Responsive Web-Based Malaysian Car Recommendation System with AI-Based Filtering

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2025 IEEE Symposium on Industrial Electronics & Applications (ISIEA) | 978-1-6654-7752-9/25/$31.00 ©2025 IEEE | DOI: 10.1109/ISIEA65768.2025.11138107

***Abstract*—Recent graduates and budget-conscious car buyers often struggle with the complexities of the automobile market, facing challenges in evaluating factors such as brand, price, quality, design, utility, and technical specifications, which can lead to decision paralysis and suboptimal choices. This study presents the development of a Car Purchase Recommendation System designed to simplify the vehicle selection process by providing personalized suggestions. Leveraging a combination of literature review and data analysis from a Kaggle dataset, the system employs MinMaxScaler for feature normalization and Cosine Similarity to match user preferences with car attributes. Comprehensive evaluations demonstrate the system's effectiveness, showing a significant improvement in user satisfaction by aligning vehicle choices with individual preferences and financial constraints. Quantitative testing confirms the system's user-friendliness, cross-device accessibility, and ability to facilitate informed car-buying decisions, achieving a high accuracy rate of 82%. The findings suggest that this responsive platform has the potential to revolutionize the car-buying experience by making it more efficient and user-friendly, particularly for recent graduates and budget-conscious buyers, in an increasingly dynamic automotive market.**

***Keywords*—Feature Normalization, Car Selection, Recommendation System, Personalized Recommendations, Decision-Making**

I. INTRODUCTION

Car purchasing can be overwhelming due to numerous factors such as price, brand, features, and user preferences. Especially for first-time buyers like recent graduates, decision paralysis is common. Recommender systems offer a practical solution by providing tailored suggestions, reducing cognitive overload and supporting better decision-making. This study presents a system that incorporates AI-based filtering to provide relevant vehicle options aligned with user financial capabilities and preferences.

To address the challenges of the car-buying process, there is an increasing need for tools that provide personalized recommendations. A Car Purchase Recommendation System can play a vital role by offering tailored suggestions that align with consumers' specific preferences and financial constraints, thereby reducing their cognitive load and helping them make more informed and satisfying decisions. Recommender systems are frequently used to assist consumers in finding products or services that match their preferences, with the primary objective being to provide suggestions based on user preferences, helping them discover new and relevant information [1], [2].

The primary target audience for this system includes recent graduates and budget-conscious consumers who may lack the experience or resources to effectively navigate the complex automotive market. By providing recommendations tailored to their practical needs and financial capabilities, the system enhances user satisfaction and remains relevant and accessible to a wide range of consumers. With numerous automobile brands such as Proton, Perodua, and Toyota, selecting the right vehicle can be challenging. In this context, recommendation systems play a crucial role by leveraging user data to deliver relevant content aligned with individual preferences. As car ownership becomes increasingly fundamental in the modern world, the expanding global vehicle market underscores the importance of these systems in offering personalized suggestions, ensuring success for both manufacturers and clients in the evolving automobile industry [1], [3].

The implementation of a Car Recommendation System with AI-based filtering holds significant potential for enhancing the car-buying process in Malaysia. Given the complexity and variety of the automotive market, such a system could greatly benefit consumers by providing personalized vehicle recommendations based on individual preferences, financial constraints, and specific needs. This approach leverages advanced AI techniques, including machine learning algorithms and data analytics, to apply best match algorithms for filtering and ranking car options more effectively than traditional methods. Studies have demonstrated that personalized recommendation systems can significantly improve decision-making and user satisfaction by reducing information overload and aligning choices with user preferences [4], [5]. In the Malaysian context, where diverse consumer preferences and economic conditions further complicate car purchasing decisions, the integration of AI-based filtering could offer a more streamlined and effective solution, addressing both the needs of individual buyers and the challenges faced by the automotive market.

Moreover, recent statistics underscore the impact of AI-based systems: according to a survey conducted by the

Malaysian Automotive Association, about 70% of consumers reported that they prefer using AI-driven recommendation tools for their car-buying decisions due to the increased accuracy and personalization offered [6]. This highlights a growing trend towards the adoption of AI technologies in the automotive market, reflecting their effectiveness in addressing the specific needs and preferences of Malaysian car buyers.

