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Evaluation of motorized wheelchairs using an integrated ARAS-TOPSIS and CRITIC approach

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Abstract**—** This research paper proposes an innovative mathematical approach for evaluating motorized wheelchairs by integrating Additive Ratio Assessment (ARAS) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method, along with the CRITIC (Criteria Importance through Intercriteria Correlation) weighting approach. By taking into account several factors at once, the integration of various approaches seeks to improve the evaluation process's accuracy and dependability. In order to handle the situation, the modelled framework takes into account 14 possible wheelchairs and 7 factors. The CRITIC weighting approach evaluates the impact of the criteria, while the TOPSIS and ARAS methodologies separately calculate the performance rating to produce an ordering of the chosen wheelchairs. Wheelchairs are evaluated using an array of factors, including recommendations from experts as well as online B2B market information. A Spearman's correlation coefficient of 0.9696 confirms strong consistency between ARAS and TOPSIS based rankings The MW-12 variant stands out as the best option. The sensitivity evaluation was performed to test robustness of the proposed method. Practically, this integrated approach equips manufacturers with datadriven product development insights, aids healthcare providers in transparent procurement, and empowers end users and caregivers to select wheelchairs that best meet individual mobility needs.

Keywords: MultiCriteria Decision Making, CRITIC, ARAS, TOPSIS, Sensitivity Analysis, Motorized wheelchair, Assistive Product Evaluation.

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I. INTRODUCTION

Motorized wheelchairs (MW), also known as power wheelchairs, are innovative mobility devices designed to provide independence and enhanced mobility for individuals with physical disabilities or limited mobility [1]. Unlike traditional manual wheelchairs, which require physical exertion to propel, motorized wheelchairs are equipped with electric motors and battery systems, enabling users to navigate their surroundings with ease and minimal effort. These advanced mobility aids have revolutionized the lives of countless individuals, offering greater freedom of movement both indoors and outdoors. From navigating through crowded spaces in shopping malls to traversing rugged terrain in outdoor environments, motorized wheelchairs provide users with the ability to engage more fully in daily activities and pursue greater independence.

a. Issue in evaluating the perfect wheelchair

Evaluating the perfect wheelchair for an individual with mobility needs can present several challenges and complexities. While motorized wheelchairs offer enhanced mobility and independence, finding the ideal match requires careful consideration of various factors, including the user's physical condition, lifestyle, environmental needs, and personal preferences. One significant issue in evaluating the perfect wheelchair is the diverse range of user requirements. Individuals with disabilities or limited mobility may have unique physical characteristics and functional limitations that influence their choice of wheelchair. Factors such as body size, strength, range of motion, and specific mobility impairments must be taken into account to ensure the wheelchair provides optimal comfort, support, and functionality [2].

Furthermore, the environment in which the wheelchair will be used plays a crucial role in the selection process. Indoor spaces, such as homes, offices, and healthcare facilities, may have different layout configurations and accessibility challenges compared to outdoor environments, such as parks, sidewalks, and public transportation [3]. Wheelchair users may require different features and specifications to navigate effectively in these varied settings. Another issue arises from the rapidly evolving technology and design innovations in the field of motorized wheelchairs. While advancements in electronics, materials, and ergonomics have led to more sophisticated and versatile wheelchair models, the abundance of choices can be overwhelming for users and healthcare professionals tasked with selecting the most suitable option. Moreover, cost considerations pose a significant challenge for many individuals seeking a motorized wheelchair [4].

These devices can represent a substantial investment, and navigating insurance coverage, funding options, and out-of-pocket expenses adds another layer of complexity to the evaluation process. Additionally, the availability of comprehensive and unbiased information about motorized wheelchairs can be limited, making it challenging for users to make informed decisions. Access to reliable resources, expert guidance, and peer support networks can greatly facilitate the evaluation process and help individuals find the perfect wheelchair that meets their needs and preferences. In light of these challenges, it is essential for users, caregivers, and healthcare professionals to engage in thorough assessments, consultations, and trials to identify the most suitable motorized wheelchair for each individual. By addressing the diverse range of user requirements, environmental considerations, technological advancements, cost factors, and information accessibility issues, we can work towards overcoming the challenges in evaluating the perfect wheelchair and ultimately improve the mobility and quality of life for individuals with disabilities.

b. Problem Formulation

Choosing the right motorized wheelchair (MW) is pivotal in improving the well-being and autonomy of individuals with disabilities. The selection process is crucial as the MW greatly impacts the daily lives of wheelchair users. However, navigating the intricate terrain of MW options demands a methodical approach to ensure well-informed decisions. MCDM techniques present a systematic framework for assessing and prioritizing different alternatives based on a range of criteria. The selection of motorized wheelchairs faces challenges due to the multiplicity of criteria and the lack of integrated approaches for evaluation.

To further the research, it is necessary to identify the factors that have a significant impact on a customer's choice to purchase a motorized wheelchair (MW). A comprehensive list of seven essential factors was determined by carefully examining the product's details, inquiries from consumers on internet sites, and relevant literature. These variables are: Cost (C), Net Weight (NW), Charging Time (CT), Estimated Range (ER), Maximum Speed (MS), Motor Power (MP), and Maximum User Weight Capacity (MUWC) as displayed in table 1. Interviews with users of motorized wheelchairs validated these factors, confirming their importance in the selection process. Concrete confirmation of the crucial role these factors play in the choice and acquisition of motorized wheelchairs was given by this validation method. After that, 14 different MW models were selected through a selection procedure that involved a range of brands and pricing points. The models were obtained from reliable internet stores that were well-known for their strong demand and favorable customer reviews. The primary objective is to utilize the CRITIC approach to determine the weights of criteria, which will then be incorporated into the ARAS and TOPSIS procedures in order to suggest the best model. By using a strategic approach, the influence of subjective considerations on indicator weights is lessened, leading to a more objective review process. In-depth explanations of the TOPSIS and ARAS techniques are given, along with a comparison of rankings to determine the consistency and dependability of each. Moreover, sensitivity studies are carried out to provide an extensive rating of MW models, thereby aiding in well-informed decision making. The ultimate objective of this research is to empower PWDs (people with disabilities) by providing them with the knowledge and skills needed to choose the best MW model, improving their mobility and general quality of life.

Table 1: Selected MW models with their specification.

Criteria/Alternatives	C in US $	NW in kg	CT in hour	MS in mile per hour	ER in mile	MW in watthour	MUWC in kg
MW-1	1099	63	6.000	3.750	15	288	396
MW-2	1499	63	5.000	3.750	15	288	396
MW-3	1599	41	6.000	3.750	10	240	220
MW-4	1634	94	8.000	3.750	8.7	216	300
MW-5	2244	60	5.000	3.600	8.6	240	250
MW-6	2499	70	6.500	3.700	9.3	288	300
MW-7	2795	39.3	5.000	3.700	9.3	288	300
MW-8	2799	53	8.000	3.700	12.4	250	250
MW-9	2899	52	4.500	3.700	8	180	275
MW-10	2999	32	8.000	2.800	9.3	240	240
MW-11	3694	168	6.000	5.100	17.6	840	300
MW-12	3747	185	6.500	4.000	24	1200	300
MW-13	4754	245	8.000	4.000	19.2	960	300
MW-14	4749	115	6.000	5.000	11.2	250	300

Source: Own elaboration.

