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Car selection in games using multi-objective optimization by ratio analysis based on player achievement

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ABSTRACT

The selection menu in some racing games usually uses a random system for vehicle selection. However, this random feature generally randomizes the selection of the index without considering factors that support the player's abilities. Therefore, this study aims to develop a racing game that can suggest vehicles that have been adjusted to the player's performance. Vehicle recommendations are made using the multi-objective optimization on the basis of ratio analysis (MOORA) method as its method. The MOORA calculation ranks vehicles based on criteria such as mileage, fuel efficiency, speed, agility, and others collected in previous games. The results of this study show the effectiveness of using the MOORA method in recommending vehicles that match the player's skills, thereby improving the overall player experience. In addition, the usability test produced a system usability scale (SUS) score of 82.4, so it is included in the very good category.

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1. INTRODUCTION

The gaming industry has experienced rapid progress in recent years, several industries engaged in the gaming world are a form of effort in developing the creative industry, in Indonesia games have high interest supported by a large population and increasingly easy access to technology in various circles, especially children to teenagers, the main cause is the rapid advancement of technology in today's era. With the rapid technology, games are not just entertainment, from simple games to the most complex games in any category. Games do not only function to eliminate boredom and add entertainment. The development of racing genre games is increasingly attracting attention, given the great potential in improving learning abilities through interactive experiences. The adversarial reinforcement learning approach has been used for procedural content generation, creating adaptive, and challenging dynamics in games [1]. In addition, several studies use racing games as research objects such as overtaking racing games in games such as Gran Turismo Sport [2] and a systematic model for the successful implementation of educational racing games [3]. This concept can be adapted in the design of educational racing games to cover various user groups. Meanwhile, technological innovations such as 3D smart gloves can work well in racing games [4], opening up opportunities to enhance human-machine interaction in games, enabling more immersive and intuitive experiences.

In the context of mental health, one study revealed that commercial games can be used to reduce stress [5] and reduce anxiety in children [6] suggesting that similar technologies can be applied in educational racing-based games to create a supportive learning environment. With the integration of these elements, as also illustrated in "The racing game," the development of educational racing games can create interactive solutions that support learning while improving user well-being [7]. Racing games are a type of game genre [8] in which players control vehicles to compete in races. The types of vehicles used in the game can be cars, motorcycles, boats and many other vehicles. Racing games have several types of racing fields such as circuits [9], [10], streets, drag [11], and off-road [12]. Racing games require several elements such as visual or graphic displays, interactions [13], and challenges in the game play an important role in attracting players. From various types of racing games, there is usually a menu for selecting a vehicle, which will later be located in the menu options which will later become an important factor as a determinant of satisfaction and victory in playing. Players are faced with various conflicting vehicle criteria during the car selection process. For example, high-speed cars tend to have lower control, while fuel-efficient cars usually don't have high acceleration. This conflict between performance attributes becomes the core issue in the vehicle selection problem. A player's ability to win races depends on finding the right balance among these criteria, which vary depending on gameplay style and skill level.

Researchers consider that rather than using a randomize system in the menu options, it is better to use a car selection in the menu which aims to recommend the best options for players to use based on the player's experience in playing the game, which can make it easier for players to determine their choices to support their level of satisfaction in playing the game. With that, the development of "Moonlight drive" not only focuses on gameplay, but this game also prioritizes the effective game menu section, especially in terms of selecting the car or vehicle used. A simulation game designed especially for this purpose was tested for this investigation. With criteria like speed, acceleration, fuel consumption, and automobile price that reflect real-world performance, the game setting replicates a vehicle racing scenario. To make sure the results are still applicable, vehicle data and evaluation criteria were created artificially but were based on game logic and actual gameplay experience.

Several previous studies have developed artificial intelligence–based (AI-based) and multi-criteria approaches to game recommendation systems. For example, the research used the preference ranking organization method for enrichment evaluation (PROMETHEE) method in an endless runner game to recommend characters based on map challenges [14]. The recommendation for multi-player online battle arena games using graph convolution network with fewer parameters (MOBARec-GCNFP) study applied a graph convolution network to select the right champion in a multiplayer online battle arena (MOBA) game, considering synergies and counterpicks [15]. Meanwhile, studies by [16]–[18] demonstrated the importance of personalization in educational games through adaptive scenarios and dynamic difficulty settings based on player parameters. The approach in this study differentiates itself from previous research by incorporating the multi-objective optimization on the basis of ratio analysis (MOORA) method to select vehicles tailored to player performance in previous gameplay sessions. Unlike approaches in automotive engineering or vehicle design that focus on technical specifications, this approach prioritizes player experience, gameplay utility, and personal user engagement.

