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The Essence of Online Trust: Evaluating a SMART-Based Decision Support System for Car Purchasing

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ABSTRACT

A decision support system is vital for aiding decision-making processes, particularly in situations involving long-term commitments. Despite its utility, user trust remains a significant concern in the adoption of such systems. This study evaluates user trust in a personalized web-based decision support system that assists consumers in car purchase decisions. The system generates personalized recommendations through the Simple Multi-Attribute Rating Technique (SMART) across five criteria of affordability, safety, fuel efficiency, comfort, and performance. These criteria were identified through literature review and consultations with certified car dealers. A total of 34 participants completed a usability test incorporating the Human-Computer Trust Scale (HCTS). The HCTS questionnaire comprises five dimensions designed to assess users' perceptions of the system's ease of understanding, technical proficiency, reliability, emotional connection, and overall trust. The overall trust mean was 4.07, with the highest sub-dimension mean in Personal Attachment (4.13) and the lowest in Faith (4.04). To assess the reliability of the HCTS instrument, Cronbach's alpha was computed and yielded a value of 0.931, indicating excellent internal consistency among the questionnaire items that measured different aspects of user trust. This high reliability supports the validity of the findings regarding users' perceptions of trust. Overall, the results suggest the prototype fosters both cognitive- and affect-based trust, positioning it as a dependable tool for car purchase deliberations. Future work should widen the recommendation pool to multi-brand and used car inventories and incorporate explainable AI features to strengthen transparency.

1. INTRODUCTION

Purchasing a vehicle is one of the most significant financial decisions made by individuals. The process involves evaluating numerous models, features, and financing plans, which can overwhelm buyers. Decision support systems (DSS) can assist consumers in evaluating and comparing vehicles based on

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multiple criteria, such as price, safety, and fuel efficiency (Anshori et al., 2022), as well as comfort (Abu Kassim et al., 2016). These systems help users make informed decisions while saving time and effort. However, trust in such systems remains a critical barrier to adoption. Factors such as poor design, lack of transparency, and limited personalization can reduce user confidence (Sutton et al., 2020). In the Malaysian context, platforms like Carlist.my and Carsome offer car listings but often lack decision support features customized to individual needs. This study investigates whether a DSS using the Simple Multi Attribute Rating Technique (SMART) can foster user trust through clear, personalized, and reliable car recommendations.

2. LITERATURE REVIEW

2.1 Role of DSS in car purchasing decisions

Buying a car is a big financial step, and the variety of models and options can leave consumers unsure of where to begin. Malaysian first-time buyers, especially fresh graduates, often feel this pressure because they must balance tight budgets against safety, efficiency, and style (Prabowol et al., 2019).

Decision Support Systems (DSS) have become an essential solution to aid in such complex decision-making processes. These systems are designed to assist users by organizing and analyzing relevant data to generate informed recommendations. In the context of car purchasing, DSS can help users compare different vehicles based on specific criteria such as cost, reliability, and technical specifications. Recent studies have shown that decision support tools can improve decision accuracy and increase decision certainty (Röbbelen et al., 2022; Yang et al., 2023). While traditional car websites like Carlist.my and Carsome offer information about car models, they often lack personalized guidance that matches cars to individual user needs.

An ideal DSS for car purchasing should not only provide access to comprehensive data but also offer recommendations that align with user-defined preferences. This level of support empowers consumers to make informed choices with greater confidence. However, users' willingness to rely on a DSS is influenced by their trust in the system. If users perceive the system as confusing, biased, or inaccurate, they may ignore its recommendations, regardless of its technical effectiveness. Hence, the development of a car purchasing DSS should prioritize both functional performance and user trust to ensure adoption and customer satisfaction.

