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Selecting the Augmented Reality Glasses Used in the Automobile Manufacturing Industry by Multi-Criteria Decision-Making Methods

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ABSTRACT

Augmented Reality Glasses (ARG) technology has entered people's lives in recent years by playing virtual games for entertainment purposes and has also begun to find use in the film industry, storage systems, military field, and engineering, depending on the desire for innovation. This study aims to select ARG via Multi-Criteria Decision-Making (MCDM) methods to accelerate, simplify, and activate operational processes in the automobile manufacturing industry. This study determined eight different ARG alternatives, and nine criteria (battery power, field of view, price, camera, brightness, display resolution, internal memory, RAM, and weight). The CRITIC method is used in criteria evaluation, and ARAS, EDAS, and CODAS methods are used in alternative rankings. Vuzix M4000 brand/model ARG, which has more optimum values than other alternatives, comes first. While finding criterion weights, it can be said that the CRITIC method finds reasonable and close criterion weights. In future studies, ARGs with different models and features can be included in the analysis and compared with the findings obtained from this study.

Keywords: Augmented Reality, Automobile Manufacturing Industry, MCDM Methods

JEL Classification: C44, D81, M10

Çok Kriterli Karar Verme Yöntemleri ile Otomotiv Üretim Sektöründe Kullanılan Artırılmış Gerçeklik Gözlüklerinin Seçimi

ÖZ

Artırılmış Gerçeklik Gözlükleri (ARG) teknolojisi son yıllarda eğlence amaçlı sanal oyunlar oynamasıyla insanların hayatına girmiş olup yenilik isteğine bağlı olarak film endüstrisi, depolama sistemleri, askeri alan ve mühendislikte de kullanım alanı bulmaya başlamıştır. Bu çalışmada, otomobil üretim endüstrisinde operasyonel süreçleri hızlandırmak, basitleştirmek ve etkinleştirmek için Çok Kriterli Karar Verme (ÇKKV) yöntemleriyle ARG seçimi yapılması amaçlanmıştır. Bu çalışmada sekiz farklı ARG alternatifi ve dokuz kriter (pil gücü, görüş alanı, fiyat, kamera, parlaklık, ekran çözünürlüğü, dahili bellek, RAM ve ağırlık) belirlenmiştir. Kriter değerlendirmesinde CRITIC yöntemi, alternatif sıralamalarında ise ARAS, EDAS ve CODAS yöntemleri kullanılmıştır. Diğer alternatiflere göre daha fazla optimum değere sahip olan Vuzix M4000 marka/model ARG ilk sırada gelmektedir. Kriter ağırlıkları bulunurken CRITIC yönteminin makul ve yakın kriter ağırlıkları bulduğu söylenebilir. Gelecekteki çalışmalarda, farklı model ve özelliklere sahip ARG'ler analize dahil edilebilir ve bu çalışmadan elde edilen bulgularla karşılaştırılabilir.

Anahtar Kelimeler: Artırılmış Gerçeklik, Otomobil Üretim Endüstrisi, MCDM Yöntemleri

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1. INTRODUCTION

Today, many transactions take place at a dizzying speed in the virtual world, much more advanced than in the past. The evolution of technological devices that began with the telegraph, radio, and then television has now been replaced by smartphones and tablets. People now spend most of their daily time in the virtual world, and artificial intelligence-powered conversational robots such as ChatGPT are emerging. Humans thus found themselves in the midst of an irreversible technological revolution. So much so that of the 8,1 billion people living in the world, almost 5.5 billion use mobile phones, 5,1 billion use the internet, and 4,7 billion use social media (Keleş, 2024:215). On the other hand, Augmented Reality (AR) is one of the smart and cutting-edge technologies, such as the Internet of Things, blockchain, cloud-based systems, big data, robots, and digital twins (Prathibha et al., 2024:63). AR pairs physical world information with digital information, creating an interactive space that helps users explore, interact, and learn. AR is attracting increasing attention from academia, entertainment, construction, government, and automotive industry because it complements reality with virtual reality by adding objects of the digital world to the real world in real-time (Mishra & Singh, 2024:173; Ikiz et al., 2019:1).

Augmented Reality Glasses - ARG technology has entered people's lives in recent years, mostly through the use of virtual games for entertainment. ARG usage areas are developing depending on the desire for innovation in the film industry, storage systems, the military field, engineering, manufacturing, maintenance, human-robot collaboration, and advertising (Mariyam et al., 2022:141). In virtual reality, users can watch and participate in all objects in an artificial environment as if they were in a different world. AR, on the other hand, is the integration of the real and the virtual by using a camera to add/overlay virtual objects in areas that users can touch, see, and feel in real environments. As a direct or indirect display of a physically real environment, AR is enriched with additional digital information about the viewed object, often in textual or pictorial form (Balco et al., 2022:315). The user can interact with both the real world and virtual data. Using optical-based ARG technology, data such as personal information, images and video can be added to the live environment that the user is viewing/presence via the screen. ARGs aim to bring various virtual environments, such as location services, the internet, and social media, in front of the eyes (Aydin, 2018:566). ARG technology involves different hardware tools attached to a pair of wearable glasses with a camera; it is used by adding elements such as sensors, screen, processor, memory, and battery.

The automotive industry has continuously remained at the forefront of taking advantage of the latest technological advances such as virtual model and prototyping, automated vehicle safety, advanced manufacturing techniques based on complex robotic systems, and user-friendly interfaces to improve driving (Boboc et al., 2020:1). AR technologies enable tasks of different content such as maintenance, repairing, diagnostics, testing, inspection, safety, and training in the automobile manufacturing industry (Dini and Mura, 2015:22). AR technologies are helping to realize the desired structural changes in the car by improving the 3D visual presentation and using visual images for effective comparison (Mishra and Singh, 2024:174). Automobile companies such as Audi, BMW, Bosch, Ford, Porsche, VW, and Volvo are the first to adopt AR in their digitalization strategies (Omerali & Kaya, 2022:8).