To achieve its objectives, the proposed system utilizes a combination of literature review and data analysis, incorporating a Kaggle dataset that encompasses a broad spectrum of vehicle attributes. Key methodologies include MinMaxScaler for feature normalization and Cosine Similarity for matching user preferences with vehicle characteristics. These techniques enable the system to efficiently process large datasets, ensuring accurate and relevant recommendations. By simplifying the decision-making process, the system has the potential to significantly enhance consumer satisfaction, particularly for recent graduates and budget-conscious buyers, in an increasingly complex automotive market.

II. Background of Study

A. Car Recommendation System

An investigation by Mahgfuri et al. [7], investigates the application of the Promethee Method for generating recommendations related to the purchase of used cars. The methodology involves the distribution of questionnaires and data scraping to offer personalized recommendations based on the criteria specified by potential buyers. The findings indicate that the Promethee Method is effective in providing recommendations that align with buyer preferences, achieving an accuracy rate of 89.2%. This result underscores the method's potential in improving the decision-making process for individuals seeking to purchase used vehicles.

Work by Singh et al. [8], employs interactive filtering techniques and leverages a dataset of consumer car reviews from Edmunds.com. The study aims to provide car recommendations based on user profiles and object characteristics. The proposed system functions both as a targeted search tool and as a digital expert advisor or community-based suggestion platform. The results, which show an accuracy rate of 79.7%, demonstrate the efficacy of using customer reviews and interactive filtering methods to enhance the car recommendation process and improve user experience.

A paper authored by Ruizi [9], presents a hybrid recommendation system integrating content-based and collaborative filtering methods. Utilizing insights from Amazon product datasets, the system is designed for smart auction platforms or websites serving car dealerships. The system measures cosine similarity between product vectors and user profile vectors, without employing machine learning. Although specific accuracy metrics are not provided, the study highlights the effectiveness of combining content-based and collaborative filtering methods in enhancing both car auction functionalities and product review experiences.

The study from Boteju and Munasinghe [10] introduces a hybrid recommendation system that incorporates Natural Language Processing techniques. The system utilizes a dataset of 14,000 Twitter reviews and is designed to guide and provide recommendations to customers through a Neural Network model. The research presents a novel approach, demonstrating the efficacy of the hybrid recommender algorithm combined with Natural Language Processing. The system achieved a high accuracy rate of 96%, underscoring the practical success of this methodology in enhancing vehicle recommendation processes for consumers.

A study conducted by Prabowol et al. [3] investigates the application of Item-Based collaborative Filtering with feedback from 103 respondents. The study aims to evaluate recommendation accuracy through mean absolute error (MAE) testing. The developed web-based Car Selection System successfully delivers recommendations with a satisfaction rate of 79.53% and an accuracy of 95.955%. These results highlight the effectiveness of Item-Based Collaborative Filtering in refining the car selection process and ensuring recommendations align closely with user preferences.

The finding from Thomas and Vaidhehi [11] details the development of a hybrid recommender algorithm that integrates user-to-user and item-to-item collaborative filtering methods. Utilizing a synthetic dataset comprising 300 users and 10,000 sessions, the study aims to recommend cars based on user models and item profiles. The findings indicate that the hybrid algorithm, which combines both collaborative filtering techniques, demonstrates efficiency in delivering car recommendations. The system achieved an accuracy rate of 83%, highlighting the effectiveness of the hybrid approach in enhancing web-based car recommendation systems and supporting users in making informed vehicle choices.

In study from Alabduljabbar, Alghamdi and Alshamlan [1] investigates the application of knowledge-based methods in car recommendation, utilizing the Driver Vehicle Module (DVM) Car Dataset. The primary objective of the study is to enhance the car selection process by recommending vehicles that align with individual user preferences. The proposed system employs a knowledge-based approach to deliver personalized recommendations, achieving an accuracy rate of 83%. This result demonstrates the effectiveness of the knowledge-based methods in refining the recommendation process and assisting users in selecting their ideal vehicles.

