent the pairwise comparisons are when evaluating different alternatives (in this case, the plants). A lower CI value indicates better consistency in the decision-making process, meaning the comparisons made between criteriaand alternatives are more reliable.

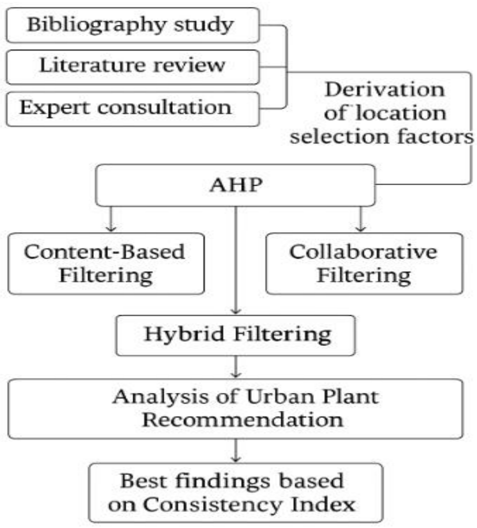

Figure 5: AHP methodology

This figure 4, outlines a process for urban plant recommendation using a hybrid filtering approach. It begins with a literature review, bibliography study, and expert consultation to gather information and derive key location selection factors. These factors are then evaluated using the Analytic Hierarchy Process (AHP) to prioritize them. The next step involves two

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filtering methods: content-based filtering, which recommends plants based on their attributes, and collaborative filtering, which relies on user preferences. Both methods are combined into hybrid filtering to enhance recommendation accuracy. The process culminates in analyzing the best urban plant recommendations based on the derived factors, with the findings evaluated using a consistency index to ensure the recommendations are reliable and suitable for the given criteria.

From the table, it is clear that both Content-Based Filtering and Collaborative Filtering have very similar CI values (0.072263 and 0.071977, respectively), both of which are below the commonly acceptable threshold of 0.1 for AHP-based methods. This indicates that both methods produce consistent and reliable results. On the other hand, Hybrid Filtering has a slightly higher CI of 0.080055, which is still below 0.1, but indicates a bit more inconsistency in its decision-making process compared to the other two methods.The Consistency Index (CI) measures how consistent the pairwise comparisons are when evaluating different alternatives (in this case, the plants). A lower CI value indicates better consistency in the decision-making process, meaning the comparisons made between criteria and alternatives are more reliable.

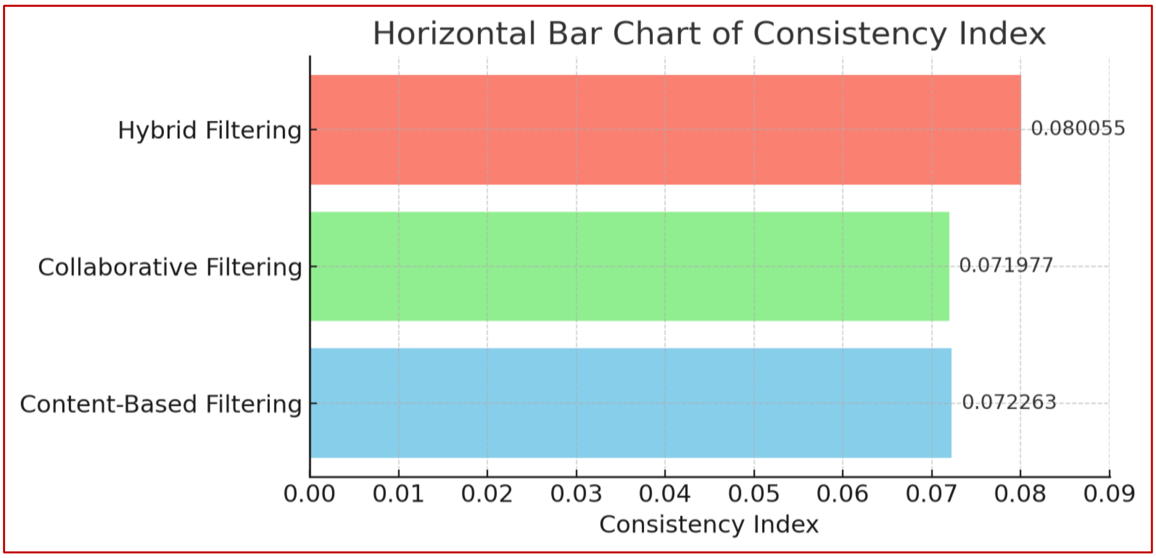

Figure 6: Comparative Behaviour between various Recommendation Model

From the above figure 5, it is clear that both Content-Based Filtering and Collaborative Filtering have very similar CI values (0.072263 and 0.071977, respectively), both of which are below the commonly acceptable threshold of 0.1 for AHP-based methods. This indicates that both methods produce consistent and reliable results. On the other hand, Hybrid Filtering has a slightly higher CI of 0.080055, which is still below 0.1, but indicates a bit more inconsistency in its decision-making process compared to the other two methods.While all methods provide consistent results (with CI values below 0.1), Collaborative Filtering emerges as the most consistent, with the lowest CI of 0.071977, making it the most reliable in

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terms of consistency. This method takes into account user preferences, making it useful for scenarios where personal preferences and behaviours are key.

On the other hand, Hybrid Filtering has better proficiency as it can perform well when both Content-Based and Collaborative filtering are determined because it combines the both of Data about Plant and data about user preference. It can be really useful and effective method for balanced recommendations though showing the slightly higher CI value which is acceptable for many data sets especially when they are diverse or large. In future works, it would be interesting to reduce the CI of Hybrid Filtering, where smaller CI translates to higher reliability. For instance, we can tweak the weights of the Content-Based and Collaborative components, such that they contribute more equally to the overall result. And it is also possible that Hybrid Filtering could be made more consistent through more nuanced user data, such as user input on recommendations, or wider attributes for species plants. Hybrid Filtering is second in consistency currently to Collaborative Filtering, but still has a lot of potential to allow for even more personalized recommendations, and with additional polishing to the technique could be the most stable method in the future.

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Declarations

Ethics approval and consent to participate

Yes. This study did not involve human participants or animals requiring ethical approval.

Consent for publication

Yes. The author consents to the publication of this manuscript.

Availability of data and material

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No external datasets were used. The values applied in this research were assumed from previously published studies and published index values.

Competing interests

The author declares no competing interests. The research is intended solely to improve the household environment using ornamental plants.

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Author contributions

Jaishree conceptualized the study, performed the analysis, and wrote the manuscript.

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