This study was motivated by the literature gap on the use of ARGs in the automobile manufacturing industry and was designed to fill this gap. In this case, there is a need to explore alternatives with different devices and equipment together. The optimal evaluation of more than one alternative according to more than one criterion indicates the existence of a multi-criteria decision problem. When a multi-criteria assessment is required in a market where there are many alternatives, it is important to select a more appropriate one from the various multi-criteria decision methods (MCDM), which includes a wide range of methods. When alternative ARGs on the market were considered for this study, it was decided that it would be more appropriate to use the CRITIC, ARAS, EDAS, and CODAS model to evaluate ARGs with different properties. This is because the CRITIC method ensures that the criteria are given greater weight by taking into account the correlation between the criteria, helping the decision maker to make more effective decisions by using mathematical methods on a scientific basis. In this context, the original contribution of the study lies in the use of the CRITIC method—a rational criterion weighting approach—to assign weights to the criteria, and in the integration of these weights into three different multi-criteria decision-making (MCDM) techniques for the evaluation of results. In this way, only the initial decision matrix containing the alternative values was used throughout all stages of the analysis, avoiding intuitive and subjective value judgments.

The remainder of the study is organized as follows: In the second section, we summarize the review of the literature, and we investigate the materials and research methodology used in Section 3. We demonstrate the analysis and results in Section 4. The conclusions, limitations, and future scope of the study are provided in the last section.

2. LITERATURE REVIEW

The use of wearable technologies is more important in creating a safe working area and is seen as a promising solution in terms of increasing the safety of employees in sectors where occupational accidents are common, contributing to reducing accidents, and improving industrial efficiency by reducing hazards and risks (Aksüt et al., 2024:1). Wearable and non-wearable devices can be used for the AR experience, depending on whether the user wants more flexibility and free hands (Mariyam et al, 2022:146). Today, many automotive industry manufacturers have shown great interest in AR, especially due to its accessibility and potential to produce innovation solutions (Boboc et al., 2020:1). Various studies have been conducted in the literature on AR, which has become increasingly important in recent years.

Renzi et al. (2017) investigate the decision-making methods in engineering design to solve the most common automotive engineering problems involved in the design process. Aydin (2018) aims to ARG selection (Sony Smart Goggles, VuzixM100, Optinvent Ora-1, Meta Pro, Epson Moverio BT-200) via the six criteria (functionality, ease of use, design standards, effectiveness, portability, price, with the criteria weight values 0.20, 0.16, 0.14, 0.16, 0.13, 0.19 respectively) based on AHP and neutrosophic MULTIMOORA. Basoglu et al (2018) investigated physicians' use of ARGs and their adoption of these products in the Turkish medical industry using an exploratory model based on the technology acceptance model. Blanco-Novoa et al. (2018) reviews the Industrial AR (IAR) applications for shipbuilding and smart manufacturing, then details the most relevant IAR hardware and software tools, and describes an IAR system. Boboc et al. (2020) presents a systematic review of existing AR systems in the automotive field. They investigated 55 studies from 2002 to 2019. Atici-Ulusu et al. (2021) investigated the effects of ARGs on the cognitive loads of employees in the automotive industry. They found that there was less cognitive load on employees when using ARGs. Danielsson et al (2020) provided an overview of the current state of knowledge and future challenges of ARGs from the assembly operators' perspective for industrial applications. They focused on the study, which includes the lack of standards in the design of assembly instructions, the limited field of view of the ARG, and the fact that guidelines for the design of instructions focus on presenting contextual information and limiting distortion of reality). Kamble et al. (2021) collected data from the purchasing, manufacturing, and logistics and marketing firms with a large group decision-making technique and used circular economy practices in the automobile component manufacturing industry.

Balco et al. (2022) analyzed the level of knowledge and interest in VR and AR technologies in Slovak manufacturing companies. Mariyam et al. (2022) investigated to determine the future of AR by analyzing how it can be used in various industries, including what types of AR devices are used and how they are tracked. Omerali and Kaya (2022) identified the most critical nine AR software selection criteria and used the spherical fuzzy COPRAS to select the AR application (Vuforia, Wikitude, Amazon Sumerian, and ARCore). Touami et al. (2022) investigates AR maintenance aid systems with a Fuzzy TOPSIS using seven criteria (3D data, extreme situation, vocal, gesture, hand free, weight, cost) and four alternatives (Hololens, Tablet, Smartphone, Vuzix). Abdelhafeez and Myvizhi (2023) investigate the feasibility of using wearable technologies in education to improve safety and reduce risks with a neutrosophic MCDM (CRITIC method) model. Gutiérrez et al. (2023) propose to describe, prioritize, and group the quality attributes related to the user experience of AR applications with fuzzy cognitive maps and DEMATEL. Koutromanos and Kazakou (2023) investigated the relative scope, theoretical framework, methodological design, and factors found to influence the acceptance or use of ARGs in 21 empirical research activities published from 2015 to 2022 on the acceptance of ARGs in all applicable fields.

Aksüt et al. (2024) investigated the use of wearable technologies in 5 different sectors (construction, mining, agriculture, textile, and chemistry) using 8 criteria (smart helmets, HAVS (Hand-Arm Vibration Syndrome), smart vests, smart glasses, armband, life bands, wearable cameras, and emergency medical information labels) and using AHP-PROMETHEE MCDM methods. Morales Méndez and Velázquez (2024) investigated an analysis of the integration of AR in the context of Industry 4.0 using 60 relevant studies from the Scopus and Web of Science databases. Nguyen (2024) discusses the selection of AR providers for educational purposes using Spherical Fuzzy Sets (SFCs), applying SF-Delphi to determine the relative importance of eight key metrics, then evaluating and ranking 10 global AR providers using SF-TOPSIS. Prathibha et al. (2024) investigated the application of AR and virtual reality technologies for the maintenance and repair of automobile and mechanical equipment.

It has been observed that studies have been carried out in recent years due to the recent introduction of AR technologies into human life. Although there are frequent studies on AR, only one study specific to ARG selection has been found. Aydin (2018) compared a limited number of alternatives (5 ARGs) with an insufficient number of criteria (6 criteria). Since the five criteria are qualitative, they were scored based on the view received from experts whose number and expertise were not specified. However, if the variable values of ARGs obtained from the market were used, more objective data could be obtained. In order to fill this gap in the literature, it is envisaged to make an evaluation using objective data of much more criteria whose data can be obtained from the market.

3. MATERIAL AND METHODS

Decision makers have some difficulties in situations where many criteria with different levels of importance must be taken into consideration. In this case, they sometimes make decisions intuitively, influenced by their own knowledge, experience and emotions. However, in such situations, which are often misleading, MCDM techniques have recently become popular in the literature and are increasingly being used.

MCDM techniques are useful for decision makers and stakeholders to make a more logical and scientifically defensible decision by providing a mathematical methodology that includes the values and technical information of decision makers and stakeholders to choose the best solution for the encountered problems (Linkov and Moberg, 2012: 3). In this context, the most appropriate alternative can be selected among eight ARGs that are affected by many criteria and have different characteristics. This study used price, screen size, weight, field of view, battery, resolution, brightness, RAM, and internal memory criteria determined by the market data to select the most suitable ARG.

