Intelligent Vehicle Recommendation System Based on Budget & User Preferences

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Abstract

Choosing a car or a bike can be hard. Buyers must think about price, mileage, fuel type, safety and how they will use the vehicle every day. Many vehicle sites give search filters, but they do not always suggest vehicles that fit a person's specific needs or explain why a particular vehicle is a good fit. To solve this problem this paper suggests a vehicle recommendation system. The system will recommend cars or bikes that fit a user's budget and preferences. It will give a ranked list, short explanations and feature comparisons. The proposed system will be built with Python, Flask and Pandas using a structured vehicle dataset. First the system will filter out vehicles that cost more than a user's budget or that do not meet requirements. The system will then score the remaining vehicles by mileage, fuel preference, intended use and other criteria to find the options. The system will be tested by comparing the weighted recommendation method with a budget-only method. The evaluation will look at how the system stays within budget, how fast it responds and what users say. Code quality will be checked with Ruff or Pylint and metrics, like Lines of Code and Cyclomatic Complexity, will be measured with Radon. Because the system has not yet been built or tested experimental results will be added later after the work is finished.

Keywords

Vehicle Recommendation System, Recommender System, Weighted Scoring, Multi-Criteria Decision Making, Content-Based Recommendation, Budget Filtering, Explainable Recommendations, Flask, Pandas

1.INTRODUCTION

1.1 Background

Buying a vehicle is a financial choice and picking the right one can be hard. Many people looking for a car or a bike often find models that fit their budget. Each model has different features like mileage, fuel type, engine size, safety systems and physical size. Comparing all these features by hand takes a lot of time. It also makes it difficult to find the vehicle that fits what the person really needs.

A recommender system is a kind of software that gives suggestions based on what a user likes and what is known about the items (Jannach et al., 2010). These systems are widely used in shopping, movies and books. The same approach can work for choosing a vehicle because cars and bikes have traits like price, fuel efficiency, type of fuel and seating capacity. These traits help buyers compare options and make smarter choices.

1.2 Motivation

car and bike websites let users filter by price, brand and type of vehicle. Still people have to check details before deciding. The results are often sorted by price or how popular the vehicle is, not by how it matches the buyer's needs. These websites also usually don't give reasons why one vehicle is suggested over another.

A vehicle recommendation system could simplify this process. It could rank vehicles based on the buyer's budget and preferences. It could also explain why each vehicle is recommended and let users compare key features side by side. This is the reason why this project is being developed.

1.3 Scope of the Study

This study focuses on developing and evaluating a vehicle recommendation system for new cars and bikes available in the Indian market. The initial version of the system has certain limitations, as outlined below:

- The system includes only petrol, diesel, and CNG vehicles. Electric vehicles may be included in future versions.
- The system uses ex-showroom prices available in the dataset. Other expenses, such as insurance, servicing, and resale value, are not considered.
- Recommendations are based on the information provided by users during the current session. The system does not use browsing or purchase history.
- Used vehicles are excluded from the study.

Since the application has not yet been developed or tested, this paper describes the proposed research plan and methodology rather than presenting completed experimental results.

2. Problem Statement and Objectives

2.1. Problem Statement

Selecting a suitable car or bike requires buyers to consider several factors, such as budget, fuel type, mileage, vehicle type, and intended use. Buyers often have to compare multiple models to find a vehicle that meets their needs. Although existing vehicle websites offer useful filtering options, they may not rank vehicles based on each user's individual preferences or clearly explain why a particular vehicle is recommended.

This study aims to develop a vehicle recommendation system that considers the user's budget, essential requirements, and personal preferences. Using a structured vehicle dataset, the system will identify unsuitable options, rank the remaining vehicles according to the user's preferences, and provide clear explanations and feature comparisons to help users make informed decisions.

The proposed system aims to address the following key problems:

- **Filtering:** Eliminate vehicles that exceed the user's budget or do not meet their essential requirements.
- **Ranking:** Rank the remaining vehicles based on the user's preferences instead of considering price alone.
- **Explanation:** Provide simple and clear reasons for recommending each vehicle.
- **Comparison:** Help users compare the important features of their selected vehicles.
- **Evaluation:** Determine whether the proposed recommendation method performs better than a basic system that considers only the budget.