B. Factors of Car Purchasing Decisions

Purchase intention represents a behavioural inclination among consumers to buy goods and serves as a crucial determinant in the ultimate decision-making process for actual purchases. There are four ways to assess purchase intention: preparing to buy, having money set aside to buy, contemplating buying, and having a strong desire to buy [12]. Research findings indicate that various influencing factors significantly impact consumers' decision to purchase a car. These factors include purchase initiation, personal needs, convenience, comfort, the reputation of the car manufacturer or dealer, specific car models, external influences, and overall satisfaction levels. Notably, among these factors, the most critical determinant that strongly influences consumers in their car purchase decision is the pricing factor [13].

The pricing of certain products serves to stimulate user perceptions before making a purchase, thereby influencing the psychological responses of consumers regarding their purchase intentions. Furthermore, research has shown that the connection between pricing and the intention to purchase is contingent upon how consumers assess the product [14]. Consumers usually make decisions by evaluating and comparing a car's price, power, fuel efficiency, configuration, and interior space [15].

Consumer preference refers to the specific choices, tendencies, and inclinations individuals or groups when making purchasing decisions. It involves the subjective assessment and ranking of product attributes, such as quality, price, brand, and features, preferences, and experiences [16].

Incorporating consumer preferences into product ordering plays a crucial role in decision-making and product rankings. Personalized decision support systems that account for factors such as risk attitudes, aspirations, and psychological characteristics can offer targeted product recommendations tailored to individual preferences [17]. This personalized approach, including push notifications aligned with consumer likes, enhances the sense of control and facilitates more informed decision-making. By focusing on consumer preferences, this method reduces information overload, improves the convenience of online shopping, and integrates individual likes into the decision-making process. This emphasis not only eases the burden of purchasing decisions for consumers but also provides manufacturers with valuable insights to refine their products based on diverse consumer preferences. Essentially, consumer preferences encompass the specific qualities or features that individuals prioritize when making purchase decisions, including product performance, pricing, brand reputation, and other subjective factors [17].

Perception refers to the way individuals interpret and make sense of the information they receive from the world around them. In the context of consumer behaviour, perception plays a crucial role in shaping how customers view and evaluate products or brands. It encompasses their attitudes, beliefs, and feelings towards a particular product or service, and can be influenced by various factors such as brand image, country of origin, marketing communications, and personal experiences. In the context of the automobile industry, consumer perception can be influenced by factors such as brand image, safety features, driving comfort, fuel efficiency, and overall value for money. Understanding consumer perceptions is essential for car manufacturers and marketers to effectively position their products and meet the needs and preferences of their target customers [18].

Consumer perception significantly shapes car purchase decisions, as highlighted in the study "Perception of Consumers Towards Car Purchase Decision." The research identifies key factors influencing consumer behaviour in the automobile industry, including the cost of the car, resale value, overall quality, and dealer services. These factors positively correlate with the perceived level of satisfaction, emphasizing the crucial role of consumer perceptions in decision making. The study underscores that external factors like government policies and market competition also impact consumer perceptions. The influence of consumer perception extends to various features of cars and affects buying behaviour. Overall, understanding and addressing consumer perceptions are vital for companies to effectively meet consumer needs and preferences in the dynamic automobile industry (Sharma & Shukla, 2019).

Another consideration for purchasing car is selecting the appropriate criteria for car purchasing is crucial to making an informed decision. One key aspect is the applicability of the vehicle, which entails assessing how well it meets specific requirements and aligns with the capabilities of the necessary testing equipment. Additionally, security considerations are paramount, focusing on the importance of standardized equipment, adherence to detection methods, and compliance with both national and industry regulations [20].

Economic principles play a significant role in the decision-making process, necessitating a thorough evaluation of the total cost of ownership. This includes not only initial costs but also ongoing operating and maintenance expenses, installation and relocation costs, and the eventual residual value of the vehicle. Technical principles such as detection efficiency, reliability, manufacturing quality, and maintainability are also integral to the overall assessment. Service-related factors, including supply timelines, transportation logistics, and the breadth of services available, further influence the purchasing decision. Energy-saving considerations, particularly regarding energy consumption, noise, vibration, and emission control, are becoming increasingly important. Finally, human factors, including operational safety, comfort, and the effectiveness of safety features, must be carefully considered to ensure the optimal selection of a vehicle [20].