For this purpose, criteria values are determined with the CRITIC technique introduced in the following sections and alternative ARGs are ranked from best to worst with the ARAS, EDAS, and CODAS techniques. These techniques were preferred because they were introduced to the literature in recent years and are up-to-date ranking techniques. Thus, while the most appropriate decision was made in a complex situation, it was also possible to compare the results of different techniques.

3.1. CRiteria Importance Through Intercriteria Correlation (CRITIC)

Subjective approaches depend on the decision makers' experience, knowledge, and perception of decision makers regarding problems while determining the weight values of criteria. In order to overcome such problems, it is preferred to use objective weighting approaches (Madic and Radovanovic, 2015:200). For such cases, the CRITIC technique proposed by Diakoulaki et al. (1995) uses the decision matrix directly instead of subjective methods such as expert opinion in criteria weighting and, unlike some other weighting methods, does not require pairwise comparison (Tuş and Aytaç Adalı, 2019:529). The application stages of the technique are as follows (Wang and Zhao, 2016: 2385-2386):

Creating the Decision Matrix; At this stage, "m x n" dimensional decision matrix is created, as shown in Equation 1. Here "m" refers the number of decision alternatives and "n" refers number of decision criteria.

$$X = \begin{matrix} x_{01} & x_{02} & \cdots & x_{0n} \\ x_{11} & x_{12} & \cdots & x_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{matrix} \quad (1)$$

Normalization of the Decision Matrix; At this stage, the decision matrix is normalized by considering whether the criteria are benefit-oriented and cost-oriented (x_{ij}^{*}). Equation 2 is used for the normalization of benefit, and Equation 3 is used for the normalization of cost criteria.

$$x_{ij}^{*} = \frac{x_{ij} - x_j^{min}}{x_j^{max} - x_j^{min}} \quad (2)$$

$$x_{ij}^{*} = \frac{x_j^{max} - x_{ij}}{x_j^{max} - x_j^{min}} \quad (3)$$

Creating the Relationship Coefficient Matrix; At this stage, the relationship coefficient matrix is created to determine the extent of the relationships between the criteria. This matrix consists of correlation coefficients. This matrix, which consists of linear relationship coefficients (ρ_{jk}), is calculated by the Equation 4.

$$\rho_{jk} = \frac{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j) * (x_{ik} - \bar{x}_k)}{\sqrt{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2 * \sum_{i=1}^{m}(x_{ik} - \bar{x}_k)^2}} \quad 4$$

Calculation of total information (C_j) in the *j*th criteria; In the process of determining the criteria weight values, both the standard deviation of the criteria and the correlation between other criteria are included. The standard deviation of the normalized criteria values according to the columns and the correlation coefficients of all column pairs are used to determine the criteria contrast. Therefore, at this stage, the total information value (C_j) in the *j*th criteria, which combines the contrast intensity and contradictions in the criteria, is calculated by the Equation 6, with the value (σ_j) calculated by the Equation 5 to express the standard deviation value of the criteria.

$$\sigma_j = \sqrt{\frac{\sum_{i=1}^{m}(x_{ij} - \bar{x}_j)^2}{m - 1}} \quad 5$$

$$C_j = \sigma_j \sum_{k=1}^{n}(1 - \rho_{jk}) \quad 6$$

Determination of criteria weights; At this stage, criteria weights are determined by dividing the information values of the criteria by the total information values by using the Equation 7.

$$w_j = \frac{C_j}{\sum_{k=1}^{n} C_j} \quad 7$$

As with all multi-criteria decision-making techniques, the application stages of the CRITIC technique, which starts with the initial matrix, can be followed in ANNEX-A.

3.2. Additive Ratio Assessment (ARAS)

Most of the MCDM techniques in the literature are based on a ranking for the selection of the best alternative. For this purpose, the relative distances of the alternatives to the ideal solution are determined or the utility function values obtained in the solution are compared with the ideal solution values. However, the ARAS method proposed by Zavadskas and Turskis (2010) is different from the others; the utility function values of the alternatives are compared with the utility function value of the optimal alternative that the decision maker later included (Ayçin, 2019: 51-52). The method takes its name from the ratio of the utility function of the alternatives to the optimal utility function at the end of the application stages and is also known as benefit-ratio analysis (Dinçer, 2019: 47). In this respect, the ARAS method is based on quantitative measurements and utility theory (Özbek, 2017: 59). The application stages of the ARAS method are as follows (Zavadskas and Turskis, 2010: 163-165);

Determination of Decision Matrix; At this stage, unlike other techniques, the optimal value row is added to the matrix specified in Equation 1 and the decision matrix is created. In determining the optimal value row; Equation 8 is used for benefit, and Equation 9 is used for cost criteria.

$$x_{0j} = \max_i x_{ij} \tag{8}$$

$$x_{0j} = \min_i x_{ij} \tag{9}$$

Creating the Normalized Decision Matrix; At this stage, Equation 10 is used for benefit-oriented criteria and Equation 11 is used for cost-oriented criteria.

$$\bar{x}_{ij} = \frac{x_{ij}}{\sum_{i=0}^{m} x_{ij}} \tag{10}$$

$$\bar{x}_{ij} = \frac{1/x_{ij}}{\sum_{i=0}^{m}(1/x_{ij})} \tag{11}$$

Obtaining the Weighted Normalized Decision Matrix; As in other MCDM techniques, the normalized decision matrix is created by multiplying the weight value (w_j) determined for each criterion with the Decision Matrix.

Calculation of Optimality Function and Benefit Degree; At this stage, the optimality function (S_i) of each alternative is calculated by using the Equation 12. Finally, by calculating the ratio of each S_i values to the optimality value of the best decision alternative (S_0), as shown with the Equation 13, the benefit degree (K_i) of the alternatives is found to rank the alternatives.

$$S_i = \sum_{j=1}^{n} \hat{x}_{ij} \tag{12}$$

$$K_i = \frac{S_i}{S_0} \tag{13}$$

As with all multi-criteria decision-making techniques, the application stages of the ARAS technique, which starts with the initial matrix, can be followed in ANNEX-B.