2.2 Objectives of the Project

The main objective of this project is to develop and evaluate a vehicle recommendation system that suggests suitable vehicles based on the user's budget and preferences.

The main objectives of the project are listed below:

1. To review existing research on recommender systems, multi-criteria decision-making methods, and recommendation evaluation techniques.

2. To create a structured vehicle dataset containing the necessary information for filtering, scoring, and comparing vehicles.

3. To develop a filtering method that removes vehicles that exceed the user's budget or do not meet their essential requirements.

4. To implement a weighted scoring method that ranks vehicles based on mileage, fuel preference, intended usage, and other selected criteria.

5. To provide clear explanations for vehicle recommendations and help users compare the features of different vehicles.

6. To evaluate the proposed weighted recommendation method against a basic budget-based approach using budget compliance, response time, user feedback, and appropriate ranking metrics.

7. To examine the quality of the code using static analysis tools, Lines of Code (LOC), and Cyclomatic Complexity.

3. Literature Review

This section examines previous research on recommender systems, content-based and knowledge-based recommendations, multi-criteria decision-making, evaluation methods, and vehicle recommendation systems. The purpose is to understand existing approaches and identify suitable techniques for the proposed system. The main studies are compared in Table 1. References marked with a dagger () were reviewed mainly through their abstracts or publisher records; therefore, the conclusions drawn from these studies are limited.

3.1 Recommender Systems

Early recommender systems mainly relied on collaborative filtering, which suggests items based on the preferences or opinions of other users. GroupLens, developed for Usenet news, is one of the early examples of this approach (Resnick et al., 1994). Later, Adomavicius and Tuzhilin (2005) reviewed major recommendation techniques, including content-based, collaborative, and hybrid methods. Their study also highlighted limitations such as insufficient user information and difficulties in recommending new items. Burke (2002) examined hybrid recommender systems that combine two or more recommendation techniques.

The study discussed how combining different methods can help overcome some of the limitations associated with individual approaches. In the proposed vehicle recommendation system, collaborative filtering may be difficult to implement initially because sufficient user ratings and purchase histories are not available. Therefore, using vehicle specifications and the preferences provided by users offers a more practical starting point for generating relevant recommendations.

3.2 Content-Based and Knowledge-Based Recommendation

Content-based recommendation suggests items by comparing their features with the user's preferences (Pazzani & Billsus, 2007). This approach is suitable for vehicle recommendation because cars and bikes have clearly defined features, such as price, mileage, fuel type, and engine capacity. However, the quality of the recommendations depends on the accuracy and completeness of the available data.

Knowledge-based and constraint-based recommendation methods use specific user requirements to identify suitable options (Felfernig & Burke, 2008). For example, vehicles that exceed the user's maximum budget can be removed before ranking the remaining options. These methods are useful when users have clear requirements, although the rules must be designed and maintained carefully.

The proposed system combines both approaches by filtering vehicles according to essential requirements and then ranking the remaining options based on individual preferences.

3.3 Multi-Criteria Decision Making in Recommendation

Choosing a suitable vehicle requires buyers to consider several factors, such as price, mileage, fuel type, comfort, and intended use. Multi-criteria decision making (MCDM) helps evaluate and rank different options based on multiple factors. One commonly used technique is the weighted sum method, which assigns weight to each criterion and combines the scores to calculate an overall result (Hwang & Yoon, 1981).

Manouselis and Costopoulou (2007) explored the use of multi-criteria decision-making methods in recommender systems. Adomavicius and Kwon (2007) studied ways to make recommendations using multiple rating criteria, while Adomavicius et al. (2011) examined recommendation as a decision-making problem involving several factors. Monti et al. (2021) also reviewed research on multi-criteria recommender systems, showing the continued interest in this area.

3.4 Explanations and User Experience

Tintarev and Masthoff (2011) highlighted the importance of explaining why a particular item is recommended. Their research discussed how explanations can improve transparency, trust, and user satisfaction. Knijnenburg et al. (2012) also pointed out that recommendation systems should be evaluated based on the user's experience, rather than accuracy alone. These findings support the use of clear explanations and user feedback in the proposed vehicle recommendation system. Chen et al. (2023) reviewed bias in recommender systems and discussed approaches to reduce it. This research is relevant to understanding potential bias and ways to address it, as discussed in Section 17.