2.2 Multi-criteria decision making with SMART

In decision-making situations like buying a car, people often consider several factors at once such as price, fuel efficiency, safety, and comfort. Multi-Criteria Decision Making (MCDM) methods help compare these factors in a structured and objective way (Taherdoost & Madanchian, 2023). Among the various MCDM techniques available, the Simple Multi-Attribute Rating Technique (SMART) is one of the most accessible and user-friendly.

SMART is widely used due to its simplicity, transparency, and ease of implementation. Unlike more complex techniques such as the Analytic Hierarchy Process (AHP) or TOPSIS, SMART works by multiplying the value assigned to each criterion by its corresponding weight and then summing the results. Users begin by assigning a weight to each criterion based on its importance and then rate each car option accordingly. The system calculates a total score for each option, which reflects how well it aligns with the user's preferences (Aprilio & Yuliani, 2022).

This method is especially useful in web-based systems, where users may not be familiar with complex decision-making models. Its simplicity enhances transparency and builds trust, as users can clearly see how their inputs influence the results (Furtado et al., 2023). The car with the highest overall score will be ranked

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as the top recommendation, indicating the best match according to the user's selected priorities. Eq. (1) shows the basic version to be implemented as the algorithm.

$$\boxed{V(a) = \sum_{i=1}^{m} w_i v_i(a)}$$

Fig. 1. SMART formula

$$\text{Overall score} = \Sigma \text{ (rating for each criterion * weight of each criterion)} \quad (1)$$

Several decision support systems for vehicle selection have been developed using different multi-criteria decision-making methods. Prabowol et al. (2019) applied collaborative filtering to generate vehicle recommendations based on user preferences and historical behaviour, while Mahgfuri et al. (2022) utilised the PROMETHEE method to rank used-car alternatives. Although these approaches can produce accurate recommendations, they often involve more complex calculations or rely on historical user data. In contrast, SMART provides a transparent and straightforward weighting mechanism that allows users to directly specify the importance of each criterion. This transparency is particularly valuable in trust-sensitive environments, where users are more likely to accept recommendations when they understand how decisions are generated.

2.3 Building user trust in recommendation systems

Trust is the bridge between good advice and real-world action. Even a system that provides accurate and personalized suggestions may still fail if users perceive it as unreliable or difficult to understand. Scholars split trust into two parts: cognitive trust, which rests on clear reasoning and solid data, and affect-based trust, which grows from a sense of comfort and rapport (Sutton et al., 2020).

Transparent explanations, interactive settings, and a friendly interface have all been shown to raise trust levels. When a system explains why it prefers one car over another in plain language, shoppers tend to feel more confident. For example, when users understand why a particular car is recommended based on their stated preferences, they are more likely to feel confident in the choice. Emotional factors also matter. A system that provides a friendly and supportive interface can foster personal attachment, making users feel more comfortable using it repeatedly.

In the car buying context, trust becomes even more significant due to the financial and emotional weight of the decision. Many consumers hesitate to rely on automated systems for such an important purchase because they fear making the wrong choice. Building a trustworthy system involves more than technical accuracy; it also requires sensitivity to user experience, communication clarity, and perceived fairness. Therefore, integrating mechanisms that foster both cognitive and affect-based trust is essential for increasing the adoption and impact of car purchasing DSS.

2.4 Measuring trust with the human-computer trust scale

To measure user trust in decision support systems, researchers use the Human-Computer Trust Scale (HCTS). Developed by Madsen and Gregor (2000), HCTS is a validated instrument that assesses trust through five dimensions. The scale includes perceived understandability, perceived technical competence, perceived reliability, personal attachment, and faith. Each of these dimensions reflects different aspects of how users interpret and emotionally respond to a system's performance. This comprehensive model allows

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for the assessment of both cognitive-based and affect-based trust, which are important in understanding user acceptance.