3.3. Evaluation Based on Distance from Average Solution (EDAS)

The basic basis of the EDAS technique proposed by Ghorabaee et al. (2015) is two distance measurements determined as Positive Distance from Average (PDA) and Negative Distance from Average (NDA) (Stanujkic et al., 2017: 7). The application stages of the EDAS technique are as follows (Ghorabaee et al., 2015: 438-441; Karabasevic, 2018: 58-59);

Determination of the Decision Matrix; At this stage, “m x n” dimensional decision matrix specified in Equation 1 is created.

Determining the average solution according to all criteria; At this stage, it is calculated the average value of each criterion by using the Equation 14, and obtained $AV = [AV_j]_{1xm}$ type of matrices.

$$AV_j = \frac{\sum_{i=1}^{n} X_{ij}}{n} \tag{14}$$

Calculation of Positive Distance from Average (PDA) Value; At this stage, Positive Distance from Average (PDA) values are calculated by the Equation 15 for benefit-oriented criteria and Equation 16 for cost-oriented criteria.

$$PDA_{ij} = \frac{maks.(0;(X_{ij} - AV_j))}{AV_j} \tag{15}$$

$$PDA_{ij} = \frac{maks.(0;(AV_j - X_{ij}))}{AV_j} \tag{16}$$

Calculation of Negative Distance from Average (NDA) Values; At this stage, Negative Distance from Average (NDA) values are calculated by the Equation 17 for benefit-oriented criteria and Equation 18 for cost-oriented criteria.

$$NDA_{ij} = \frac{maks.(0;(AV_j - X_{ij}))}{AV_j} \tag{17}$$

$$NDA_{ij} = \frac{maks.(0;(X_{ij} - AV_j))}{AV_j} \tag{18}$$

As a result of the calculations, a matrix is obtained in the form of $PDA = \left[PDA_{ij}\right]_{nxm}$ for PDA and in the form of $NDA = \left[NDA_{ij}\right]_{nxm}$ for NDA to indicate the positive and negative distances of the *i*th alternative according to the *j*th criterion.

Calculation of Weighted Total Values of PDA and NDA; At this stage, the criteria weight values (w_j) determined with different methods and the PDA and NDA values calculated in the previous stage are used in Equation 19 to calculate the Weighted Total Vales of PDA (SP_i) and in Equation 20 to calculate the Weighted Total Vales of NDA (SN_i).

$$SP_i = \sum_{j=1}^{m} w_j \, PDA_{ij} \tag{19}$$

$$SN_i = \sum_{j=1}^{m} w_j \, NDA_{ij} \tag{20}$$

Normalizing SP and SN Values; At this stage, Normalized Weighted Total PDA Values (NSP_i) are calculated by the Equation 21 and Normalized Weighted Total NDA Values (NSN_i) are calculated by the Equation 22.

$$NSP_i = \frac{SP_i}{maks._i \, (SP_i)} \tag{21}$$

$$NSN_i = 1 - \frac{SN_i}{maks._i \, (SN_i)} \tag{22}$$

Calculating the Evaluation Score; At this stage, an evaluation score is calculated for all alternatives by taking the average of the calculated NSP_i and NSN_i values and the alternatives are ranked.

As with all multi-criteria decision-making techniques, the application stages of the EDAS technique, which starts with the initial matrix, can be followed in ANNEX-C.

3.4. COmbinative Distance-based ASsessment (CODAS)

The CODAS technique, which determines the preferability of alternatives to each other according to Euclidean and Taxicab[1] distances, was proposed by Ghorabaee et al. (2016). Accordingly, the Euclidean distance is determined first. If two alternatives have equal or very close to Euclidean distances, the solution is reached using the Taxicab distance. In the CODAS method, Euclidean and Taxicab distance values are measured for the l^2-norm and l^1-norm indifference fields, respectively. In other words, in the CODAS method, alternatives in the l^2-norm indifference field are evaluated first (Euclidean distance approach). If the alternatives cannot be compared in this field (they are equal or very close to each other), the l^1-norm field is taken into consideration (Taxicab distance approach). In this process, each alternative pair must be compared pairwise (Bakir and Alptekin, 2018: 1341). The application stages of the CODAS method can be listed as follows (Badi et al., 2018: 616-617);

Determination of the Decision Matrix; At this stage, “m x n” dimensional decision matrix specified in Equation 1 is created.

Normalization of the Decision Matrix; At this stage, the decision matrix is normalized by using the Equation 23 for the benefit-oriented criteria and Equation 24 for the cost-oriented criteria.

$$n_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \qquad 23$$

$$n_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \qquad 24$$

Obtaining the Weighted Normalized Decision Matrix; A weight value (w_j) is determined for each criteria by using some other MCDM techniques or expert opinion. Then, the weighting of the normalized decision matrix is provided by the Equation 25.

$$r_{ij} = w_j n_{ij} \qquad 25$$

Determination of Negative Ideal Solution Value; At this stage, the negative ideal value is determined by the Equation 26 and Equation 27.

$$ns = [ns_j]_{1xm} \qquad 26$$

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[1] It expresses the distance between two points in the coordinate system, calculated only in vertical and horizontal routes. For example; Taxicab Distance between points A and B, where A (0, 0) and B (3, 5), is 8 units. In other words, Taxicab Distance expresses the longest route between two points in the coordinate system.

$$ns_j = \min_i r_{ij} \tag{27}$$

Determination of Euclidean and Taxicab Distance Values; In order to determine the distance with the negative ideal solution value at this stage; Euclidean Distance Value (E_i) is determined by the Equation 28 and Taxicab Distance Value (T_i) is determined by the Equation 29.

$$E_i = \sqrt{\sum_{j=1}^{m} \left(r_{ij} - ns_j\right)^2} \tag{28}$$

$$T_i = \sum_{j=1}^{m} \left|r_{ij} - ns_j\right| \tag{29}$$

Creating the Relative Evaluation Matrix; At this stage, the Relative Evaluation Matrix is created by the Equation 30 and Equation 31.

$$Ra = [h_{ik}]_{nxn} \tag{30}$$

$$h_{ik} = (E_i - E_k) + (\psi(E_i - E_k) * (T_i - T_k)) \tag{31}$$

The k index in Equation 31 means $k \in \{1, 2, \ldots, n\}$. In addition, the threshold value ψ, which is used to define the equality of the Euclidean Distance Value between two alternatives, is found by the Equation 32.

$$\psi(x) = \begin{cases} 1 \text{ eğer } |x| \geq \tau \\ 0 \text{ eğer } |x| < \tau \end{cases} \tag{32}$$

The τ index in Equation 32 is a threshold value determined by the decision maker, usually between 0.01 and 0.05. If the difference between the Euclidean distance values of two alternatives is less than τ, these two alternatives are compared according to the Taxicab distance value.