3.5 Research Gap

The studies reviewed in this section highlight several areas that need further investigation. The following research gaps are identified from the selected papers and may not cover all existing research.

1. Limited use of rating-based methods for new systems Many multi-criteria recommendation methods rely on ratings provided by users (Adomavicius & Kwon, 2007; Monti et al., 2021). However, a new vehicle recommendation system may not have enough user ratings to make suitable recommendations. In such cases, using vehicle specifications and user preferences can be a practical alternative.

2.Limited evaluation in vehicle-related studies Some of the reviewed studies use small datasets or provide limited information about their evaluation methods. For example, Nishad et al. (2025) used 100 records. However, the available abstract does not report ranking measures such as nDCG\K.

3Need to combine filtering, ranking, and explanations: The reviewed vehicle studies mainly focus on selecting or ranking vehicles. Based on the available abstracts, it is unclear whether they combine strict budget filtering, adjustable weights, simple explanations, side-by-side comparisons, and evaluation against a clearly defined baseline.

4. Limited reporting of software quality: Many recommendation studies focus on recommendation performance but provide limited details about code quality. Measuring code size, using static analysis tools, and checking code complexity could help assess the maintainability of the proposed system.

This project aims to address these gaps by developing a vehicle recommendation system that considers the user's budget and preferences. The system will use vehicle specifications to generate recommendations, explain the reasons behind its suggestions, and allow users to compare vehicle features. Its weighted scoring method will be compared with a basic budget-based approach. Recommendation performance and software quality will also be evaluated after the application has been developed and tested.

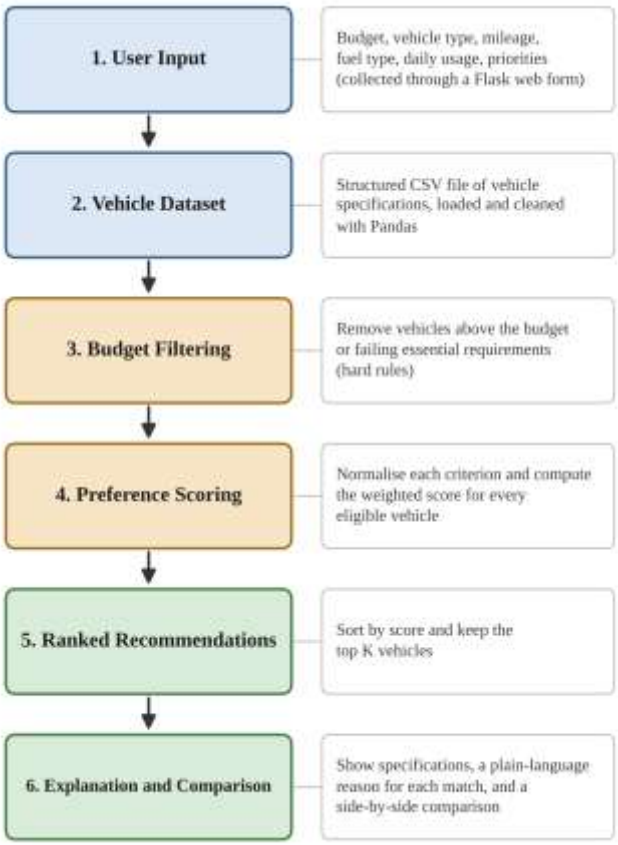
Align the gap with my planned methods Clarify my scoring method

4. Workflow

Figure: This figure presents the workflow of the proposed vehicle recommendation system, from collecting user preferences to displaying recommendations and comparisons.

Figure: Workflow of the Proposed Vehicle Recommendation System

The process begins when the user enters a budget and selects preferences through a web form. The system then loads the vehicle dataset and removes vehicles that exceed the budget or fail to meet essential requirements. Each remaining vehicle is assigned a score based on the user's preferences. The vehicles are then sorted by their scores, and the highest-ranked options are displayed along with their specifications, recommendation explanations, and comparison details.