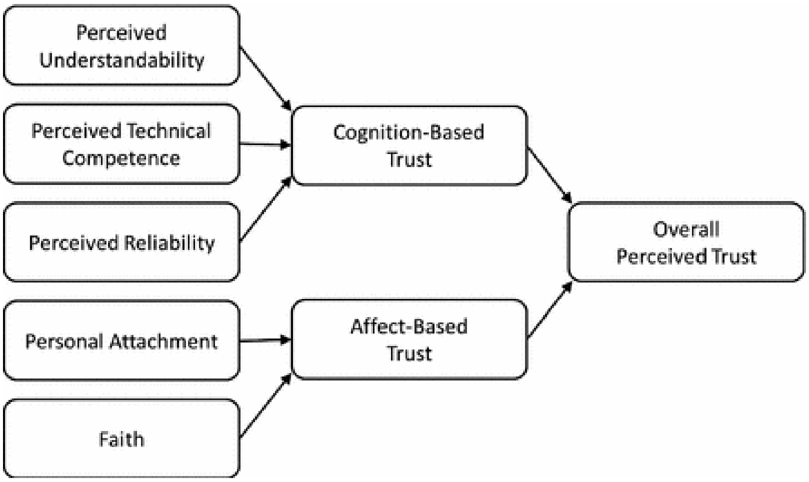

Fig. 2. HCTS model

Source: Adapted from Madsen and Gregor (2000)

Perceived understandability refers to how easily users can grasp how the system works and makes recommendations. Technical competence assesses whether the system appears to be knowledgeable and capable of handling user input accurately. Reliability relates to whether the system behaves consistently and delivers dependable results. Personal attachment is about the emotional bond users form with the system, and faith measures the extent to which users are willing to rely on the system even without full understanding of its inner workings.

Using HCTS in evaluating a car purchasing DSS offers valuable insights into whether the system fosters trust in real-world usage. A high trust score indicates not only that users understand and agree with the recommendations, but also that they feel comfortable and confident in relying on the system. This is especially useful when assessing new systems like web-based car recommendation tools, where trust can determine whether users adopt or abandon the technology. As such, HCTS serves as both a diagnostic and validation tool in the development of trustworthy DSS applications.

3. METHODOLOGY

This study adopts the Waterfall Model as the research methodology for developing the proposed car purchasing decision support system. The Waterfall Model consists of five sequential phases: Plan, Analysis, Design, Implementation, and Testing. Each phase was completed before proceeding to the next phase, ensuring a structured and systematic development process.

3.1 Plan

The planning phase established the direction and scope of the project. During this phase, the problem statement, research objectives, project scope, and significance of the study were identified. A review of relevant literature, industry reports, and local car purchasing platforms was conducted to understand existing challenges in online car purchasing and recommendation systems. Findings from the literature review and consultations with certified car dealers identified five key decision criteria: affordability, safety,

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fuel efficiency, comfort, and performance. These criteria formed the foundation of the recommendation model developed in this study.

3.2 Analysis

The analysis phase focused on determining the functional and technical requirements of the system. Requirements gathered during the planning stage were refined and translated into system specifications. This phase also involved evaluating suitable decision-making techniques for generating personalized recommendations. Based on its simplicity, transparency, and suitability for web-based applications, the Simple Multi-Attribute Rating Technique (SMART) was selected as the recommendation method.

The recommendation model evaluates vehicles using five criteria: affordability, safety, fuel efficiency, comfort, and performance. Affordability was represented using the vehicle selling price, where lower-priced vehicles received higher ratings. Safety was assessed based on available safety features and manufacturer-published safety information. Fuel efficiency was measured using reported fuel consumption values. Comfort was evaluated using interior features, seating capacity, and convenience features, while performance was assessed using engine specifications such as horsepower and torque. Each criterion was converted into a standardized rating scale before being processed by the SMART algorithm to ensure consistency in the recommendation process.

3.3 Design

During the design phase, the system architecture, database structure, and user interface were developed. Wireframes were created using Balsamiq to illustrate the navigation flow and interface layout from login to recommendation results. An Entity Relationship Diagram (ERD) was developed using Draw.io to define the database structure, including tables for user information, vehicle data, and recommendation results. Activity diagrams were also created to model the interaction between users and the recommendation engine. The design phase provided a blueprint for system implementation and ensured consistency throughout development.