In Malaysia, selecting appropriate criteria for car purchasing is crucial for making well-informed decisions amidst the complexity of the automotive market. This process involves evaluating the vehicle's applicability to meet specific needs and align with the required testing equipment. Security considerations are significant, emphasizing adherence to national and industry safety standards [4]. Economic principles also play a key role, requiring a thorough assessment of the total cost of ownership, including initial expenses, ongoing operating and maintenance costs, and residual value. In the Malaysian context, these factors are influenced by regional economic conditions. Additionally, technical factors such as detection efficiency, reliability, and maintainability, as well as service-related aspects like supply timelines and logistics, are critical. Energy-saving considerations, including energy consumption, noise, and emission control, are increasingly relevant, alongside human factors such as operational safety and comfort, which align with local consumer expectations [4].

III. METHODOLOGY

The proposed car recommender system, as illustrated in Fig. 1, is structured into four principal layers to provide personalized recommendations through Content-Based Filtering (CBF). At the top, the User Layer interfaces with end-users via a web-based platform, allowing them to input preferences and receive customized car suggestions. Directly below, the User Interface Layer manages user interactions and displays the recommendations. The Content-Based Filtering Layer utilizes MinMaxScaler for data normalization, calculates similarity using Cosine Similarity, and ranks results based on relevance. Finally, the Data Preparation Layer processes raw Malaysian car data, preparing it for structured storage in a database. This systematic architecture facilitates the delivery of efficient, accurate, and personalized car recommendations, thereby enhancing users' decision-making processes in selecting appropriate vehicles.

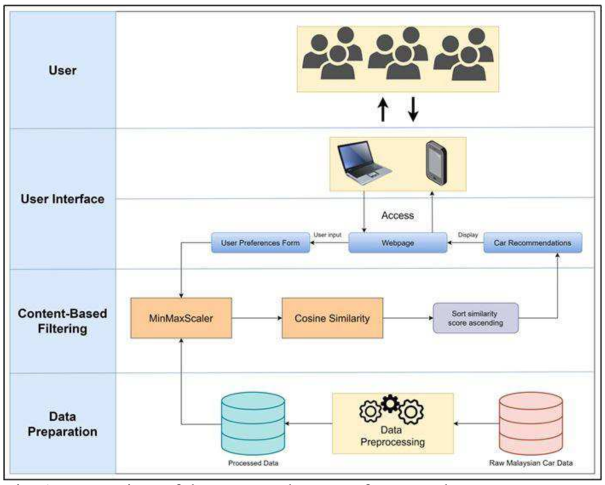

Fig. 1. Overview of the proposed system framework

A. Dataset

The primary dataset is collected through the official car brand websites such as Perodua, Proton, Honda, and Toyota, focusing on models available in the Malaysian market. This dataset provides detailed information on various aspects of Malaysian cars, including specifications, features and pricing. By directly sourcing data from official sources, this primary dataset ensures accuracy and reliability, making it ideal for the final product of the recommender car system. The Malaysian car dataset includes comprehensive details essential for evaluating and recommending cars based on specific user preferences and requirements.

Fig. 2 displays the primary dataset that was self-collected through the official car brand website, intended for use in the final product of the system. This dataset includes crucial attributes such as Brand, Name, Price (RM), Fuel Consumption, Seats Type, Luggage Capacity (L), Engine Type, Total Displacement (CC), Fuel Tank Capacity (L), Electric Power Steering (EPS), Airbags, and image of the car.