II. LITERATURE REVIEW

Due to its ability to take into account numerous competing criteria at once, MCDM approaches are very effective tools in a variety of sectors. By balancing ecological, economic, and social aspects, MCDM assists in the selection of the most sustainable policies or strategies in environmental management. In the same way, it helps engineers assess design options according to standards like cost, reliability, and efficiency. In the healthcare industry, MCDM integrates variables such as patient preferences, cost-effectiveness, and efficacy to assist medical practitioners in choosing treatments. Furthermore, in the financial industry, it aids investors in navigating a variety of investment options by thoroughly evaluating risks, rewards, and market circumstances. Through the balance of elements such as transportation, infrastructure, and environmental effect, MCDM approaches in urban planning help to optimize city development plans. By taking into account factors like cost, dependability, and sustainability, it also helps with supplier selection, logistics planning, and inventory management in supply chain management. In general, as table 2 illustrates, MCDM techniques provide vital support in a variety of fields, empowering stakeholders to make decisions that are consistent with their goals and beliefs even in the face of complicated and conflicting factors.

Table 2: Application of multiple MCDM techniques in numerous areas.

Authors	Method	Descriptions	References
Gheibdoust et al.	SWARA-ARAS	Study prioritizes SERVQUAL factors in 5-star Iranian hotels during COVID-19. Delivery of service promise ranked highest; A1 hotel excelled.	[5]
Antunes et al.	DEA-TOPSIS	Assessment of Chinese healthcare system over 10 years reveals importance of synergy, machine learning predicts performance, highlighting heterogeneity across provinces.	[6]
Beheshtinia et al.	PROMETHEE-TOPSIS	This study introduces PROMSIS, a hybrid MCDM method, for healthcare waste disposal center location. Economic, environmental, and social factors are prioritized.	[7]
Boonsothonsatit et al.	AHP-TOPSIS	Study proposes a decision-making framework for hospital technology selection, focusing on medication dispensing. Pick-to-Light system favoured for improving operational efficiency and accuracy.	[8]
Chen et al.	Fuzzy IWP-TOPSIS-GRA	This study addresses healthcare waste treatment technology selection using a novel index system and an integrated approach. The developed framework, validated through real-world case analysis, offers a feasible and robust method for evaluation under uncertain conditions.	[9]
Deretarla et al.	AHP-COPRAS	This study proposes an integrated method for supplier evaluation and vendor selection, demonstrating its effectiveness through a case study in precision parts production, providing a detailed analysis and step-by-step guidance for similar decision-making processes.	[10]
Nafteh & Shahrokhi	COPRAS	This paper introduces mcdm approach for sustainable supplier selection, integrating linguistic variables transformed into fuzzy numbers and analyst expertise degrees represented by intuitionistic fuzzy numbers, facilitating uncertainty management in group decision-making.	[11]
Ghose et al.	Fuzzy COPRAS	This study proposes a systematic approach for selecting the optimal material for solar car manufacturing, utilizing a hybrid MCDM model. Sensitivity analysis confirms the effectiveness of this method.	[12]
Wang et al.	CRITIC-MACROS	This paper introduces a method for sustainable food supplier selection. Numerical example and sensitivity analysis demonstrate its effectiveness in handling uncertain data.	[13]
Karahan et al.	CRITIC-MULTIMOORA	This research identifies warehouse manager selection criteria and utilizes hybrid method to select the best candidate. Results emphasize the importance of skills in managing warehouse activities for successful operations.	[14]
Menekșe & Akdağ	fuzzy CRITIC-WASPAS	This paper introduces fuzzy MCDM methodologies for medical waste disposal selection for ranking alternatives. Single and interval-valued spherical fuzzy environments model uncertainty effectively, aiding decision-makers in healthcare and related sectors.	[15]
Mete et al.	BWM-COPRAS	This paper introduces an integrated MCDM approach using MC-BWM to prioritize indicators and COPRAS to rank countries based on INFORM COVID-19 Risk Index. Comparative evaluation and scenario analyses offer recommendations for COVID-19 risk assessment.	[16]
Sun et al.	QFD-MCDM	This paper proposes an integrated methodology combining QFD, MCDM, and IFS to design resilient strategies for the bauxite maritime supply chain. A real case study demonstrates the effectiveness in addressing crucial risks and enhancing resilience.	[17]
Yadav et al.	ENTROPY-VIKOR	This study employs a hybrid method to select and rank dental restorative composite materials based on eleven performance defining attributes. DHZ6 ranks highest, demonstrating the method's significance in biomedical decision-making for enhancing patient outcomes and healthcare advancements.	[18]
Mishra et al.	fuzzy MULTIMOORA	This study proposes a novel integrated framework for solid waste disposal method selection. It incorporates entropy and discrimination measures for q-ROFS, validated through a case study and comparison analysis.	[19]

Banadkouki et al.	Entropy-fuzzy TOPSIS	This study investigates energy efficiency improvement strategies in the ceramic tile industry in Iran. It identifies priority strategies such as reducing leakage in compressed air systems and optimizing power consumption.	[20]
Esangbedo & Wei	ENTROPY-GRA	This paper addresses uncertainty in multi-criteria decision making caused by normalization methods, proposing a grey hybrid normalization approach. Applied to select a branch office location for a Chinese electric vehicle manufacturer, it ranks New York City highest.	[21]

Source: Own elaboration.

a. *Past studies on MCDM application related to wheelchair*

MCDM is being used more and more in a variety of sectors to handle complicated decision issues. Within the realm of wheelchair technology and accessibility, MCDM techniques provide useful frameworks for maximizing features, designs, and budget allocation. Prior research has investigated the application of MCDM techniques to improve wheelchair usability, user happiness, and functionality. These research enhance the quality of life for wheelchair users by advancing wheelchair technology by including many factors like affordability, comfort, and maneuverability.

Sahoo and Choudhury talked about evaluating wheelchairs using the mcdm approach. In this work, the best electric power wheelchair (EPWC) in low-resource environments is chosen using three MCDM approaches: EDAS for assessment, COPRAS for parameter weighting, and ENTROPY for parameter weighting. The results show that EPWC-1 is the best option, whereas EPWC-7 and EPWC-10 perform badly in COPRAS and EDAS, respectively [22]. Haddad and Sanders, on the other hand, assess which compromise path is preferable for motorized wheelchairs. The study presents a fresh application in this field: using PROMETHEE II to determine the direction of a motorized wheelchair. It makes safe navigation possible by combining obstacle avoidance and user choices. Joystick override allows users to maintain control while sensitivity analysis guarantees robustness [23]. Mistarihi et al. used a fuzzy MCDM technique to compute wheelchair design attributes. This study proposes a wheelchair design with nested seat backs and hand rests to improve user and companion comfort. When QFD and FANP are coupled, the importance of engineering features is highlighted, with material quality ranking first. This comprehensive technique is helpful in making ambiguous decisions in ergonomic design and product development [24].

A unique Bayesian network-based approach for recurrent multi-criteria, multi-attribute decision problems was presented by Delcroix et al. By taking into account the qualities of the decision-maker, contextual considerations, alternative features, and choice criteria—all of which are illustrated through the selection of manual wheelchairs—the model helps make decisions easier [25]. A thorough methodology for assessing material options was put out by Sahoo and Choudhury in order to create low-cost robotic wheelchair chassis. By integrating the CRITIC, EDAS, and COPRAS techniques, it tackles intricate decision-making problems. The best option is gray cast iron as it provides a good mix of both affordability and technical qualities [26].