The use of the MOORA method has become one of the popular approaches in decision making, especially in the manufacturing environment [19], [20] material selection [21], scholarship recipients [22] and best techniques [23]. In other studies, several collaborations and comparisons were carried out such as the MOORA method extended with the fuzzy concept [24], the simple additive weighting (SAW) and MOORA methods were also compared using rank order centroid (ROC), MOORA with fuzzy Fermatean [25], showing how ROC can strengthen the determination of attribute weights in the decision-making process [26]. By combining ROC based weighting with the MOORA method, the system will provide recommendations for cars that can be used by players based on the player's ability and playing style. Focusing on the car selection menu using a more modern selection unlike many other games will give players satisfaction, while also providing an element of strategy in choosing the car that best suits the challenges they will face.

2. METHOD

A major obstacle in decision-making procedures is multi-criteria decision-making (MCDM) [27], [28] which seeks to determine the best option by taking into account a number of criteria. To provide a systematic and structured approach, this study uses a combination of ROC [29] methodology used to measure and determine the weight of each research variable or in this study referred to as criteria in order to facilitate the use of the main method decision, namely MOORA as a multi-criteria process optimizer simultaneously. This method effectively combines positive aspects (beneficial criteria) and negative aspects (adverse criteria) in an evaluation to determine the best choice. Beneficial criteria, such as efficiency and profitability, the higher the value the better. Conversely, detrimental criteria, such as cost and time, the lower the value the better. Thus, MOORA is able to choose the most optimal alternative by considering all relevant factors.

2.1. Rank order centroid

The ROC method is one of the decision-making techniques that can be used to determine the ranking or priority of several alternatives based on predetermined weights. The weighting in ROC involves the use of relative rankings of each alternative based on certain criteria [30]. In the context of determining weights, ROC is used to evaluate how well the criteria can distinguish each existing alternative, which is desired and which is not. In (1) ROC to determine the weight of the *i*-th criterion.

$$W_i = \frac{1}{k}\left(\frac{1}{i} + \frac{1}{i+1} + \ ... + \frac{1}{n}\right) \quad (1)$$

Where *Wi* is weight for the i-th criterion; *k* is total number of criteria; *i* is rank of the i-th criterion (from highest to lowest rank); and *n* is total number of alternatives or criteria

2.2. Multi-objective optimization on the basis of ratio analysis

In this study, the author uses a quantitative method, namely a method that is carried out systematically and also collects data and analyzes the selection in the form of numerical values that can later be calculated [31]. The MOORA method is a method introduced by Brauers and Zavadkas [32]. Brauers [33] initially used the newly developed method in terms of multi-criteria selection. This method is applied as a solution to various types of complex decision-making problems in the manufacturing environment using mathematical formula calculations with precise results [34]. The MOORA method is an innovative method that has good potential to solve various challenges consisting of a number of attributes and also conflicting with each other. The performance of each alternative is determined by calculating the difference between the total standard values associated with each existing criterion [35]. Also, the reference point approach can help identify more optimal alternative combinations. The steps for solving the MOORA method according to previous study are as follows.

Prior works in the area of game personalization have mostly focused on adaptive difficulty levels [36] and real-time behavior-driven adjustments [37]. Research on multi-objective optimization in games has also been conducted, though typically using fewer alternatives or simpler criteria. The main distinction in this study lies in the larger number of vehicle alternatives (15 options) and the more comprehensive and domain-specific criteria (11 in total) used in the MOORA evaluation. While the optimization method itself is not novel, its combination with a more detailed dataset in a gaming context provides new insights and practical applications for recommendation systems in racing games.

2.2.1. Formation of multi-objective optimization on the basis of ratio analysis matrix

After collecting the criteria values on alternative data, the next step is to create a MOORA decision matrix. The X matrix has dimensions m×n, expressed in (2).

$$\mathrm{X} = \begin{vmatrix} X_{11} & X_{12} & \dots & X_{mn} \\ X_{21} & X_{22} & \dots & X_{mn} \\ \dots & \dots & & \dots \\ X_{n1} & X_{n2} & \dots & X_{mn} \end{vmatrix} \quad (2)$$

Where *i* is 1, …, *m;* and *j* is 1, ..., *n*.

2.2.2. Determining multi-objective optimization on the basis of ratio analysis normalization

The next step is to determine the normalization, which aims to make the elements in the matrix have the same value or one uniform. This is shown in (3).

$$X^{*}ij = \frac{xij}{\sqrt{\left|\sum_{i=j}^{m} xij^2\right|}} \quad (3)$$

Where *xij* illustrates the normalized value of decision matrix of *i*th alter native in *j*th attribute.