Calculation of Evaluation Scores of Alternatives; At this stage, the scores (H_i) of each alternative, as the basis for evaluation, are calculated by the Equation 33.

$$H_i = \sum_{k=1}^{n} h_{ik} \tag{33}$$

Obtaining the Ranking Value; Finally, the alternatives are ranked according to their evaluation scores. Here, due to the nature of the CODAS method (since the negative ideal solution is taken as basis), the alternative with the smallest score will be the best alternative.

As with all multi-criteria decision-making techniques, the application stages of the CODAS technique, which starts with the initial matrix, can be followed in ANNEX-D.

4. RESULTS

As in many decisions, the ARG procurement decision is made depending on many criteria of different importance levels. At this point, MCDM techniques are important for decision makers. There are many techniques in the literature of MCDM techniques, which have made significant progress in recent years. These techniques, which are used in a wide range of areas and whose numbers are increasing day by day, not only make the job of decision makers easier, but also encourage them to act rationally depending on the application stages. Because most of the decisions that do not include these techniques are intuitive and are affected by the personal characteristics of the decision makers.

The motivation of this study is that there are not many studies (except for Aydin, 2018) that provide a solution to a decision problem regarding ARG procurement in the literature research. In this context, the procurement decision of the most suitable one among eight different ARGs sold in the market (Vuzix M4000, Rokid Glass 2 Wifi, RealWear Navigator 500, Magic Leap 2 Developer Pro, Lenovo ThinkReality A3, Nreal Light Developer Kit, TCL RayNeo X2, Epson Moverio BT-45C) was made depending on nine different criteria (price, screen size, weight, field of view, battery, resolution, brightness, RAM memory, internal memory). In the study where alternative ARGs were ranked by the three different MCDM techniques (ARAS, EDAS, CODAS), CRITIC technique was used to determine the weight values of the criteria. Data on the alternatives were collected (360avm, 2024 and the decision matrix was prepared as shown in Table 1.

Table 1: Decision Matrix

ARG	Price-TL	Field of View - Degree	Battery-Mah	Resolution-MP	Screen size (mm2)	Brightness-nit	Ram-GB	Internal memory-GB	Weight-Gr
Vuzix M4000	161352	28	3350	12,8	40,992	5000	6	64	222
Rokid Glass 2 Wifi	192540	40	10000	8	92,16	1800	2	32	105
RealWear Navigator 500	141758	20	2600	48	42,48	450	4	64	270
Magic Leap 2 Developer Pro	414924	70	590	12,6	253,44	2000	16	256	260
Lenovo ThinkReality A3	114113	45	590	8	207,36	200	3	32	130
Nreal Light Developer Kit	101337	52	7100	5	207,36	280	6	64	106
TCL RayNeo X2	37171	25	590	16	207,36	1000	6	128	60
Epson Moverio BT-45C	139990	34	3400	8	207,36	1000	4	64	185

In determining the weight values of the criteria, the CRITIC technique, which provides a rational approach, was preferred. The CRITIC method helps the decision makers make more effective decisions giving more weight to the criteria by taking into account the correlation between them. At this stage, the criteria; price, screen size, and weight were evaluated in terms of cost-oriented, while the field of view, battery, resolution, brightness, RAM, and internal memory were evaluated in terms of benefit-oriented. The weight values of the criteria were calculated by CRITIC technique and presented in Table 2.

Table 2: Criteria Weight Values

Criteria	Price	FoV	Battery	Resolution	Screen size	Brightness	Ram	Internal Memory	Weight
Criteria Weight Values	0,1072	0,1092	0,1152	0,1093	0,1272	0,0995	0,0981	0,1052	0,1290

As a result of the analysis conducted with the CRITIC technique, the criteria that should be taken into consideration the most by decision makers were determined as the "*weight*" criterion with a weight value of 12.90%. This was followed by the "*screen size*" with 12.72% and the "*battery*" criteria with 11.52%, respectively.

In the second stage of the analysis, the alternatives were ranked by using three different MCDM techniques (ARAS, EDAS, CODAS), with the criteria weight values obtained with the CRITIC. The preference rankings, for decision makers, made by the three techniques are presented in Table 3.

Table 3: Preference Ranking of Alternatives

Alternatives	ARAS Technique	EDAS Technique	CODAS Technique
Vuzix M4000	**1**	**1**	**1**
Rokid Glass 2 Wifi	5	2	5
RealWear Navigator 500	4	3	4
Magic Leap 2 Developer Pro	2	4	2
Lenovo ThinkReality A3	8	8	8
Nreal Light Developer Kit	6	5	6
TCL RayNeo X2	3	6	3
Epson Moverio BT-45C	7	7	7

As a result of the analysis which are repeated with all three techniques, the "*Vuzix M4000*" brand/model ARG stands out as the most optimum alternative that should be preferred in the decision problem.

5. CONCLUSION

Today, ARGs have found a wide range of uses and have become widespread in parallel with technological developments. In the automobile manufacturing industry, ARGs enable assembly assistance, training, maintenance and repair, quality control, design and prototyping, optimizing production processes, increasing business efficiency and remote support. ARG procurement, which attracts the attention of individual and business users as well as in almost every field of industry, requires a critical decision stage due to its high costs. MCDM techniques can be used in the supply of products that require high investment costs and offer different features. MCDM techniques, an example application of which is presented for ARG supply in the study, are important in terms of providing very similar results to each other. However, in practice, it is generally preferred to use several methods together both in terms of revealing that the techniques produce strong results and allowing each other to provide them.

The same decision matrix in the study was solved with ARAS, EDAS and CODAS techniques and used in the ARG supply decision. Perhaps the most important stage of MCDM techniques is the weighting stage of the criteria. Although there are many techniques used in the literature for this stage, the CRITIC technique, which is not affected by personal intuitions and can produce completely rational results, was preferred in the study. As in this study, the most important constraint for similar studies is seen in the preparation of the decision matrix. At this stage, it is sometimes not possible to obtain all data for each alternative. After determining the criteria that will affect the decision, the most important problem for the correct decision is the inability to complete the dataset for decision matrix. At this point, although it is necessary to abandon any of the criteria and/or alternative subject to analysis, this is not a preferred situation in terms of good results. There are differences in the ranking of alternatives in analyses conducted with different techniques. Nevertheless, it is seen that the results are quite close to each other. Accordingly, it is recommended to use several methods together in similar studies. This is important both for the comparison of results and for making the right decision.