Using MCDM techniques, Sahoo and Choudhury concentrated on choosing and prioritizing design requirements for a smart robotic powered wheelchair prototype. It assists decision-makers in the evaluation of early-stage product designs by identifying functional performance as critical and by adding new criteria and utilizing AHP and FAHP [27]. Hezam et al. evaluated autonomous smart wheelchairs (ASWs) from five manufacturers using a hybridized CoCoSo technique based on Dombi operators and similarity metrics. The approach rates organizations according to sustainability criteria using interval-valued Fermatean fuzzy sets; sensitivity analysis and comparison with current models show the method's viability and stability [28]. The goal of Chwał et al. was to create a prototype canine wheelchair that is strong, lightweight, and adaptable for tiny dogs that are paralyzed in their rear limbs. The finished product improves dogs' quality of life and mobility through measures, mobility evaluations, and multi-criteria analysis, which helps with rehabilitation and the possibility of a return to maximum fitness [29].

b. *Novelty and Research Gap*

By integrating ARAS, TOPSIS, and CRITIC for motorized wheelchair evaluation, this study presents a revolutionary methodology. It tackles the requirement for well-informed decision-making, the underutilization of cutting-edge approaches, and inadequacies in comprehensive procedures.

Novelty of the proposed study: This study is novel because it combines three different approaches to evaluate motorized wheelchairs in a comprehensive way: ARAS, TOPSIS and CRITIC although each technique has been used separately in decision-making situations, the combination of these approaches in assessing motorized wheelchairs is novel. This method provides a comprehensive framework for evaluation that takes into account a variety of factors and the interactions between them, perhaps resulting in better informed choices for the best motorized wheelchairs.

Research gap of the proposed study: Notwithstanding the progress made in the domain of motorized wheelchair evaluation, a significant study lacuna remains with regard to the absence of all-encompassing approaches that take into account many factors and their mutual influences. Previous research frequently applies one-method techniques or ignores important aspects of wheelchair assessment. Furthermore, there is still a lack of integration of newer methods like ARAS and CRITIC in this setting. Therefore, by putting forth a fresh strategy that meets the demand for an all-encompassing, integrated methodology for motorized wheelchair assessment.

c. *Identifying the criteria for the proposed study*

I. Criteria for assessing motorized wheelchairs are essential for informed decision-making in wheelchair selection as follows:
II. Cost: The financial investment required for acquiring the motorized wheelchair, including initial purchase price and potential long-term maintenance expenses.
III. Net Weight: The weight of the wheelchair itself, which impacts portability, maneuverability, and transportation requirements.
IV. Charging Time: The duration required to fully charge the wheelchair's battery, influencing usability and convenience for users.
V. Maximum Speed: The highest achievable speed of the wheelchair, affecting the efficiency of travel and overall user experience.
VI. Estimated Range: The distance the wheelchair can travel on a single battery charge, crucial for planning longer trips and ensuring uninterrupted mobility.

VII. Power: The motor's strength and efficiency in propelling the wheelchair, impacting performance on various terrains and under different conditions.
VIII. Maximum User Weight Capacity: The maximum weight the wheelchair can safely support, ensuring suitability for users of different sizes and needs.

d. Objective of this study

The objective of this research paper as follows:

I. This study proposes an integrated framework for the evaluation of motorized wheelchairs, combining MCDM methodologies such as ARAS and TOPSIS methods with the CRITIC weighting to improve accuracy and objectivity in decision making.
II. This study conducts a sensitivity analysis of a robust framework for evaluating wheelchair options.
III. This study facilitates informed decision-making in wheelchair selection through the application of the combined methodology.

III. MATERIAL AND METHODS

While methods like PROMETHEE and AHP are suitable for wheelchair selection problems, they rely heavily on qualitative judgments and pairwise comparisons, which can introduce subjectivity and become time-consuming with larger datasets. In contrast, our integrated approach using CRITIC, TOPSIS, and ARAS allows for a more objective, data-driven analysis, making it more practical and scalable for evaluating multiple wheelchair alternatives. Our methodological proposal is effective because it combines the strengths of CRITIC, ARAS, and TOPSIS—ensuring objective weight determination, handling inter-criteria correlations, and delivering robust, consistent rankings. This integrated MCDM approach enhances decision-making accuracy and provides a transparent, reproducible framework suitable for evaluating complex assistive technologies like motorized wheelchairs. Figure 1 shows a comprehensive flowchart model that depicts the complete research process. This section's organization is outlined as follows: First, CRITIC is applied to establish the weights of the criterion. After that, TOPSIS evaluates the distances from an average answer, whereas ARAS uses a scoring method to produce an overall rating of the options. Lastly, a sensitivity analysis is carried out with a particular focus on the cost criterion in order to confirm the robustness of the employed approaches. The alternatives were selected based on a review of recent literature and specifications from reputable online B2B platforms, ensuring relevance and variety in features. Additionally, expert opinions and user reviews were consulted to validate qualitative factors. This mixed approach enhances the credibility of our data and reflects real-world preferences, making the evaluation framework both practical and grounded. This methodology guarantees a comprehensive analysis of the decision-making procedure, thus augmenting the dependability of the research findings.