2.2.3. Multi-objective optimization on the basis of ratio analysis optimization calculation

The last stage is the stage to calculate the value of the calculation results from the method which will later be divided into two calculation equations depending on whether the criteria attribute is weighted or not. The calculation equation for the optimization value if the criteria are not given an importance weight in (4).

$$Yi = \sum_j^g = 1X^*ij - \sum_j^n = g + 1X^*ij \tag{4}$$

The calculation equation for the optimization value if the criteria are given an importance weight, by reducing the maximax and minimax values which indicate that the attribute is more important can be multiplied by the appropriate weight. This is shown in (5).

$$Y1 = \sum_j^g = W\ jX^*ij - \sum_j^n = g + 1W\ jX^*ij \tag{5}$$

Where *g* represents the number of positive attributes and *n-g* displays the number of negative attributes, and according to the type of attribute, the ideal points of the *j*th attribute are deducted from all values of the *j*th attribute. So that later the results of the optimization can be sorted from the highest value to the lowest value.

2.2.4. The final ranking of alternatives

Based on the preceding step's computations in (5), the maximum values of Y1 for each vehicle alternative are established. To allow for direct performance comparisons, these data are then sorted in descending order. As a result, the alternative with the highest numerical value is assigned the highest rank, suggesting that it is the most optimum option for the player. From these calculations, this option will be selected by the game system. Where the multi-criteria used as the basis for calculation has provided a choice that must be passed by the game player.

2.3. Finite state machine

In computer science, the finite state machine (FSM) is a fundamental concept for modeling system behavior. Experts routinely apply decomposition principles using FSMs to simplify complex logic during software development [38]. The state-action decision diagram depicts a simple flowchart with additional bubbles depicting pending input states, while command hierarchy analysis serves as a decomposition technique that systematically breaks down complex commands into sub-commands by analyzing the sequence of events. Based on Figure 1, the process begins at the main menu. From here, the player can access the AutoShop to view car choices or press the start button to initiate the gameplay. Once the game session concludes, the 'GameDataManager' automatically saves the player's performance criteria. The system then executes the recommendation process using the MOORA method calculation to evaluate the 15 available scenarios. Finally, these personalized recommendations become accessible via the recommendation button on the AutoShop page.

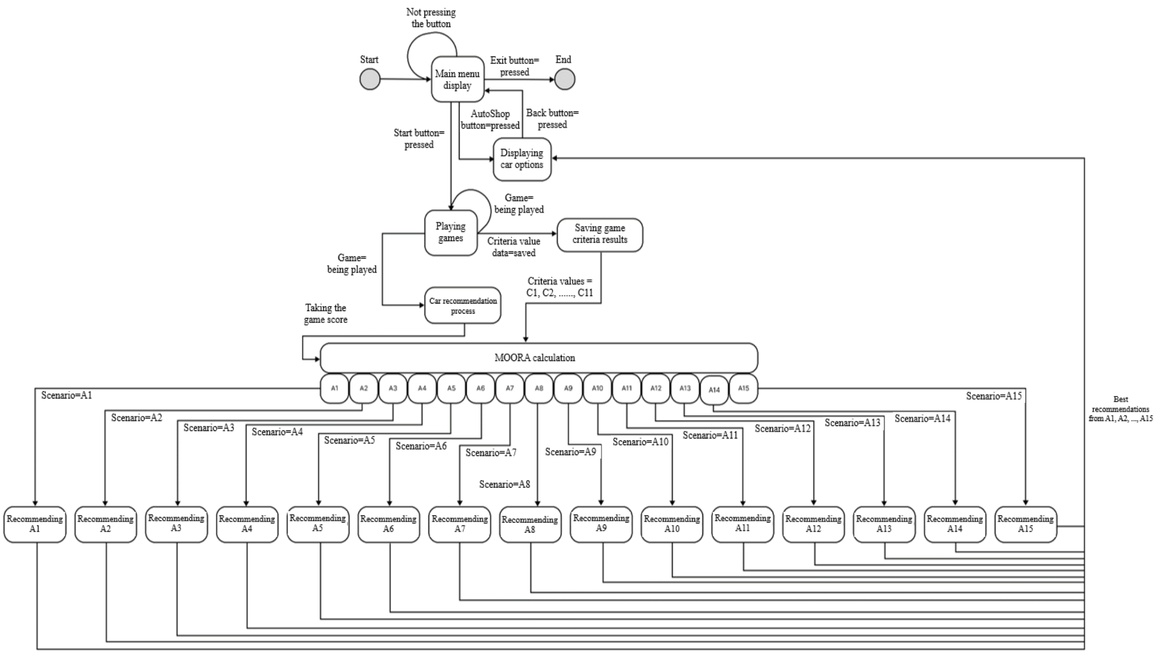

Figure 1. Finite state machine

2.4. Alternative

Alternative data is a solution to a problem that comes from several solution options available to a problem, in this problem the solution in question is alternative data in the form of 15 types of cars available in the game "Moonlight drive" that players can use in playing the game. Information about various choices is an important factor in making decisions, especially in this game which requires players to choose a vehicle that suits their playing style or the mission being carried out. The names of these various vehicles represent various specifications, so players can adjust their choices to the challenges in the game. Table 1 explains each alternative is given a symbol (A1 to A15) to facilitate identification and reference during the analysis process. These alternatives include various car names.