ARGs (Augmented Reality Glasses) are widely used, particularly in technology-driven sectors, with the automotive industry standing out among them. ARGs are frequently utilized in situations such as employee onboarding and training, as well as in helping workers grasp complex production and maintenance processes more efficiently. In this context, the automotive sector—where ARGs have found the most widespread application—was selected for the study. In this sector, ARGs play a critical role in employee training, enhancing comprehension of technological details, and accelerating workflow completion. ARGs are extensively employed due to the significant time and cost savings they offer. However, given the high investment costs associated with this technology, making the correct decision from the outset is particularly crucial. This study was inspired by the literature gap regarding the use of ARGs in the automotive manufacturing sector, which has entered people's lives and found use in the industrial field in recent years, in parallel with the developments in the age of technology. Within this scope, the study is considered significant as it employs three different multi-criteria decision-making (MCDM) techniques for the selection of ARGs in the automotive sector—both in terms of identifying the most appropriate technology and in demonstrating the comparability and robustness of the methods used.

Since no similar study has been identified in the existing literature, it can be stated that the current study makes significant contribution to the field, to decision makers who will choose ARGs, and to those in the field of application. Aydın (2008) utilized six criteria—functionality, ease of use, design standards, effectiveness, portability, and price—that allow for subjective evaluations within the AHP method. In contrast, the present study conducted comparisons using only objective data, applying criteria such as price, screen size, weight, field of view, battery, resolution, brightness, RAM, and internal memory. Given that the only common criterion between the two studies is price, it would be insufficient to draw direct comparisons. Furthermore, the criteria selected in this study are noteworthy for enabling objective evaluation, which strengthens the contribution it makes to the literature.

Accessing data from open-access sources can be considered as a limitation in the selection of criteria and brands that make up the data set. In future studies, ARGs with different models and features can be included in the analysis. However, due to the nature of MCDM methods, choosing from more alternatives with more evaluation criteria allows for more robust results. Since the price criterion is an important choice variable in this type of decision problem, access to accurate information is important. Similarly, the analysis can be repeated by using different techniques in both the weighting of the criteria and the ranking of the alternatives. Since different results may be obtained in future studies, it may be recommended to use hybrid models carried out with at least two techniques to compare the findings and prevent possible processing errors.

Ethic Statement Acknowledgement

This study was prepared in accordance with scientific research and publication ethics rules.

Authors' Contribution

The author(s) planned the study, collected the data, and performed the analyses. The author(s) wrote, read, and approved the article.

Conflict of Interest Statement

The author(s) has no conflicts of interest to declare.

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ANNEX-A (CRITIC Application Stages)

Table 1: Decision Matrix (Equation 1)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	161352	28	3350	12,8	40,992	5000	6	64	222
Rokid Glass 2 Wifi	192540	40	10000	8	92,16	1800	2	32	105
RealWear Navigator 500	141758	20	2600	48	42,48	450	4	64	270
Magic Leap 2 Developer Pro	414924	70	590	12,6	253,44	2000	16	256	260
Lenovo ThinkReality A3	114113	45	590	8	207,36	200	3	32	130
Nreal Light Developer Kit	101337	52	7100	5	207,36	280	6	64	106
TCL RayNeo X2	37171	25	590	16	207,36	1000	6	128	60
Epson Moverio BT-45C	139990	34	3400	8	207,36	1000	4	64	185

Table 2: Normalization of the Decision Matrix (Equation 2 and Equation 3)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.3287	0.0000	0.7714	0.8400	0.7067	0.8186	0.0000	0.7143	0.8571
Rokid Glass 2 Wifi	0.4113	0.2408	0.2143	0.6000	0.0000	0.9302	0.6667	1.0000	1.0000
RealWear Navigator 500	0.2769	0.0070	1.0000	1.0000	0.7864	0.0000	0.9479	0.8571	0.8571
Magic Leap 2 Developer Pro	1.0000	1.0000	0.9524	0.0000	1.0000	0.8233	0.6250	0.0000	0.0000
Lenovo ThinkReality A3	0.2037	0.7831	0.3333	0.5000	1.0000	0.9302	1.0000	0.9286	1.0000
Nreal Light Developer Kit	0.1699	0.7831	0.2190	0.3600	0.3082	1.0000	0.9833	0.7143	0.8571
TCL RayNeo X2	0.0000	0.7831	0.0000	0.9000	1.0000	0.7442	0.8333	0.7143	0.5714
Epson Moverio BT-45C	0.2722	0.7831	0.5952	0.7200	0.7014	0.9302	0.8333	0.8571	0.8571

Table 3: Creating the Relationship Coefficient Matrix (Equation 4)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	1.0000	0.1803	0.6192	-0.7080	0.0873	0.0475	-0.2959	-0.7740	-0.7070
Rokid Glass 2 Wifi	0.1803	1.0000	-0.3143	-0.6580	0.3454	0.5421	0.4650	-0.4650	-0.5042
RealWear Navigator 500	0.6192	-0.3143	1.0000	-0.0727	0.3083	-0.5420	-0.3233	-0.4382	-0.3478
Magic Leap 2 Developer Pro	-0.7080	-0.6580	-0.0727	1.0000	0.0143	-0.5260	-0.0935	0.6746	0.5646
Lenovo ThinkReality A3	0.0873	0.3454	0.3083	0.0143	1.0000	-0.2586	0.0483	-0.4262	-0.4892
Nreal Light Developer Kit	0.0475	0.5421	-0.5420	-0.5260	-0.2586	1.0000	-0.1400	-0.0643	0.0124
TCL RayNeo X2	-0.2959	0.4650	-0.3233	-0.0935	0.0483	-0.1400	1.0000	0.2242	0.1255
Epson Moverio BT-45C	-0.7740	-0.4650	-0.4382	0.6746	-0.4262	-0.0643	0.2242	1.0000	0.9600