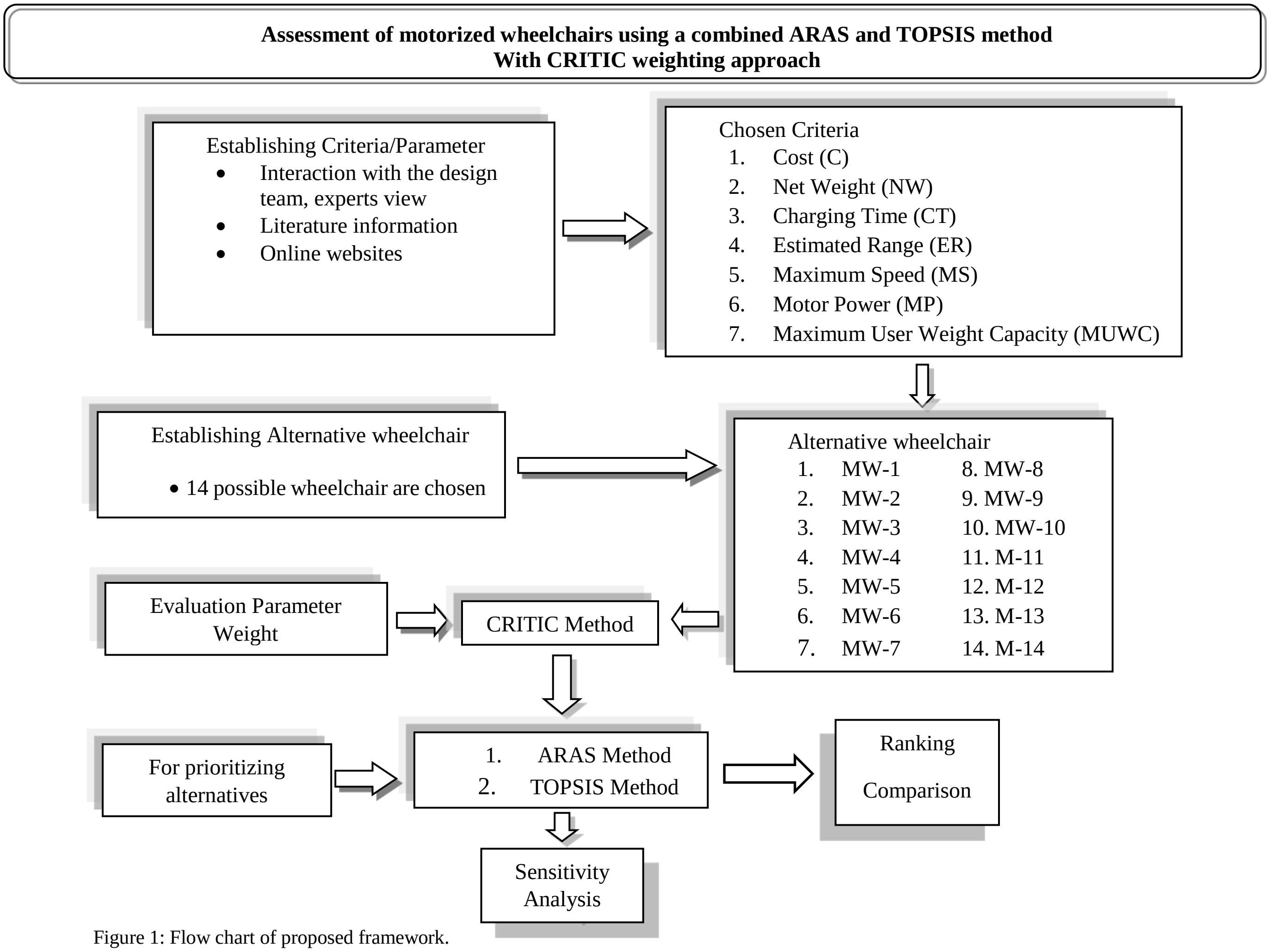

Figure 1: Flow chart of proposed framework.
Source: Own elaboration.

a. Applying CRITIC Approach to Determine Weight

Diakoulaki et al. [30] established the CRITIC approach. CRITIC is a methodology based on correlation that uses statistical analysis to reveal inherent facts in choices. CRITIC makes weight determination easier by leveraging the inherent conflicts and contrast intensity between criteria. Conflict is being included into MCDM procedures for the first time with this technique. It may also be used to create objective weights for MCDM algorithms that are used to rank different entities. The CRITIC method outlines a structured procedure for determining weightages, which involves the following steps:

Step-1: Firstly, a selection matrix is developed with m alternative and n criteria, based on eq. 1 and the data is displayed in table 3.

$$S(m_i \times n_j) = \begin{bmatrix} s_{11}s_{12}s_{13} & \cdots & s_{1n} \\ \vdots & \ddots & \vdots \\ s_{m1}s_{m2}s_{m3} & \cdots & s_{mn} \end{bmatrix} \qquad (1)$$

At this point, s_{mn} represents the information collected for each parameter respective to their alternative, and i=1,2….,m; j=1,2….,n

Table 3: Selection Matrix.

Criteria/Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	1099	63	6.000	3.750	15	288	396
MW-2	1499	63	5.000	3.750	15	288	396
MW-3	1599	41	6.000	3.750	10	240	220
MW-4	1634	94	8.000	3.750	8.7	216	300
MW-5	2244	60	5.000	3.600	8.6	240	250
MW-6	2499	70	6.500	3.700	9.3	288	300
MW-7	2795	39.3	5.000	3.700	9.3	288	300
MW-8	2799	53	8.000	3.700	12.4	250	250
MW-9	2899	52	4.500	3.700	8	180	275
MW-10	2999	32	8.000	2.800	9.3	240	240
MW-11	3694	168	6.000	5.100	17.6	840	300
MW-12	3747	185	6.500	4.000	24	1200	300
MW-13	4754	245	8.000	4.000	19.2	960	300
MW-14	4749	115	6.000	5.000	11.2	250	300
max	4754	245	8.000	5.100	24	1200	396
min	1099	32	4.500	2.800	8	180	220

Source: Own elaboration.

Step-2: Table 3 is transformed to normalized selection matrix (NS_{ij}) utilizing eq.2. Consequently, the scores 'NS_{ij}' below indicate the degree to which the substitute 'i' approaches the ideal value at best. In criteria "j," the best performance is represented by ij, which is distant from the anti-ideal valuess_{ij}^{min}, which indicates the worst performance. A minimum of one of the options under consideration attains both the highest and lowest ij. The normalized decision matrix is displayed in Table 4.

$$NS_{ij} = \frac{s_{ij}-s_{ij}^{min}}{s_{ij}^{max}-s_{ij}^{min}} \qquad (2)$$

Table 4: Normalized Selection Matrix.

Criteria/Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	0.000	0.146	0.429	0.413	0.438	0.106	1.000
MW-2	0.109	0.146	0.143	0.413	0.438	0.106	1.000
MW-3	0.137	0.042	0.429	0.413	0.125	0.059	0.000
MW-4	0.146	0.291	1.000	0.413	0.044	0.035	0.455
MW-5	0.313	0.131	0.143	0.348	0.038	0.059	0.170
MW-6	0.383	0.178	0.571	0.391	0.081	0.106	0.455
MW-7	0.464	0.034	0.143	0.391	0.081	0.106	0.455
MW-8	0.465	0.099	1.000	0.391	0.275	0.069	0.170
MW-9	0.492	0.094	0.000	0.391	0.000	0.000	0.313
MW-10	0.520	0.000	1.000	0.000	0.081	0.059	0.114
MW-11	0.710	0.638	0.429	1.000	0.600	0.647	0.455
MW-12	0.724	0.718	0.571	0.522	1.000	1.000	0.455
MW-13	1.000	1.000	1.000	0.522	0.700	0.765	0.455
MW-14	0.999	0.390	0.429	0.957	0.200	0.069	0.455
σj	0.314	0.302	0.357	0.248	0.302	0.322	0.289

Source: Own elaboration.

Step-3: The standard deviation (σj) for each indicator is then determined once each indicator's value has been normalized to fall inside the [0, 1] interval. Standard deviation is a measure for determining the contrast strength of indicator j; it is represented as σj as displayed in table 4.

Step-4: Eq.3 describes the construction of a symmetric selection matrix $SS_{(n_j \times n_k)}$with dimensions ($n_j \times n_k$) and a standard component "LC_{jk}” denotes the linear correlation coefficient between the parameters. It is a fact that the substitutes' scores for parameter "j" and "k" are increasingly at odds with one another. The symmetric selection matrix is displayed in Table 5. In this case, n = 7.

$$SS_{(n_j \times n_k)} = \begin{bmatrix} LC_{11} & \cdots & LC_{1n} \\ \vdots & \ddots & \vdots \\ LC_{n1} & \cdots & LC_{nn} \end{bmatrix} \qquad (3)$$

Table 5: Symmetric Selection Matrix.

Parameter	C	NW	CT	MS	ER	MP	MUWC
C	1.000	0.682	0.218	0.506	0.388	0.565	-0.236
NW	0.682	1.000	0.310	0.554	0.785	0.884	0.156
CT	0.218	0.506	1.000	-0.184	0.177	0.213	-0.248
MS	0.506	0.554	-0.184	1.000	0.382	0.383	0.206
ER	0.388	0.785	0.177	0.382	1.000	0.910	0.375
MP	0.565	0.884	0.213	0.383	0.910	1.000	0.105
MUWC	-0.236	0.156	-0.248	0.206	0.375	0.105	1.000

Source: Own elaboration.