5.Research Methodology

5.1 Overview of the Proposed Method

The proposed system uses six main steps to recommend suitable vehicles based on the user's budget and preferences. It gathers the necessary information, removes vehicles that do not meet the requirements, scores the remaining options, and displays the most suitable recommendations with clear explanations.

1. Collect the user's budget and preferences through a web form.
2. Load the vehicle dataset.
3. Remove vehicles that exceed the budget or do not meet essential requirements.
4. Calculate a weighted score for each eligible vehicle.
5. Rank the vehicles and select the top K results.
6. Display vehicle specifications, comparisons, and explanations for the recommendations.

5.2 Collecting User Preferences

The system will collect user preferences through a web form developed using Flask.

Users will provide the following information: -

Budget: The maximum amount the user is willing to spend, entered in rupees. This field is mandatory.

Vehicle type: Car or bike, with an optional body type such as hatchback, sedan, SUV, commuter bike, sports bike, or scooter.

Fuel type: Petrol, diesel, CNG, or no preference.

Mileage expectation: The desired mileage in km/l or a preference for high or normal mileage.

Daily usage: The intended use of vehicles, such as city driving, highway travel, mixed usage, or family trips.

Additional preferences: Seating capacity, transmission type, and the importance of different criteria, rated on a scale of 1 to 5.

5.3 Filtering by Budget and Essential Requirements

The system first removes vehicles that do not meet the user's basic requirements. Vehicles will be excluded if their prices exceed the specified budget, their type does not match the user's selection, or they fail to meet any mandatory requirement, such as fuel type, seating capacity, or transmission. If no vehicles meet all the selected conditions, the system will inform the user that no suitable match is available. It may also suggest alternative vehicles that are slightly above the budget, clearly indicating that they exceed the user's spending limit. This approach is consistent with the concept of handling situations in which no option satisfies all the specified constraints (Felfernig & Burke, 2008). Such alternatives will be provided for reference only and will not be counted as valid recommendations during evaluation.

Table: Proposed scoring criteria and initial (default) weights

Criterion	How its score s_j is obtained (0 to 1)	Direction	Default weight
Mileage	Min–max normalized mileage in km/l among eligible vehicles	Higher is better	0.30
Fuel preference	1 if the fuel type matches the user's choice, otherwise 0	Match	0.20
Usage suitability	Stored 0–1 suitability score for the chosen usage (city, highway, mixed or family), set by documented rules from size, power and similar attributes	Higher is better	0.20
Safety	Scaled safety rating or safety features such as airbags and ABS	Higher is better	0.10
Budget margin	(Budget − price) ÷ Budget, rescaled to 0–1; rewards vehicles that leave some money unspent	Lower price is better	0.10
Comfort and space	Normalized seating capacity and feature count (cars) or rider comfort features (bikes)	Higher is better	0.10
Total			**1.00**

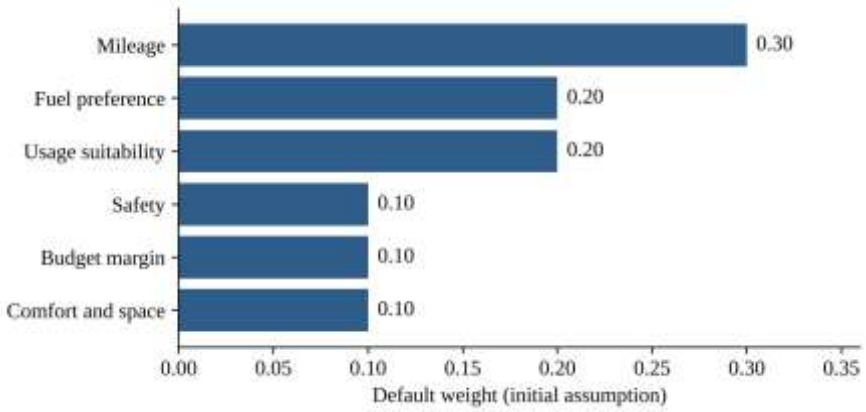


Figure: Default criterion weights (initial assumptions, not research findings)

The usage suitability score requires special attention because it involves some subjectivity when converting a vehicle's intended use into a numerical value. To make this process more transparent, the dataset will include separate columns for city, highway, and family suitability. The rules used to assign these scores will also be documented so that reviewers can understand and verify how the values are determined.