Table 1. Alternative

Symbol	Vehicle name
A1	Gladiator
A2	Mountain rover
A3	Desert warrior
A4	Adventure beast
A5	Rock climber
A6	Thunderbolt
A7	Vortex
A8	Falcon
A9	Phoenix
A10	Inferno
A11	Urban
A12	Sedan
A13	Compact
A14	Astra
A15	Wagon

2.5. Criterion

Criteria data is a decision from considering each factor owned by each existing alternative. To enable multi-objective optimization using MOORA, all vehicle attributes must first be standardized onto a uniform scale. Each real-world or in-game measurement. Each real-world or in-game measurement (e.g., speed in km/h, acceleration in seconds, and fuel capacity in liters) is mapped onto a discrete scale from 1 to 5, with 5 representing the most favorable value depending on whether the criterion is a benefit or cost. Each criterion follows a similar transformation, as detailed in Tables 2. These scales ensure all criteria, regardless of units or measurement ranges, are comparable and suitable for optimization. The cars used in this game have several criteria, each of which will later be used as a determinant of systematic calculations using the MOORA method, the results of which will determine the recommendations that will be given in the game, where the weight of the criteria has also been calculated using the ROC method. The criteria and weights of each car in this game are shown in Table 2.

Player achievement metrics–such as race completion time, fuel consumption, and prior vehicle usage history–are recorded after each game session. These metrics influence the optimization process by adjusting the relative importance (weights) of each criterion in the MOORA calculation. For example, if a player frequently finishes with excessive fuel consumption, the system will increase the importance of fuel efficiency (C3) and decrease the emphasis on acceleration (C1). This personalization ensures that car recommendations align with the player's actual in-game performance, thus constraining and guiding the optimization toward practical, skill-aligned outcomes. For more details, we compare each of the listed criteria to see how they compare:

i) Speed vs control: faster vehicles are often harder to handle, especially on narrow or curved tracks.
ii) Acceleration vs fuel efficiency: vehicles with high acceleration tend to consume more fuel, which may not be ideal for longer races.
iii) Weight vs stability: lighter vehicles are more agile but may lose traction or stability at high speeds.
iv) Performance vs price: high-performing vehicles usually come with higher in-game prices, which may not be accessible to all players.

2.6. Calculation

Each alternative (vehicle) is evaluated against all criteria (C1–C11), using scores scaled from 1 to 5 as shown in Table 2. Based on the scale of importance of each criterion that has been determined by ROC weighting, a decision matrix will be determined for each existing alternative. In the decision matrix, each alternative is assessed based on its previously determined criteria, then assessed with a certain assessment scale, namely as in Table 3 which is the value of the criteria for each car alternative in this game.

After obtaining the decision matrix, the next stage will be the calculation of the normalization value for each criterion and alternative. This normalization is used to unite each matrix element so that the matrix element will have a uniform value. Which later the ratio *Xij* in this study is the *i* criterion on alternative vehicle *je j*. while m is the number of alternatives, or as many as the number of vehicles that have been selected and n is the criterion index, namely the *i* criterion index on alternative *j.s*.

$$A_{11} = \frac{1}{\sqrt{(1+2+2+3+2+5+3+4+1+1+2+3+1+2+3)^2}} = 0.2$$

$$A_{12} = \frac{1}{\sqrt{(1+3+2+1+3+4+5+4+5+3+1+2+3+3+4)^2}} = 0.2$$

Table 2. Criterion

Symbol	Criterion	Type	Weight Description	Score
C1	Accelerate	Benefit	<=0.2	1
			>=0.2 and <=0.4	2
			>=0.4 and <=0.6	3
			>=0.6 and <=0.8	4
			>=0.8	5
C2	Speed	Benefit	<=70	1
			>=70 and <=110	2
			>=110 and <=150	3
			>=150 and <=190	4
			>=190	5
C3	Fuel	Benefit	<=20	1
			>=20 and <=45	2
			>=45 and <=70	3
			>=70 and <=95	4
			>=95	5
C4	Fuel Usage	Cost	>=5.2	5
			>=7.5 and <=5.2	4
			>=9.75 and <=7.5	3
			>=12 and <=9.75	2
			<=12	1
C5	Weight	Cost	<=40	5
			>=60 and <=40	4
			>=80 and <=60	3
			>=100 and <=80	2
			>=100	1
C6	Acceleration	Cost	<=1.5	5
			>=2.5 and <=1.5	4
			>=3.5 and <=2.5	3
			>=4.5 and <=3.5	2
			<=4.5	1
C7	Lights	Benefit	<=20	1
			>=20 and <=40	2
			>=40 and <=60	3
			>=60 and <=80	4
			>=80	5
C8	Distance	Benefit	<=300	1
			>=300 and <=750	2
			>=750 and <=1200	3
			>=1200 and <=1650	4
			>=1650	5
C9	Travel time	Benefit	<=1.00	1
			>=1.00 and <=2.00	2
			>=2.00 and <=3.00	3
			>=3.00 and <=4.00	4
			>=4.00	5
C10	Money	Benefit	<=200	1
			>=200 and <=400	2
			>=400 and <=600	3
			>=600 and <=800	4
			>=800	5
C11	Price	Cost	>=800	5
			>=600 and <=800	4
			>=400 and <=600	3
			>=200 and <=400	2
			<=200	1