Step-5: Eq.4's summing measures the conflict (MC_{jk}) that the jth parameter causes with respect to the choice scenario that is estimated by the other parameters. Eq.4 is used to derive the degree of conflict, which is displayed in Table 6.

$$MC_{jk} = \sum_{k,j=1}^{n} (1 - LC_{jk}) \qquad (4)$$

Step-6: Eq. 5 calculates the quantity of information (C_j) based on each parameter and its score are shown in Table 6.

$$C_j = \sigma_j \times \sum_{k,j=1}^{n} (1 - LC_{jk}) \qquad (5)$$

Step-7: Eq. 6, lastly calculate the weight of each parameter (W_j) taken for the assessment of substitutes. More information is sent by the related criteria and it has a higher relative relevance in the decision-making process the higher the value of (Cj). Table 6 shows the weights for the final objective parameter. The weightage of each parameter reflects its relative importance in influencing the overall decision outcome.

$$W_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \qquad (6)$$

Table 6: Measures the Conflict, Quantity of Information, and Weight of Each Parameter.

Parameter/Alternatives	C	NW	CT	MS	ER	MP	MUWC	MC_{jk}	C_j	W_j
C	0.000	0.318	0.782	0.494	0.612	0.435	1.236	3.877	1.218	0.152
NW	0.318	0.000	0.690	0.446	0.215	0.116	0.844	2.629	0.410	0.051
CT	0.782	0.494	0.000	1.184	0.823	0.787	1.248	5.319	1.899	0.236
MS	0.494	0.446	1.184	0.000	0.618	0.617	0.794	4.154	1.028	0.128
ERFC	0.612	0.215	0.823	0.618	0.000	0.090	0.625	2.984	0.902	0.112
MP	0.435	0.116	0.787	0.617	0.090	0.000	0.895	2.940	0.946	0.118
MUWC	1.236	0.844	1.248	0.794	0.625	0.895	0.000	5.643	1.632	0.203

Source: Own elaboration.

Top of Form.

b. Applying ARAS for Setting Prioritization for Alternatives

ARAS is a relatively new MCDM method established by Zavadskas and Turskis [31]. The ARAS technique states that the relative influence of the scores and proportions of the primary criteria taken into consideration in a utility function value that determines the complicated comparison performance of a viable alternative is directly related to the proposed study. The ARAS method outlines a structured procedure for estimating the rank of different substitutes, which involves the following steps:

Step-1: Firstly, a selection matrix is developed, same as step-1 of CRITIC method in section 3.1.

Step-2: Determined the Normalized selection matrix ($NS_{m \times n}$) according to the parameter's nature, utilizing eq.7 for benefit parameter and eq.8 and 9 for non-benefit parameter and its score are displayed in table 7.

$$NS_{m \times n} = \frac{s_{ij}}{\sum_{i=1}^{m} s_{ij}} \text{for benefit parameter} \qquad (7)$$

$$s_{ij}^{*} = \frac{1}{s_{ij}} \qquad (8)$$

$$NS_{m \times n} = NS_{ij} = \frac{s_{ij}^{*}}{\sum_{i=1}^{m} s_{ij}^{*}} \text{ for non-benefit parameter} \qquad (9)$$

At this Point, $i = 1,2,3 \ldots, m$ and $j = 1,2,3 \ldots, n$

Table 7: Normalized Selection Matrix.

	Non-Benefit Parameter			**Benefit Parameter**			
Parameter/ Alternatives	**C**	**NW**	**CT**	**MS**	**ER**	**MP**	**MUWC**
MW-1	0.151	0.073	0.073	0.069	0.084	0.050	0.096
MW-2	0.111	0.073	0.087	0.069	0.084	0.050	0.096
MW-3	0.104	0.113	0.073	0.069	0.056	0.042	0.053
MW-4	0.102	0.049	0.054	0.069	0.049	0.037	0.073
MW-5	0.074	0.077	0.087	0.066	0.048	0.042	0.061
MW-6	0.067	0.066	0.067	0.068	0.052	0.050	0.073
MW-7	0.060	0.117	0.087	0.068	0.052	0.050	0.073
MW-8	0.059	0.087	0.054	0.068	0.070	0.043	0.061
MW-9	0.057	0.089	0.097	0.068	0.045	0.031	0.067
MW-10	0.055	0.144	0.054	0.052	0.052	0.042	0.058
MW-11	0.045	0.027	0.073	0.094	0.099	0.146	0.073
MW-12	0.044	0.025	0.067	0.074	0.135	0.208	0.073
MW-13	0.035	0.019	0.054	0.074	0.108	0.166	0.073
MW-14	0.035	0.040	0.073	0.092	0.063	0.043	0.073

Source: Own elaboration.

Step-3: Estimated the Weighted Normalized selection matrix ($WNS_{m\times n}$) utilizing eq.10. Where, w_j is weight vector of parameter calculated from critic approach and its score are displayed in table 8.

$$WNS_{m\times n} = NS_{m\times n} \times w_j \tag{10}$$

Step-4: Using Eq.11 compute the optimality function (O_i) for each possible choice.

$$O_i = \sum_{j=1}^{n} NS_{ij} \tag{11}$$

Step-5: Using Eq. (12), obtain the degree of utility (DU_i) for each option.

$$DU_i = \left|\frac{O_i}{O_o}\right| \times 100 \tag{12}$$

The optimum substitutes' optimality function score at this stage is O_o . The utility degree(DU_i) spans from 0% to 100%. It establishes a substitute's relative effectiveness in comparison to the best possible substitute. The best substitute is defined as the one with the highest degree of utility value. The substitutes are ranked in decreasing order of DU_i score, which indicates best to worst and its score are displayed in table 8.

Table 8: Weighted Normalized Selection Matrix, Optimality Function, Degree of Utility and Rank.

Parameter/ Alternatives	**C**	**NW**	**CT**	**MS**	**ER**	**MP**	**MUWC**	O_i	DU_i	**Rank**
MW-1	0.023	0.004	0.017	0.009	0.009	0.006	0.019	0.088	0.969	2
MW-2	0.017	0.004	0.021	0.009	0.009	0.006	0.019	0.085	0.939	3
MW-3	0.016	0.006	0.017	0.009	0.006	0.005	0.011	0.070	0.770	7
MW-4	0.015	0.003	0.013	0.009	0.005	0.004	0.015	0.064	0.712	11
MW-5	0.011	0.004	0.021	0.008	0.005	0.005	0.012	0.067	0.741	9
MW-6	0.010	0.003	0.016	0.009	0.006	0.006	0.015	0.065	0.715	10
MW-7	0.009	0.006	0.021	0.009	0.006	0.006	0.015	0.071	0.784	6
MW-8	0.009	0.004	0.013	0.009	0.008	0.005	0.012	0.060	0.668	13
MW-9	0.009	0.005	0.023	0.009	0.005	0.004	0.014	0.067	0.743	8
MW-10	0.008	0.007	0.013	0.007	0.006	0.005	0.012	0.058	0.640	14
MW-11	0.007	0.001	0.017	0.012	0.011	0.017	0.015	0.080	0.891	4
MW-12	0.007	0.001	0.016	0.009	0.015	0.024	0.015	0.088	0.971	1
MW-13	0.005	0.001	0.013	0.009	0.012	0.020	0.015	0.075	0.831	5
MW-14	0.005	0.002	0.017	0.012	0.007	0.005	0.015	0.063	0.700	12

Source: Own elaboration.

c. Applying TOPSIS for Setting Prioritization for Alternatives

The traditional TOPSIS method was first developed by Hwang and Yoon [32]. The fundamental premise is that the option that is selected should be the one that is the furthest from the ideal solution and the shortest from it separation from the solution that is negative-ideal. The TOPSIS method outlines a structured procedure for estimating the rank of different substitutes, which involves the following steps:

Step-1: Firstly, a selection matrix is developed, same as step-1 of CRITIC method in section 3.1.