Table 4: Calculation of Total Information (C_j) (Equation 5 and Equation 6)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.0000	0.8197	0.3808	1.7080	0.9127	0.9525	1.2959	1.7740	1.7070
Rokid Glass 2 Wifi	0.8197	0.0000	1.3143	1.6580	0.6546	0.4579	0.5350	1.4650	1.5042
RealWear Navigator 500	0.3808	1.3143	0.0000	1.0727	0.6917	1.5420	1.3233	1.4382	1.3478
Magic Leap 2 Developer Pro	1.7080	1.6580	1.0727	0.0000	0.9857	1.5260	1.0935	0.3254	0.4354
Lenovo ThinkReality A3	0.9127	0.6546	0.6917	0.9857	0.0000	1.2586	0.9517	1.4262	1.4892
Nreal Light Developer Kit	0.9525	0.4579	1.5420	1.5260	1.2586	0.0000	1.1400	1.0643	0.9876
TCL RayNeo X2	1.2959	0.5350	1.3233	1.0935	0.9517	1.1400	0.0000	0.7758	0.8745
Epson Moverio BT-45C	1.7740	1.4650	1.4382	0.3254	1.4262	1.0643	0.7758	0.0000	0.0400
Total	9.5506	8.4087	9.1109	8.8048	8.3703	8.9290	7.9897	8.3090	8.3856
Standart Deviation	0.2957	0.3987	0.3732	0.3268	0.3625	0.3226	0.3281	0.3112	0.3307

c_j	2.8242	3.3525	3.4000	2.8778	3.0343	2.8808	2.6214	2.5858	2.7727

Table 5: Weights of Criteria (Equation 7)

C1	C2	C3	C4	C5	C6	C7	C8	C9
0.1072	0.1272	0.1290	0.1092	0.1152	0.1093	0.0995	0.0981	0.1052

ANNEX-B (ARAS Application Stages)

Table 1: Decision Matrix (Equation 1)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	161352	28	3350	12,8	40,992	5000	6	64	222
Rokid Glass 2 Wifi	192540	40	10000	8	92,16	1800	2	32	105
RealWear Navigator 500	141758	20	2600	48	42,48	450	4	64	270
Magic Leap 2 Developer Pro	414924	70	590	12,6	253,44	2000	16	256	260
Lenovo ThinkReality A3	114113	45	590	8	207,36	200	3	32	130
Nreal Light Developer Kit	101337	52	7100	5	207,36	280	6	64	106
TCL RayNeo X2	37171	25	590	16	207,36	1000	6	128	60
Epson Moverio BT-45C	139990	34	3400	8	207,36	1000	4	64	185
Optimal Value Row (Eq. 8 and Eq.9)	37171	40.992	60	70	10000	48	5000	16	256

Table 2: Normalization of the Decision Matrix (Equation 10 and Equation 11)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Optimal Value Row	0.2679	0.2292	0.2152	0.1823	0.2616	0.3404	0.2989	0.2540	0.2667
Vuzix M4000	0.0617	0.2292	0.0582	0.0729	0.0877	0.0908	0.2989	0.0952	0.0667
Rokid Glass 2 Wifi	0.0517	0.1020	0.1230	0.1042	0.2616	0.0567	0.1076	0.0317	0.0333
RealWear Navigator 500	0.0702	0.2212	0.0478	0.0521	0.0680	0.3404	0.0269	0.0635	0.0667
Magic Leap 2 Developer Pro	0.0240	0.0371	0.0497	0.1823	0.0154	0.0894	0.1195	0.2540	0.2667
Lenovo ThinkReality A3	0.0873	0.0453	0.0993	0.1172	0.0154	0.0567	0.0120	0.0476	0.0333
Nreal Light Developer Kit	0.0983	0.0453	0.1218	0.1354	0.1858	0.0355	0.0167	0.0952	0.0667
TCL RayNeo X2	0.2679	0.0453	0.2152	0.0651	0.0154	0.1135	0.0598	0.0952	0.1333
Epson Moverio BT-45C	0.0711	0.0453	0.0698	0.0885	0.0890	0.0567	0.0598	0.0635	0.0667

Table 3: Weighted Normalized Decision Matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Optimal Value Row	0.0287	0.0246	0.0231	0.0195	0.0280	0.0365	0.0320	0.0272	0.0286
Vuzix M4000	0.0066	0.0246	0.0062	0.0078	0.0094	0.0097	0.0320	0.0102	0.0071
Rokid Glass 2 Wifi	0.0055	0.0109	0.0132	0.0112	0.0280	0.0061	0.0115	0.0034	0.0036
RealWear Navigator 500	0.0075	0.0237	0.0051	0.0056	0.0073	0.0365	0.0029	0.0068	0.0071
Magic Leap 2 Developer Pro	0.0026	0.0040	0.0053	0.0195	0.0017	0.0096	0.0128	0.0272	0.0286
Lenovo ThinkReality A3	0.0094	0.0049	0.0106	0.0126	0.0017	0.0061	0.0013	0.0051	0.0036
Nreal Light Developer Kit	0.0105	0.0049	0.0131	0.0145	0.0199	0.0038	0.0018	0.0102	0.0071
TCL RayNeo X2	0.0287	0.0049	0.0231	0.0070	0.0017	0.0122	0.0064	0.0102	0.0143
Epson Moverio BT-45C	0.0076	0.0049	0.0075	0.0095	0.0095	0.0061	0.0064	0.0068	0.0071

Table 4: Optimality Function Degree (Eq. 12), Benefit Degree (Eq. 13.) and Ranking

	S_i	K_i	Rank
Optimal Value Row	0.2483	2.1825	
Vuzix M4000	0.1137	1.0000	**1**
Rokid Glass 2 Wifi	0.0934	0.8216	**5**
RealWear Navigator 500	0.1026	0.9017	**4**
Magic Leap 2 Developer Pro	0.1113	0.9781	**2**
Lenovo ThinkReality A3	0.0551	0.4845	**8**
Nreal Light Developer Kit	0.0858	0.7545	**6**
TCL RayNeo X2	0.1083	0.9524	**3**
Epson Moverio BT-45C	0.0654	0.5752	**7**

ANNEX-C (EDAS Application Stages)

Table 1: Decision Matrix (Equation 1)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	161352	28	3350	12,8	40,992	5000	6	64	222
Rokid Glass 2 Wifi	192540	40	10000	8	92,16	1800	2	32	105
RealWear Navigator 500	141758	20	2600	48	42,48	450	4	64	270
Magic Leap 2 Developer Pro	414924	70	590	12,6	253,44	2000	16	256	260
Lenovo ThinkReality A3	114113	45	590	8	207,36	200	3	32	130
Nreal Light Developer Kit	101337	52	7100	5	207,36	280	6	64	106
TCL RayNeo X2	37171	25	590	16	207,36	1000	6	128	60
Epson Moverio BT-45C	139990	34	3400	8	207,36	1000	4	64	185
Average Value (Eq. 14)	162898.1	157.314	167.25	39.25	3527.5	15.5	1466.25	5.875	88