Table 3. Decision matrix

Alternative	Criterion										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	1	1	3	2	2	2	3	2	1	5	1
A2	2	3	5	5	3	3	4	5	3	5	5
A3	2	2	3	5	5	5	3	3	2	5	2
A4	3	1	4	2	2	2	5	2	2	5	3
A5	2	3	4	2	4	3	4	4	5	5	4
A6	5	5	2	4	1	4	2	5	3	5	5
A7	3	5	3	4	3	3	1	2	5	5	3
A8	4	4	3	1	4	3	2	4	3	5	4
A9	1	5	1	1	5	5	1	2	3	1	5
A10	1	3	2	4	4	3	2	3	2	5	2
A11	2	1	3	3	2	3	3	2	2	5	5
A12	3	2	2	3	3	3	2	2	1	5	3
A13	1	3	1	4	2	5	4	1	2	5	2
A14	2	3	2	2	3	2	3	5	5	5	4
A15	3	4	4	3	3	4	2	5	4	5	1

We applied this calculation method to every entry in the decision matrix to ensure consistency across the dataset. This step effectively converts the raw attribute values into a uniform scale, allowing for direct comparison between different criteria types. The resulting comprehensive normalized dataset is displayed in Table 4. It can be seen that some alternatives, for certain criteria, have a value of 5 in the table, which is shown with a green background. Based on the normalization calculation, the normalized value of 5 is 1, as shown in Table 4. Before determining the Yi value, the weighted normalization value must be found first. Te result is obtained from the normalization of the decision matrix multiplied by the weights that have been determined based on the previous ROC method in Table 5. After the weighted normalization process, the calculation results ranking process is carried out to sort the cars that are most recommended by the MOORA method, which can later be played by users, based on the highest value results obtained in Table 6 from the user's playing experience.

Table 4. Normalization of decision matrix

Alternative	Criterion										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	0.2	0.2	0.6	0.5	0.5	0.5	0.6	0.4	0.25	1	0.2
A2	0.4	0.6	1	1	0.333	0.333	0.8	1	0.75	1	1
A3	0.4	0.4	0.6	1	1	1	0.6	0.6	0.5	1	0.5
A4	0.6	0.2	0.8	0.5	0.5	0.5	1	0.4	0.5	1	0.333
A5	0.4	0.6	0.8	0.5	0.25	0.333	0.8	0.8	1	1	0.25
A6	1	1	0.4	0.25	0.2	0.25	0.4	1	0.75	1	1
A7	0.6	1	0.6	0.25	0.333	0.333	0.2	0.4	1	1	0.333
A8	0.8	0.8	0.6	0.2	0.25	0.333	0.4	0.8	0.75	1	0.25
A9	0.2	1	0.2	0.2	0.2	0.2	0.2	0.4	0.75	0.2	1
A10	0.2	0.6	0.4	0.25	0.25	0.333	0.4	0.6	0.5	1	0.5
A11	0.4	0.2	0.6	0.333	0.5	0.333	0.6	0.4	0.5	1	1
A12	0.6	0.4	0.4	0.333	0.333	0.333	0.4	0.4	0.25	1	0.333
A13	0.2	0.6	0.2	0.25	0.5	0.2	0.8	0.2	0.5	1	0.5
A14	0.4	0.6	0.4	0.5	0.333	0.5	0.6	1	1	1	0.25
A15	0.6	0.8	0.8	0.333	0.333	0.25	0.4	1	1	1	0.2