3.4 Implementation

In the implementation phase, the prototype was developed according to the specifications defined during the design phase. The system was built using HTML, CSS, and PHP within the Visual Studio Code development environment, while phpMyAdmin was used to manage the database. The SMART algorithm was integrated into the application to process user-defined criterion weights and generate personalized vehicle recommendations. Upon completion of this phase, the system was fully functional and ready for evaluation.

3.5 Testing

The testing phase consisted of system verification and usability evaluation. System verification was conducted to ensure that the prototype operated according to the specified requirements. The verification process included testing the criteria input module, SMART score calculation module, recommendation generation module, and recommendation display module. Integration testing was also performed to verify correct interaction between the user interface, recommendation engine, and database components. The system successfully produced the expected outputs for all test scenarios and was deemed suitable for user evaluation.

Following successful system verification, usability testing was conducted to evaluate user trust in the proposed system. A total of 34 participants were recruited through convenience sampling and represented potential users of online vehicle recommendation platforms. Each participant interacted with the system by assigning weights to decision criteria and reviewing the generated recommendations. After completing the

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interaction, participants were required to complete the Human-Computer Trust Scale (HCTS) questionnaire developed by Madsen and Gregor (2000). The questionnaire evaluates five dimensions of trust: perceived understandability, perceived technical competence, perceived reliability, personal attachment, and faith. Responses were analysed using descriptive statistics to determine users' perceptions of trust towards the recommendation system, while Cronbach's alpha was calculated to assess the internal consistency of the instrument.

4. RESULTS AND DISCUSSIONS

This section presents the results of usability testing conducted with 34 participants. The primary aim was to assess user trust in the recommendation system using the Human-Computer Trust Scale (HCTS), which evaluates both cognitive-based and affect-based trust dimensions.

4.1 User interfaces

The system features a simple and user-friendly interface to help users interact easily with the recommendation process. On the criteria rating page (Fig. 3), users assign importance to features like price, fuel efficiency, and safety using sliders or numeric inputs. After submitting their ratings, the system calculates and displays a ranked list of car recommendations (Fig. 4). The results are shown clearly, along with basic car details to help users make quick comparisons. Most participants found the interface easy to use and appreciated how their inputs directly influenced the results.