Step-2: Determined the Normalized selection matrix ($NS_{m\times n}$) according to the parameter's nature, utilizing eq.13 and its score are displayed in table 9.

$$NS_{m\times n} = \frac{s_{ij}}{\sum_{i=1}^{m} s_{ij}} \tag{13}$$

At this Point, $i = 1,2,3 \ldots, m \; and \; j = 1,2,3 \ldots, n$

Step-3: Estimated the Weighted Normalized selection matrix ($WNS_{m\times n}$) utilizing eq.14. Where, w_j is weight vector of parameter calculated from critic approach and its score are displayed in table 10.

$$WNS_{m\times n} = NS_{m\times n} \times w_j \tag{14}$$

Table 9: Normalized Selection Matrix.

Parameter/ Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	0.098	0.152	0.249	0.256	0.297	0.148	0.354
MW-2	0.134	0.152	0.208	0.256	0.297	0.148	0.354
MW-3	0.143	0.099	0.249	0.256	0.198	0.124	0.197
MW-4	0.146	0.227	0.332	0.256	0.172	0.111	0.268
MW-5	0.200	0.145	0.208	0.246	0.170	0.124	0.224
MW-6	0.223	0.169	0.270	0.252	0.184	0.148	0.268
MW-7	0.249	0.095	0.208	0.252	0.184	0.148	0.268
MW-8	0.250	0.128	0.332	0.252	0.245	0.129	0.224
MW-9	0.258	0.126	0.187	0.252	0.158	0.093	0.246
MW-10	0.267	0.077	0.332	0.191	0.184	0.124	0.215
MW-11	0.329	0.407	0.249	0.348	0.348	0.432	0.268
MW-12	0.334	0.448	0.270	0.273	0.475	0.618	0.268
MW-13	0.424	0.593	0.332	0.273	0.380	0.494	0.268
MW-14	0.423	0.278	0.249	0.341	0.222	0.129	0.268

Source: Own elaboration.

Table 10: Weighted Normalized Selection Matrix.

Parameter/ Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	0.015	0.008	0.059	0.033	0.033	0.017	0.072
MW-2	0.020	0.008	0.049	0.033	0.033	0.017	0.072
MW-3	0.022	0.005	0.059	0.033	0.022	0.015	0.040
MW-4	0.022	0.012	0.079	0.033	0.019	0.013	0.054
MW-5	0.030	0.007	0.049	0.031	0.019	0.015	0.045
MW-6	0.034	0.009	0.064	0.032	0.021	0.017	0.054
MW-7	0.038	0.005	0.049	0.032	0.021	0.017	0.054
MW-8	0.038	0.007	0.079	0.032	0.028	0.015	0.045
MW-9	0.039	0.006	0.044	0.032	0.018	0.011	0.050
MW-10	0.041	0.004	0.079	0.024	0.021	0.015	0.044
MW-11	0.050	0.021	0.059	0.045	0.039	0.051	0.054
MW-12	0.051	0.023	0.064	0.035	0.053	0.073	0.054
MW-13	0.064	0.030	0.079	0.035	0.043	0.058	0.054
MW-14	0.064	0.014	0.059	0.044	0.025	0.015	0.054

Source: Own elaboration.

Step-4: Estimation of positive (IS^+) and negative (IS^-) ideal solutions utilizing eq.15 and 16 and its corresponding score are displayed in table 11 and table 12.

$$IS^+ = \{WNS_1^+, WNS_2^+, WNS_3^+ \ldots\ldots WNS_n^+\} = \left\{\left(maxWNS_{ij} | \, i \,\forall\, P^+\right), \left(minWNS_{ij} | \, i \,\forall\, P^-\right)\right\} \tag{15}$$
$$IS^- = \{WNS_1^-, WNS_2^-, WNS_3^- \ldots\ldots WNS_n^-\} = \left\{\left(maxWNS_{ij} | \, i \,\forall\, P^+\right), \left(minWNS_{ij} | \, i \,\forall\, P^-\right)\right\} \tag{16}$$

At this point, P^+ is related to benefit parameter, and P^- is related to non-benefit parameter.

Table 11**:** Positive Ideal Solutions.

Parameter/ Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-2	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-3	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-4	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-5	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-6	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-7	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-8	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-9	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-10	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-11	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-12	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-13	0.015	0.004	0.044	0.045	0.053	0.073	0.072
MW-14	0.015	0.004	0.044	0.045	0.053	0.073	0.072

Source: Own elaboration.

Table 12: Negative Ideal Solutions.

Parameter/ Alternatives	C	NW	CT	MS	ER	MP	MUWC
MW-1	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-2	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-3	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-4	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-5	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-6	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-7	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-8	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-9	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-10	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-11	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-12	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-13	0.064	0.030	0.079	0.024	0.018	0.011	0.040
MW-14	0.064	0.030	0.079	0.024	0.018	0.011	0.040

Source: Own elaboration.

Step-4: Determine the measures of separation by use the n-dimensional Euclidean distance formula. Each option's distance from the best option (MS_j^+) is provided utilizing eq. 17 and separation from negative solution (MS_j^-) is provided utilizing eq. 18 and its corresponding score are displayed in table 13.

$$MS_j^+ = \sqrt{\sum_{i=1}^{n}(WNS_{ij} - WNS_{ij}^+)^2}, j=1,\dots\dots,J \tag{17}$$

$$MS_j^- = \sqrt{\sum_{i=1}^{n}(WNS_{ij} - WNS_{ij}^-)^2}, j=1,\dots\dots,J \tag{18}$$

Step-5: Determine how near the perfect solution are in relation to it. The relative closeness (C_j^*) of the substitutes related to WNS_{ij} are determined by utilizing eq.19 and the rank of chosen order as displayed in table 13.

$$C_j^* = \frac{MS_j^-}{(MS_j^- + MS_j^+)}, j = 1, \dots\dots, J \tag{19}$$

Table 13: Positive and Negative Measures of Separation, Relative Closeness, and Rank.

Parameter/ Alternatives	MS_j^+	MS_j^-	C_j^*	Rank
MW-1	0.062	0.069	0.526	4
MW-2	0.060	0.068	0.531	2
MW-3	0.076	0.054	0.416	6
MW-4	0.080	0.049	0.380	10
MW-5	0.076	0.051	0.405	8
MW-6	0.073	0.044	0.376	11
MW-7	0.072	0.050	0.413	7
MW-8	0.081	0.038	0.321	12
MW-9	0.079	0.050	0.388	9
MW-10	0.087	0.036	0.293	14
MW-11	0.052	0.058	0.526	3
MW-12	0.049	0.077	0.609	1
MW-13	0.071	0.056	0.443	5
MW-14	0.085	0.036	0.298	13

Source: Own elaboration.

IV. RESULTS AAND DISCUSSION

The ARAS and TOPSIS protocols were both used in the evaluation of motorized wheelchair devices. These techniques were used to calculate the relative closeness score (for TOPSIS) and the optimality function (for ARAS) for each alternative model. Based on the analysis, it was found that MW-12 has the highest optimality function, degree of utility, and relative closeness score, making it the best motorized wheelchair alternative out of those that were examined. This also determines the order in which all motorized wheelchairs are ranked according to their decreasing utility scores.