Table 5. Weighted normalization

Alternative	Criteria										
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	0-Jan	0.04	0.088	0.053	0.042	0.029	0.031	0.016	0.007	0.017	0.002
A2	0-Jan	0.121	0.146	0.105	0.028	0.019	0.042	0.039	0.02	0.017	0.008
A3	0-Jan	0.08	0.088	0.105	0.083	0.058	0.031	0.023	0.014	0.017	0.004
A4	0-Jan	0.04	0.117	0.053	0.042	0.029	0.052	0.016	0.014	0.017	0.003
A5	0-Jan	0.121	0.117	0.053	0.021	0.019	0.042	0.031	0.027	0.017	0.002
A6	0-Jan	0.201	0.058	0.026	0.017	0.015	0.021	0.039	0.02	0.017	0.008
A7	0.203	0.201	0.088	0.026	0.028	0.019	0.01	0.016	0.027	0.017	0.003
A8	0.27	0.161	0.088	0.021	0.021	0.019	0.021	0.031	0.02	0.017	0.002
A9	0.068	0.201	0.029	0.021	0.017	0.012	0.01	0.016	0.02	0.003	0.008
A10	0.068	0.121	0.058	0.026	0.021	0.019	0.021	0.023	0.014	0.017	0.004
A11	0.135	0.04	0.088	0.035	0.042	0.019	0.031	0.016	0.014	0.017	0.008
A12	0.203	0.08	0.058	0.035	0.028	0.019	0.021	0.016	0.007	0.017	0.003
A13	0.068	0.121	0.029	0.026	0.042	0.012	0.042	0.008	0.014	0.017	0.004
A14	0.135	0.121	0.058	0.053	0.028	0.029	0.031	0.039	0.027	0.017	0.002
A15	0.203	0.161	0.117	0.035	0.028	0.015	0.021	0.039	0.027	0.017	0.002

Based on Table 6, it can be seen the value of the car based on the Yi value which has been sorted from the highest to the lowest value, and alternative 6 has been obtained as the car with the highest value, and alternative 15 as the car with the lowest value of the 15 cars for which the value of each criterion has been determined. A trade-off occurs when a car is good in one respect but bad in another (e.g., fast but fuel-hungry). In MOORA, this is resolved by the aforementioned subtraction method: the advantages and disadvantages are directly calculated into a single Yi value, allowing us to see which car is the most optimal overall.

Table 6. Yi value

Rank	Vehicle name	Yi value
1	A6	0.7598
2	A2	0.67965
3	A8	0.671133
4	A15	0.662967
5	A3	0.6383
6	A7	0.637317
7	A5	0.583983
8	A4	0.583567
9	A14	0.539567
10	A12	0.486417
11	A11	0.444133
12	A9	0.40465
13	A10	0.391633
14	A1	0.39055
15	A13	0.38065

3. RESULT

The development of the game "Moonlight drive" focuses on the application of the MOORA method as an algorithm to adjust the type of vehicle that can be used by players based on their abilities. This system automatically adjusts the available choices by analyzing performance values recorded from previous game sessions. At this stage, the calculations that have been done in the previous chapter are implemented and designed using the Unity application and developed so that they are in accordance with the needs that have been set. The selections made by the game system make it easier for players to achieve high scores. It is hoped that players will find it easy to play this game.

3.1. Multi-objective optimization on the basis of ratio analysis implementation

The implementation of the MOORA method in this game is done by doing it on Unity using the C# programming language. The trial will be carried out several times with the aim of being able to show different recommendation results because the criteria values obtained from the player's game results will be calculated using the MOORA method. This aims to ensure that the creation of the recommendation system in the game is appropriate and runs correctly. In Figure 2, the system gets input values from players who have played the game. After using the car selected by the previous player from the AutoShop menu. Then based on the values obtained, it will be carried out to the next process, namely the input normalization process and weighted normalization, where the values are changed to a scale of 1-5 based on each provision owned by the criteria.

Figure 2. Input value

Based on Table 7, the value is from the recommendation process that has reached the weighted normalization stage. Each aspect of the vehicle (e.g. acceleration capability, maximum speed, fuel efficiency) is given a score according to its scale, then multiplied by the weight of the importance of each aspect. For example, acceleration capability has a fairly high weight compared to price, which means that this aspect is considered more in the selection. The final result of this calculation will be used to determine which vehicle best fits the criteria that have been set. The next process is to calculate the optimization value as shown in the Figure 3.

Based on Figure 3, the value is the final result of the MOORA method recommendation process, the calculation result is displayed in the debug log with a score of 0.3162. However, this calculation is not displayed directly on the player UI so players can only directly receive vehicle name recommendations. Then in the next stage, the value will be used to determine which vehicle is suitable for the user based on previous game experience. Based on Figure 4, the system has selected the Gladiator, Sedan, and Astra cars as recommended cars based on calculations using the MOORA method which can later be used by players in the next game to be played by the player.

Based on Table 8, the value owned by the player is 0.4849833, but the recommended vehicles are Gladiator, Astra, and Sedan and not cars with the same or similar values. This is because the money owned by the player when playing the game is 560, and therefore the system will choose it based on the order and then based on the amount of money owned by the player, therefore the three vehicles are selected by the system so that the recommendations in this game can be maximally useful in facilitating players in playing this game. The following is a table showing changes in recommendations based on player achievements. Table 9 shows that different achievements lead to different car recommendations, even when the player identity is the same.