6. CHALLENGES AND LIMITATIONS

6.1 Data-Related Challenges

Data availability: Finding a complete and updated vehicle dataset with proper usage permissions can be difficult. Information may need to be gathered from manufacturer websites and checked to ensure it is accurate.

Price changes: Vehicle prices can vary depending on the location and may change over time. Therefore, ex-showroom prices, on-road prices, and promotional offers must be clearly identified to avoid confusion.

New-user problem: The system will not have access to previous browsing or purchase history. As a result, recommendations will depend on the information users provide during the current session. This is related to the cold-start problem in recommender systems (Adomavicius & Tuzhilin, 2005).

Missing and inconsistent data: Information collected from different sources may contain different units, formats, or vehicle variant names. These inconsistencies must be addressed before the data can be analyzed.

6.2 User-Related Challenges

Personal preferences: Terms such as comfortable, sporty, and reliable can have different meanings for different users. Converting these preferences into numerical scores requires careful consideration.

Selection of weights: Users may find it difficult to decide how much importance to give to mileage, safety, price, and other features. Inappropriate default weights may result in unsuitable recommendations.

New-user problem: The system will not use previous browsing or purchase history. Therefore, it must rely on the information provided during the current session, which is related to the cold-start problem (Adomavicius & Tuzhilin, 2005).

6.3 Technical Challenges

Feature normalization: Price, mileage, and seating capacity use different measurement scales. Their values must be normalized before they are combined in a weighted scoring model.

Different vehicle types: Cars and bikes have different features and requirements. The dataset must support common attributes as well as fields specific to each vehicle type.

Clear explanations: The system must convert numerical scores into simple explanations so that users can understand why a particular vehicle has been recommended.

7. Conclusion

This paper presents a recommendation system designed to suggest suitable cars and bikes based on the user's budget and personal preferences The system will first remove vehicles that exceed the specified budget or fail to meet essential requirements. It will then rank the remaining vehicles using a weighted scoring method based on factors such as mileage, fuel type, safety, and intended usage. The recommendations will include vehicle specifications, simple explanations, and feature comparisons. The literature review examined content-based recommendation, constraint-based filtering, and multi-criteria decision-making methods that support the proposed approach. It also highlighted the need to combine budget filtering, weighted scoring, explanations, and vehicle comparisons in a single system while assessing recommendation performance and software quality. An evaluation plan has been prepared to compare the proposed method with a basic budget-based approach. The evaluation will consider budget compliance, response time, user feedback, and ranking metrics. Software quality will also be assessed using static code analysis, Lines of Code (LOC), and Cyclomatic Complexity. Since the application has not yet been developed or tested, experimental results and code measurement tables are still pending. The actual performance of the proposed method will be determined after implementation and evaluation.

8. Future Work

The system can be improved in several ways after the initial version has been developed and tested.

Ownership costs: Include fuel and maintenance expenses to help users understand the overall cost of owning a vehicle.

Insurance and servicing: Add insurance estimates, servicing expenses, and information about nearby service centers.

Resale value: Consider the expected resale value when comparing vehicles.

Electric vehicles: Expand the dataset to include electric cars and bikes, with features such as driving range, charging time, and charging availability.

Location-based recommendations: Use the buyer's city to provide relevant pricing, tax information, dealer details, and service center information.

Learning from user feedback: Use feedback and user choices to improve recommendation weights and explore hybrid recommendation methods (Burke, 2002).

Improved scoring methods: Compare weighted scoring with other multi-criteria decision-making techniques, including approaches discussed by Rahmadani and Risnawati (2021)

Dataset and interface improvements: Replace CSV storage with a database, update vehicle information using reliable sources, and improve the interface for mobile devices.

Fairness and diversity: Examine whether recommendations favor particular brands or price ranges and improve the variety of suggested vehicles (Chen et al., 2023).

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