The following is the order of preference for users of motorized wheelchairs:

- MW-12>MW-1>MW-2>MW-11>MW-13>MW-7>MW-3>MW-9>MW-5>MW-6>MW-4>MW-14>MW-8>MW-10 corresponds to CRITIC-ARAS approach.
- MW-12>MW-2>MW-11>MW-1>MW-13>MW-3>MW-7>MW->MW-9>MW-4>MW-6>MW-8>MW-14>MW-10 corresponds to CRITIC-TOPSIS approach.

The end rankings and outcomes from both methods are very similar. In the APRAS and TOPSIS approaches, MW-12 is the best-performing model, whereas MW-10 is always the least-beneficial choice. The comparison of ranks between the two approaches is shown graphically in figure 2, emphasizing the alignment of their evaluations.

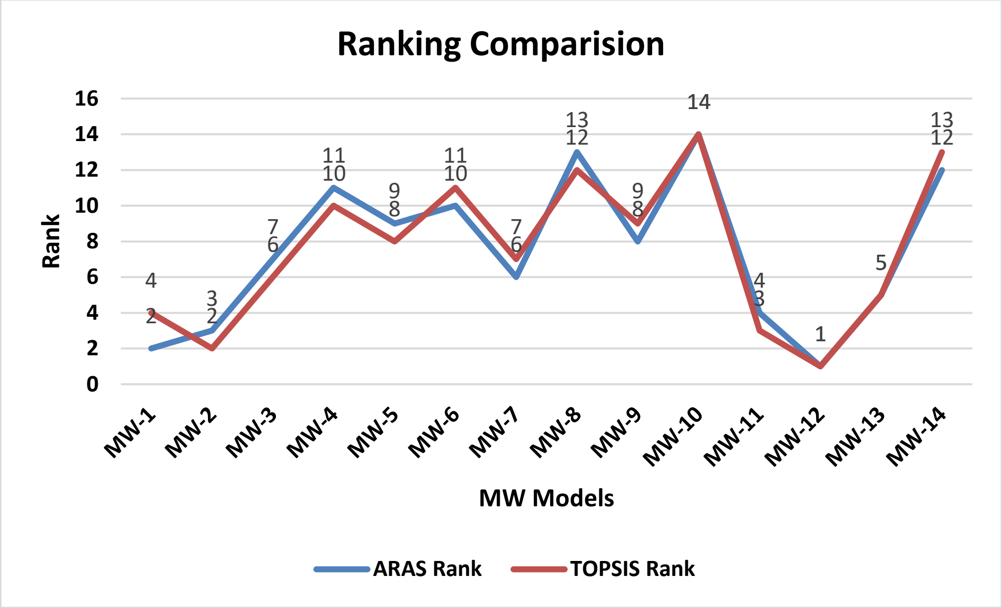

Figure 2: Ranking Comparisons of the motorized wheelchair models by ARAS and TOPSIS.
Source: Own elaboration.

a. *Spearman Correlation Analysis*

In order to evaluate the consistency of the performance rankings of the different options, this study analyzes the outcomes. The extent of correlation between the rankings produced by various combination processes is measured using the Spearman rank correlation coefficient. Spearman's correlation coefficient, which reveals the degree of concordance between the ranks derived from different techniques, is computed using Equation 20.

$$C_r = 1 - \frac{6 \times \sum D_r^2}{N \times (N^2 - 1)} \qquad (20)$$

Equation 20 computes the Spearman coefficient (C_r), which assesses the variance in ranking across CRITIC-ARAS and CRITIC-TOPSIS, with C_r scores falling between 1 and -1. It also accounts for the total amount of MW options (denoted by N). As the estimated value of C_r near to 1, typically lying within the range of 0.8 to 1.0, an almost perfect correlation is found that is 0.9696. Strong consistency in the performance ratings across the approaches is indicated by this high C_r score. Consequently, it is demonstrated that the methodology used in this study is equally effective in identifying the optimal MW selection strategy.

b. *Sensitivity analysis on CRITIC based ARAS and TOPSIS*

Seven distinct parameters determining the selection of motorized wheelchairs for use by people with disabilities are investigated in this study. Even though there are numerous criteria to consider when making a decision, in the real world, buyer preference for MWs is heavily influenced by cost-related factors, as evidenced by the CRITIC calculation of this study, which shows that the weight coefficient of MRP is 0.152, as shown in Table 6.

The Sensitivity Analysis technique is frequently cited by researchers [33] as a reasonable methodology for testing the effectiveness of obtained outcomes by varying price factors. For each of the wheelchairs studied for the proposed study, just one cost-based criterion, particularly "C of MWs," was used in the selection process. The sensitivity analysis is the sturdy way of demonstrating the uncertainties by changing the judgment of the decision-maker and presenting afterward the effects of the various options. The value of β in this study is between 0 and 1, with an increase of 0.1. The mathematical Eq.21 and 22 is utilized to create the graphs between selective score and objective value (β) as shown in figure 3 and 4. The principal equations of the framework stated are:

$$SS_i = \{(\beta \times SM_i) + (1 - \beta) \times OM_i\} \qquad (21)$$

$$OM_i = \frac{1}{\{OC_i \sum_{i=1}^{n} OC_i^{-1}\}} \qquad (22)$$

The objective value (β), subjective measure (SM_i), objective measure (OM_i), and objective cost (OC_i) are the factors that are used to calculate the selective score (SS_i). As shown in Table 3, OC_i stand for the cost for every wheelchair. Eq.22, which shows how OM_i are created, shows how cost components from every MW are standardized. The SM values for each MW that correlate to each factor are shown in Tables 8 and 13. These numbers are produced from the normalized appraisal vector values for MW candidates received by CRITIC-ARAS and CRITIC-TOPSIS. Additionally, Figures 3 and 4 provide a graphic representation of the Sensitivity Analysis results. These evaluations shed light on how changes in various parameters affect MW selection and overall performance.