Table 7. Normalized values and weighted normalization

Criterion type	Input normalization	Normalization of weights
Accelerate	1-Jan	0.0676
Speed	1-Jan	0.0402
Fuel	1-Jan	0.0292
Fuel Usage	2-Jan	0.0525
Weight	2-Jan	0.0415
Acceleration	2-Jan	0.029
Lights	3-Jan	0.0312
Distance	1	0.0078
Travel time	1	0.0054
Money	3	0.0102
Price	5	0.0016

Figure 3. Optimization value

Figure 4. Recommendation results

Table 8. MOORA ranking value

Ranking	Alternative	Optimization value	Price
1	Thunderbolt	0.7196	420
2	Mountain Rover	0.6796	850
3	Falcon	0.6711	370
4	Wagon	0.663	780
5	Desert Warrior	0.6383	670
6	Vortex	0.6373	600
7	Rock Climber	0.584	375
8	Adventure Beast	0.5836	500
9	Astra	0.5396	370
10	Sedan	0.4864	520
11	Urban	0.4441	610
12	Phoenix	0.4046	900
13	Inferno	0.3916	630
14	Gladiator	0.3906	190
15	Compact	0.3807	690

Table 9. Car selection and player achievement

Trial	Mileage (km)	Fuel consumption (L/km)	Speed (km/h)	Money ($)	Recommended car
1	73.49	10	69	400	A6
2	65	8.5	62	350	A8
3	85	12	72	420	A2

3.2. System usability scale

Usability testing in this study was conducted using the system usability scale (SUS) with a questionnaire given to respondents. The test was conducted on 25 people with 1 respondent aged over 25 years, 5 people aged 23-25 years, 17 respondents aged 19-22 years, and 2 respondents aged 16-18 years. There are 10 questions given to Table 10, there are 10 questions given to the examiner with 5 positive questions and also 5 negative questions.

Table 10. SUS question

Code	Question
Q1	I anticipate using this recommendation feature frequently.
Q2	I find this recommendation feature difficult to navigate.
Q3	I find this recommendation feature user-friendly.
Q4	I require assistance from others to utilize the recommendation feature in this game.
Q5	I believe this recommendation feature functions as intended.
Q6	I perceive inconsistencies in the recommendation feature's performance.
Q7	I believe others will quickly learn to use this recommendation feature.
Q8	I find this recommendation feature perplexing.
Q9	I encounter no difficulties in using this recommendation feature.
Q10	I need to familiarize myself with this recommendation feature before using it.

After completing the questionnaire, Table 11 shows the final results of the SUS score calculation, then the average SUS score will be compared with the SUS assessment. Including the test result category with the score that has been obtained. This comparison process is essential to determine where the application stands relative to global usability benchmarks before visualizing it. Figure 5 is a rating scale to show the overall average SUS score obtained in the usability test, namely 82.4, which is included in the Adjective ratings group in the excellent category, and grade scale B. This value shows that respondents consider the recommendation feature used to be very good and worthy of use.

Table 11. Final SUS score results

Respondent	Sus score (totalx2.5)
R_1	82.5
R_2	75
R_3	72.5
R_4	100
R_5	75
R_6	75
R_7	65
R_8	75
R_9	72.5
R_{10}	75
R_{11}	125
R_{12}	80
R_{13}	90
R_{14}	82.5
R_{15}	77.5
R_{16}	62.5
R_{17}	75
R_{18}	77.5
R_{19}	70
R_{20}	75
R_{21}	87.5
R_{22}	100
R_{23}	97.5
R_{24}	92.5
R_{25}	100
Total SUS score	2060
Average SUS score	82.4

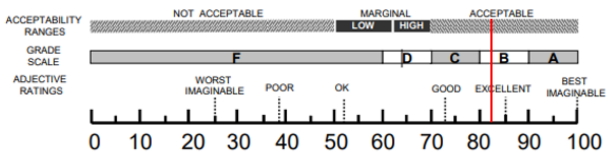

Figure 5. SUS score

3.3. System usability scale relationship with Nielsen's attribute of usability

Usability aspects based on each SUS statement using the Nielsen's attributes of usability (NAU) are categorized into five groups, as presented in Table 12, which is adapted from findings reported in previous research. The NAU method has been widely applied in usability testing across various domains, for instance, for a vocabulary game prototype [39], test a recycling application [40], assess the usability of a web portal [41], [42], quality assurance systems [43], and education [44]. Table 11 illustrates how the NAU method's categories relate to the usability characteristics in the SUS statements. These categories are used to assess the questionnaire results in a more systematic manner and are founded on tried-and-true usability principles. We may gain a better understanding of how each of these factors influences the system's overall usability assessment by connecting particular SUS questions to factors like learnability, efficiency, memorability, mistakes, and satisfaction.