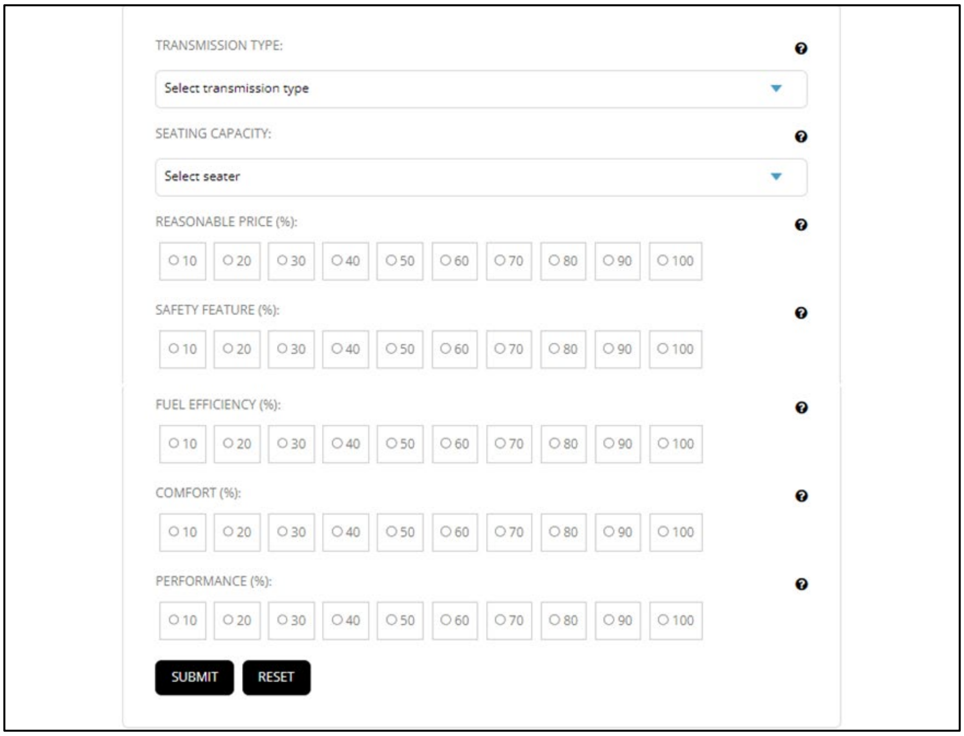

Fig. 3. Criteria rating page

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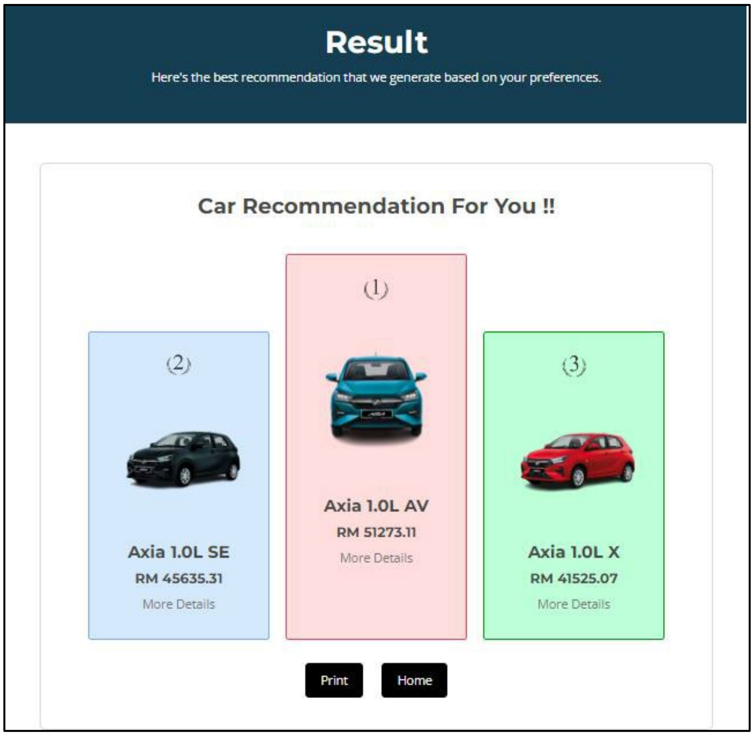

Fig. 4. Recommendation result

4.2 Quantitative findings

HCTS scores show strong trust across dimensions (Table 1). Personal Attachment recorded the highest mean (4.13), signalling positive emotional response, while Faith scored lowest yet favourable (4.04). The overall mean of 4.07, alongside Cronbach's alpha of 0.931, confirms high credibility and excellent internal consistency.

Table 1. Results analysis of HCTS

HCTS Dimension	Mean	SD
Perceived Understandability	4.08	0.47
Perceived Technical Competence	4.08	0.45
Perceived Reliability	4.00	0.52
Personal Attachment	4.13	0.44
Faith	4.04	0.50
Overall Trust	**4.07**	**0.38**

Average scores for all dimensions were above 4.0, indicating that participants found the system easy to understand, capable, and generally trustworthy. Many appreciated how their selected weights directly influenced the recommendations, reinforcing their confidence in the system's decision-making process. This transparency appeared to strengthen both understanding and engagement. However, the limited number of car models included in the system may have affected how users perceived its reliability, with some participants expressing a desire for a wider range of vehicle options. These observations align with

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previous research showing that systems with clear explanations and user-aligned outputs tend to build stronger trust (Sutton et al., 2020).