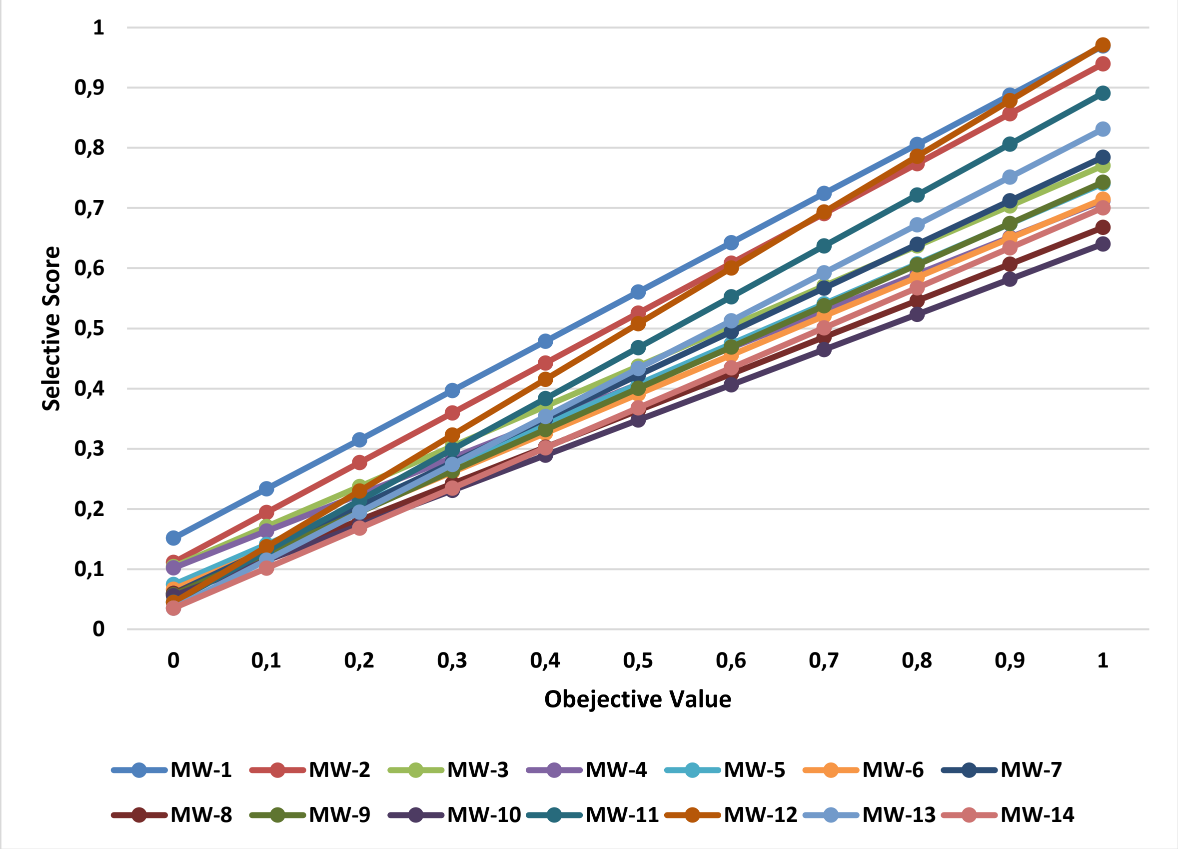

Figure 3: CRITIC-ARAS based sensitivity analysis.
Source: Own elaboration.

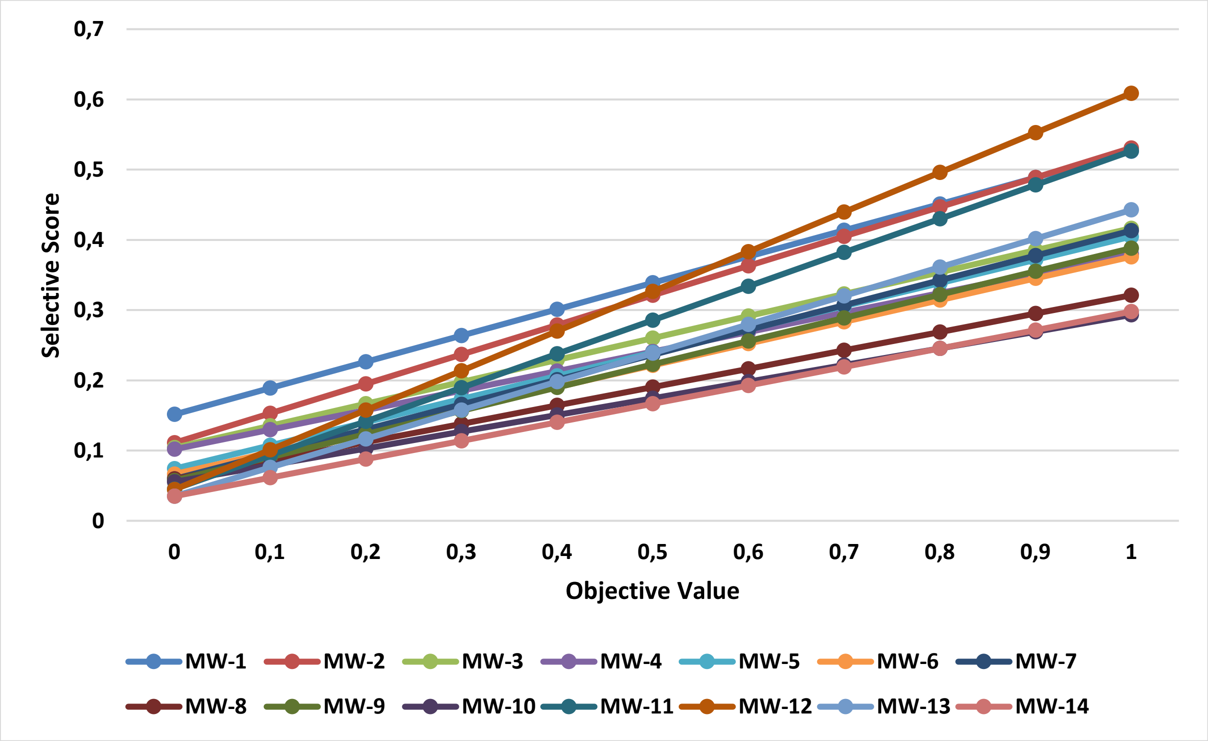

Figure 4: CRITIC-TOPSIS based sensitivity analysis.
Source: Own elaboration.

V. CONCLUSION

The results of this study show that, out of the 14 motorized wheelchair (MW) models that were assessed from the online website, MW-12 comes out on top when using the CRITIC-ARAS technique. MW-1 and MW-2 come in second and third, respectively. Similarly, MW-2 and MW-11 hold the second and third positions in the CRITIC-TOPSIS method. It is therefore advised that those looking to buy a motorized wheelchair give MW-12 more thought. In the event that shortages prevent MW-12 from being available, MW-2 offers a good substitute.

Although there are many other models available, it is advisable to avoid MW-10 because it performs worse than other models, as shown by its lowest rankings in the CRITIC-ARAS and CRITIC-TOPSIS assessments.

a. Practical Implication

This study does a thorough evaluation of motorized wheelchairs for people with impairments, emphasizing important. To give a full understanding of wheelchair appropriateness, a comprehensive evaluation framework is designed that incorporates both quantitative metrics. Data on wheelchair is collected using a variety of methods, such as expert reviews, objective testing, and user feedback surveys. A cost-effectiveness study is also carried out to evaluate the viability of various wheelchair solutions from an economic standpoint. The study's conclusions are intended to educate wheelchair users, carers, and medical experts about the best products on the market, ultimately resulting in increased accessibility and improved quality of life for people with disabilities.

b. Limitation

One potential weakness of this study is the possible underrepresentation of various types of disabilities and user preferences in the sample, which might potentially undermine the generalizability of the results. Furthermore, the study's narrow focus on motorized wheelchairs may have overlooked other mobility aids that would be more appropriate for particular people in particular situations. To address these constraints and provide more thorough insights into satisfying the diverse requirements of people with disabilities, a wider selection of assistive mobility devices would need to be taken into consideration, along with broader participant recruiting tactics.

c. Future Work

Further research endeavors may investigate the incorporation of supplementary MCDM techniques, like ELECTRE, PROMETHEE, or VIKOR, in order to augment the resilience and exhaustiveness of wheelchair evaluation procedures. Additionally, longitudinal studies might be carried out to assess the motorized wheelchairs' long-term performance and user happiness, offering important insights into the wheelchairs' longevity, dependability, and user adaptability over time.

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VII. CONFLICTS OF INTEREST

The authors declare no conflicts of interest related to this research.

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