Table 12. Nielsen's attributes of usability

Usability aspect	Questionnaire symbols
Learnability	Q1, Q3, Q7
Efficiency	Q5, Q3, Q8, Q9
Memorability	Q7
Errors	Q2, Q4, Q6, Q8, Q10
Satisfaction	Q1, Q9

3.3.1. Aspects of learnability, efficiency, and memorability

Based on questions Q1, Q3, Q5, Q7, Q8, and Q9, most respondents agreed in assessing the aspects of learnability, efficiency, and memorability. The frequency of respondents' answers to the questions on the quiz given by the author shows that from questions Q1, Q2, and Q3 which are added up with 25 respondents, 71 out of 75 questions given to respondents stated that they could understand how to use the recommendation feature in the game (learnability). Then based on questions Q3, Q5, Q9 which were given to 25 respondents, 89 out of 100 answers, respondents can use the recommendation feature in the game easily without any obstacles (efficiency), and based on question Q7 25 out of 25 respondents can remember what can be done and what must be done to use the recommendation feature without learning from the beginning repeatedly (memorability).

3.3.2. Errors aspect

Based on the frequency of answers to question Q2, 18 out of 25 respondents chose to disagree that the recommendation feature in this game is difficult to play. Based on the frequency of answers to question Q4, 19 out of 25 respondents disagreed that it took someone else's help to run the recommendation feature in the game. Based on the frequency of answers to question Q6, 17 out of 25 respondents chose that there were not many inconsistent things in the recommendation feature, which shows that there were no inconsistent changes in the recommendation feature while the game was running. Based on the frequency of answers to question Q8, 17 out of 25 respondents indicated that the recommendation feature in the game was not confusing and easy to play. Based on the frequency of answers to question Q10, 16 out of 25 respondents easily adapted to the recommendation feature in the game and did not need help from others to run the recommendation feature in the game.

3.3.3. Satisfaction aspect

Based on the frequency of answers to question Q1, 22 out of 25 respondents felt that they would often use the recommendation feature in the game, which shows that respondents are satisfied with the playing experience that players get when running the recommendation feature in the game. Based on the frequency of answers to question Q9, 23 out of 25 respondents can use the recommendation feature in the game easily and without any obstacles. Based on the two questionnaire questions, respondents considered that the recommendation feature in the game was satisfactory because players felt like playing the game more often and could also complete the game easily without any obstacles because of the recommendation feature. So that the satisfaction aspect can be met based on the answers from respondents in playing "Moonlight drive".

4. DISCUSSION

The MOORA method, which uses previous player performance to select vehicles, significantly impacts the Moonlight drive gameplay experience. The system automatically recommends vehicles that best suit each player's playing style. The system can only provide recommendations after a player has completed at least one game session. This means that new players won't receive accurate recommendations in their first game because there's no performance data to analyze:

i) Scalability to the number of alternative vehicles: when the number of vehicles in the game increases significantly, the optimization and normalization calculations in the MOORA method may require more computation time.
ii) Dynamic changes in player ability: the system isn't yet able to handle real-time or gradual changes in player ability. For example, as a player progresses from beginner to expert, the system still relies on previous data and doesn't adapt unless a new game is played.

Some potential future developments to improve this system include the integration of real-time player feedback, such as live preference notifications (“I like this car”) to strengthen recommendations. Additional adjustments in multiplayer mode, taking into account combined team performance, to ensure recommendations remain relevant collectively and not just individually. The implementation of dynamic learning methods, such as reinforcement learning or online learning, to ensure the system can continuously learn and adapt recommendations adaptively as gameplay patterns change.

5. CONCLUSION

The comparison results between the results of the MOORA calculation and on "Moonlight drive" have the appropriate value results based on the optimization value which is the final result of the MOORA method calculation. This explains that the MOORA method can provide consistent results and can also be used in determining the selection of vehicles in the game based on the player's ability to use the vehicle based on the results of the previous game. The results of the usability testing measurement, whose questions have been categorized based on NAU and have been tested so that they get an average SUS score of 82.4, included in the adjective ratings group in the excellent category, and grade scale B. This value shows that respondents consider the recommendation feature used to be very good and worthy of use.

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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

The research related to human use has been complied with all the relevant national regulations and institutional policies in accordance with the tenets of the Helsinki Declaration and has been approved by the authors' institutional review board or equivalent committee.

DATA AVAILABILITY

Data supporting the findings of this study are available at Universitas Islam Negeri Maulana Malik Ibrahim Malang, Malang City, East Java, Indonesia.

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