ID	Brand	Name	Price (RM)	Fuel Consu	Seats Type	Luggage Ca	Engine Typ	Total Displ	Fuel Tank (	Electric Po	Airbags	Image
1	Perodua	Axia AV	49500	27.4	5	265	1KR-VE, D(	998	36	With	6 (Front, Si	images/Ca
2	Perodua	Axia SE	44000	27.4	5	265	1KR-VE, D(	998	36	With	2 (Front)	images/Ca
3	Perodua	Axia X	40000	25.3	5	265	1KR-VE, D(	998	36	With	2 (Front)	images/Ca
4	Perodua	Axia G	38600	25.3	5	265	1KR-VE, D(	998	36	With	2 (Front)	images/Ca
5	Perodua	Axia E	22000	22.5	5	260	1KR-VE, D(	998	33	With	2 (Front)	images/Ca
6	Perodua	Bezza AV	49980	22	5	508	1NR-VE	1329	36	With	Driver and	images/Ca
7	Perodua	Bezza X	43980	21	5	508	1NR-VE	1329	36	With	Driver and	images/Ca
8	Perodua	Bezza G	36580	21.3	5	508	1KR-VE	998	36	With	Driver and	images/Ca
9	Perodua	Bezza G	34580	22.8	5	508	1KR-VE	998	36	With	Driver and	images/Ca
10	Perodua	Myvi AV	59900	21.1	5	277	2NR-VE, D	1496	36	With	6 (Front, Si	images/Ca

Fig. 2. Malaysian Car Dataset

B. Content-Based Filtering Algorithm

The system employs a Content-Based Filtering Algorithm to generate personalized car recommendations by analyzing and comparing the characteristics and features of cars. This algorithm operates by identifying similarities between cars based on their attributes, such as make, model, and specifications. By understanding the user's preferences, the system suggests vehicles that align closely with these criteria. This approach not only enhances user satisfaction by providing recommendations that fit individual tastes and needs but also aids in informed decision-making during the car selection process.

C. Normalization of Features

In addition to filtering, the system utilizes MinMaxScaler for normalization of features and preferences. This technique scales numerical data to a uniform range, typically between 0 and 1, ensuring that all features contribute equally to the analysis. By subtracting the minimum value and dividing by the range (the difference between the maximum and minimum values) of each feature, MinMaxScaler standardizes the data and mitigates the risk of any single feature dominating the recommendation process. This process is crucial in machine learning tasks such as recommender systems to improve model performance and accuracy in predicting user preferences based on normalized feature values.

$$X_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

Equation (1) shows the calculation to find the normalization of car features and the user preferences.

D. Cosine Similarity

Furthermore, Cosine Similarity is applied to evaluate the similarity between feature vectors of cars. By computing the cosine of the angle between these vectors, the system measures how closely related two cars are based on their attributes. This similarity measure is crucial for refining recommendations, thereby improving the relevance and accuracy of the suggestions provided to users. Cosine Similarity is used to compare the feature vectors representing cars in the dataset. By computing the cosine of the angle between these vectors, the system determines how similar or related one car is to another based on their feature attributes. This similarity measure helps in recommending cars that closely match a user's preferences, enhancing the relevance and effectiveness of the recommender system.

$$cos(\theta) = \frac{A \cdot B}{||A|| \cdot ||B||} \quad (2)$$

Equation (2) shows the calculation to find cosine similarity using the normalization of car features and the user preferences.

E. System User Interface Design

The interface prototype serves as a visual representation of the system's user interface design, developed to demonstrate the functionality and interaction flow envisioned for the final product. It typically includes graphical elements such as buttons, menus, and screens that simulate how users will navigate through the system and interact with its features. The prototype aims to provide a tangible preview of the user experience, allowing stakeholders to evaluate the layout, design aesthetics, and usability early in the development process. By incorporating key features and workflows, the interface prototype facilitates feedback and iterative refinement, ensuring that the final product meets user expectations and usability requirements effectively. This iterative approach also allows for adjustments based on user testing and stakeholder input, ultimately guiding the development towards delivering an intuitive and user-friendly interface in the final implementation.

Fig. 3. Best match of car recommendation by salary

Fig. 4. The highest and lowest result by salary

IV. Results

A. Experiments and Evaluation

The study utilizes a finalized dataset sourced directly from official automotive websites, including Perodua, Proton, Toyota, and Honda. The acquisition of this dataset is integral to achieving the study's primary objectives by ensuring a comprehensive and accurate representation of the data. By incorporating this self-collected dataset, the study enhances its ability to meet its goals, supporting a thorough evaluation and validation of the developed methodologies and algorithms. This dataset forms a critical foundation for robust analysis and modelling, aligning with the study's aim of delivering reliable car recommendations based on current and detailed information.