The relatively high score for Personal Attachment (4.13) suggests that participants felt comfortable interacting with the system and perceived the recommendations as relevant to their preferences. This finding may be attributed to the personalised weighting mechanism provided by SMART, which allows users to directly influence recommendation outcomes. Although Faith recorded the lowest mean score (4.04), the value remains positive and may indicate a cautious approach towards relying entirely on automated recommendations for high-value purchases such as vehicles. Similar observations have been reported in previous DSS studies, where transparency and user involvement positively influenced trust perceptions and system acceptance (Sutton et al., 2020).

4.3 Limitations and unexpected observations

Participants noted that unlike generic portals such as Carsome or Carlist.my, the prototype provided a clear rationale for each recommendation. This transparency appears to bridge the gap between raw listings and personalised advice, enhancing both cognitive and affect-based trust. The system's SMART weighting allowed users to see direct links between their preferences and the ranked cars, a feature absent in most commercial sites.

The limited inventory restricted to only two national models likely influenced the lower Reliability score. Users also expressed a desire for explanations of trade-offs. Additionally, the evaluation involved only 34 participants, which may limit the generalisability of the findings. Trust was measured through self-reported perceptions using the HCTS questionnaire rather than long-term behavioural observations. Future studies may include larger and more diverse participant groups, comparative benchmarking against alternative recommendation methods, and longitudinal evaluations to better understand how trust develops over time.

4.4 Implications for future works

To strengthen Reliability and Faith dimensions in HCTS, future iterations should expand the database to include multi-brand and used-car options and incorporate an explainable AI module that highlights trade-offs and uncertainty levels. Broader demographic testing will help validate trust across diverse user groups. Integrating larger datasets and real-time updates can further reduce perceived risk and enhance user confidence.

5. CONCLUSION

This study set out to design, develop, and evaluate a web-based car purchasing decision support system, focusing on how users perceive and trust its recommendations. The system was developed using the Waterfall methodology, with a structured flow from planning through implementation and testing. The decision-making logic was driven by the Simple Multi-Attribute Rating Technique (SMART), allowing users to prioritize key car selection criteria such as affordability, safety, fuel efficiency, comfort, and performance.

To assess the effectiveness of the system in gaining user trust, usability testing was conducted with 34 participants. The Human-Computer Trust Scale (HCTS) was used to measure five dimensions of trust: understandability, technical competence, reliability, personal attachment, and faith. The results showed consistently high scores across all dimensions, with an overall trust mean of 4.07 out of 5. Personal Attachment emerged as the strongest dimension, indicating that users developed a positive emotional connection with the system. Cronbach's alpha was 0.931, signifying excellent internal reliability of the instrument.

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The findings suggest that a transparent, preference-driven recommendation system can effectively support both cognitive and affect-based trust. Compared to existing commercial platforms, the proposed system offers a more personalized and explainable recommendation experience. However, the limited scope of car options and the relatively small user base represent areas for future improvement.

In conclusion, the prototype has demonstrated its potential as a dependable tool for assisting users in making informed car purchase decisions. To further enhance trust and usability, future versions should expand the car database to include more brands and used vehicles, incorporate explainable AI features, and test with a broader user demographic. These enhancements can help transform the system into a more comprehensive and widely adopted solution in the car buying ecosystem.

6. ACKNOWLEDGEMENTS/FUNDING

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Siti Sarah Md Ilyas: initiated the research by defining the core ideas, objectives, and testing direction; **Nur Aliah Mufek Zailani**: handled system development and conducted usability testing with HCTS data collection; **Aznoora Osman**: ensured the correct methodology employed during the implementation of the project.; **Nadia Abdul Wahab**: validated the system's usability compliance prior to user evaluation; **Norfiza Ibrahim**: assisted with the preparation of diagrams and visualisation.

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