Users can choose between two types of output: results based on salary or results based on a specified budget. The primary distinction between these options is in the calculation of the monthly payment. For outputs based on salary, the monthly payment is calculated as one-third of the user's salary. In contrast, for outputs based on the specified budget, the monthly payment is directly derived from the user's budget amount. This differentiation ensures that recommendations are tailored to either the user's income or their financial constraints.

Fig. 3 illustrates the car recommendation results page that appears after a user input their preferences into the preference form. This page is organized into two primary categories: recommendations based on salary and recommendations based on user budget. Each category features two interactive buttons: "Best Match," which displays the percentage match of the recommended cars relative to the user's specified preferences, and "Monthly Payment," which presents cars that are affordable based on the user's salary or budget constraints. This layout facilitates a clear and comprehensive overview of the recommendations, tailored to both financial and preference-based criteria.

Fig. 4 displays the results based on the user's salary. These results will serve as examples for the evaluation section, specifically for analysing outputs derived from the user's salary.

Fig. 6 shows the user input that has been collected by the system through the user preferences form in Fig. 5. Fig. 7 show the car features for the highest results, Perodua Myvi AV and the lowest results, Perodua Bezza G (Manual) respectively.

Fig. 5 User preferences form

USER INPUT	
SALARY	3000
DESIRED	800
LOAN	9
DEPOSIT	10
INTEREST	0.034
CC	1.5
LUGGAGE	265
TANK	36
FUEL CONSUMP	12.4
CAR SEATER	5

Fig. 6 User input

CAR FEATURES	
CAR PRICE	59900
CC	1496
LUGGAGE	277
TANK	36
FUEL CONSUMP	21.1
CAR SEATER	5

CAR FEATURES	
CAR PRICE	34580
CC	998
LUGGAGE	508
TANK	36
FUEL CONSUMP	22.8
CAR SEATER	5

Fig. 7 Car features for Perodua Myvi AV and Perodua Bezza G (Manual)

MIN_PRICE	MIN_FUEL	MIN_SEAT	MIN_LUG	MIN_CC	MIN_TANK
22000	12.4	5	265	998	33
MAX_PRICE	MAX_FUEL	MAX_SEAT	MAX_LUG	MAX_CC	MAX_TANK
77900	27.4	7	514	1597	45

Fig. 8 Minimum and maximum of the data

Fig. 8 shows the minimum and maximum for each of the car features to validate calculations within the system for determining normalization of features.

DOT VECTOR:		1.796773506		
SQUARE	3.120566		SQRT	1.766512
SQUARE	1.552104		SQRT	1.245835
COSINE SIMILARITY:			82	

Fig. 9 Cosine similarity score for Perodua Myvi AV

Fig. 9 shows the cosine similarity score for Perodua Myvi AV is 82 which is the same as the result on the recommendation page in Fig. 4.

B. Discussion

This chapter discusses the development and evaluation of a responsive web-based car recommender system using Content-Based Filtering. The system architecture, built through iterative prototyping, integrated both primary and secondary datasets to ensure accuracy. Techniques like MinMaxScaler and Cosine Similarity were applied to enhance personalization, despite challenges in data collection and feature complexity. Ultimately, the system showed strong potential in delivering tailored car recommendations aligned with user needs and financial constraints. Despite its achievements, the study faced limitations such as data collection challenges, complex feature engineering, and multi-criteria decision-making difficulties. Scalability issues and a less intuitive user interface also impacted performance and user satisfaction. Future improvements should focus on enhancing data accuracy, adopting advanced feature engineering, and refining decision-making algorithms. Additionally, optimizing scalability and improving the user interface can significantly boost system performance and user engagement.

V. Conclusion

In conclusion, this paper presents a responsive car recommendation system for Malaysian consumers. The system simplifies the car buying process using content-based filtering. It achieved an accuracy rate of 82% and delivered competitive results when compared to previous works. Through the integration of AI techniques such as feature normalization and similarity scoring, the system improves user satisfaction and decision-making efficiency. Future upgrades will focus on hybridization, real-time deployment, and expanding the dataset to cover a broader spectrum of vehicle options.

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