Table 2: Positive Distance from Average (PDA) (Equation 15 and Equation 16)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.0095	0.7394	0.0000	0.0000	0.0000	0.0000	2.4101	0.0213	0.0000
Rokid Glass 2 Wifi	0.0000	0.4142	0.3722	0.0191	1.8349	0.0000	0.2276	0.0000	0.0000
RealWear Navigator 500	0.1298	0.7300	0.0000	0.0000	0.0000	2.0968	0.0000	0.0000	0.0000
Magic Leap 2 Developer Pro	0.0000	0.0000	0.0000	0.7834	0.0000	0.0000	0.3640	1.7234	1.9091
Lenovo ThinkReality A3	0.2995	0.0000	0.2227	0.1465	0.0000	0.0000	0.0000	0.0000	0.0000
Nreal Light Developer Kit	0.3779	0.0000	0.3662	0.3248	1.0128	0.0000	0.0000	0.0213	0.0000
TCL RayNeo X2	0.7718	0.0000	0.6413	0.0000	0.0000	0.0323	0.0000	0.0213	0.4545
Epson Moverio BT-45C	0.1406	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 3: Negative Distance from Average (NDA) (Equation 17 and Equation 18)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.0000	0.0000	0.3274	0.2866	0.0503	0.1742	0.0000	0.0000	0.2727
Rokid Glass 2 Wifi	0.1820	0.0000	0.0000	0.0000	0.0000	0.4839	0.0000	0.6596	0.6364
RealWear Navigator 500	0.0000	0.0000	0.6143	0.4904	0.2629	0.0000	0.6931	0.3191	0.2727
Magic Leap 2 Developer Pro	1.5471	0.6110	0.5546	0.0000	0.8327	0.1871	0.0000	0.0000	0.0000
Lenovo ThinkReality A3	0.0000	0.3181	0.0000	0.0000	0.8327	0.4839	0.8636	0.4894	0.6364
Nreal Light Developer Kit	0.0000	0.3181	0.0000	0.0000	0.0000	0.6774	0.8090	0.0000	0.2727
TCL RayNeo X2	0.0000	0.3181	0.0000	0.3631	0.8327	0.0000	0.3180	0.0000	0.0000
Epson Moverio BT-45C	0.0000	0.3181	0.1061	0.1338	0.0361	0.4839	0.3180	0.3191	0.2727

Table 4: Weighted Total Values of PDA (NSP_i) (Equation 19)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.0010	0.0941	0.0000	0.0000	0.0000	0.0000	0.2398	0.0021	0.0000
Rokid Glass 2 Wifi	0.0000	0.0527	0.0480	0.0021	0.2113	0.0000	0.0226	0.0000	0.0000
RealWear Navigator 500	0.0139	0.0929	0.0000	0.0000	0.0000	0.2292	0.0000	0.0000	0.0000
Magic Leap 2 Developer Pro	0.0000	0.0000	0.0000	0.0856	0.0000	0.0000	0.0362	0.1691	0.2009
Lenovo ThinkReality A3	0.0321	0.0000	0.0287	0.0160	0.0000	0.0000	0.0000	0.0000	0.0000
Nreal Light Developer Kit	0.0405	0.0000	0.0473	0.0355	0.1166	0.0000	0.0000	0.0021	0.0000
TCL RayNeo X2	0.0827	0.0000	0.0827	0.0000	0.0000	0.0035	0.0000	0.0021	0.0478
Epson Moverio BT-45C	0.0151	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Table 5: Weighted Total Values of NDA (NSN_i) (Equation 20)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	0.0000	0.0000	0.0422	0.0313	0.0058	0.0190	0.0000	0.0000	0.0287
Rokid Glass 2 Wifi	0.0195	0.0000	0.0000	0.0000	0.0000	0.0529	0.0000	0.0647	0.0670
RealWear Navigator 500	0.0000	0.0000	0.0793	0.0536	0.0303	0.0000	0.0690	0.0313	0.0287
Magic Leap 2 Developer Pro	0.1658	0.0777	0.0716	0.0000	0.0959	0.0205	0.0000	0.0000	0.0000
Lenovo ThinkReality A3	0.0000	0.0405	0.0000	0.0000	0.0959	0.0529	0.0859	0.0480	0.0670
Nreal Light Developer Kit	0.0000	0.0405	0.0000	0.0000	0.0000	0.0741	0.0805	0.0000	0.0287
TCL RayNeo X2	0.0000	0.0405	0.0000	0.0397	0.0959	0.0000	0.0316	0.0000	0.0000
Epson Moverio BT-45C	0.0000	0.0405	0.0137	0.0146	0.0042	0.0529	0.0316	0.0313	0.0287

Table 6: Normalizing SP and SN Values (Eq. 21 and Eq. 22) and Ranking

	SPi	*SNi*	*NSPi*	*NSNi*	*ASi*	Ranking
Vuzix M4000	0.3370	0.1271	0.6852	0.7055	0.6953	**1**
Rokid Glass 2 Wifi	0.3367	0.2041	0.6847	0.5270	0.6059	**2**
RealWear Navigator 500	0.3360	0.2921	0.6833	0.3231	0.5032	**3**
Magic Leap 2 Developer Pro	0.4918	0.4315	1.0000	0.0000	0.5000	**4**
Lenovo ThinkReality A3	0.0768	0.3902	0.1562	0.0957	0.1260	**8**
Nreal Light Developer Kit	0.2419	0.2237	0.4920	0.4815	0.4867	**5**
TCL RayNeo X2	0.2189	0.2077	0.4451	0.5187	0.4819	**6**
Epson Moverio BT-45C	0.0151	0.2175	0.0306	0.4959	0.2633	**7**

ANNEX-D (CODAS Application Stages)

Table 1: Decision Matrix (Equation 1)

	C1	C2	C3	C4	C5	C6	C7	C8	C9
Vuzix M4000	161352	28	3350	12,8	40,992	5000	6	64	222
Rokid Glass 2 Wifi	192540	40	10000	8	92,16	1800	2	32	105
RealWear Navigator 500	141758	20	2600	48	42,48	450	4	64	270
Magic Leap 2 Developer Pro	414924	70	590	12,6	253,44	2000	16	256	260
Lenovo ThinkReality A3	114113	45	590	8	207,36	200	3	32	130
Nreal Light Developer Kit	101337	52	7100	5	207,36	280	6	64	106
TCL RayNeo X2	37171	25	590	16	207,36	1000	6	128	60

Epson Moverio BT-45C	139990	34	3400	8	207,36	1000	4	64	185
Average Value (Eq. 14)	162898.1	157.314	167.25	39.25	3527.5	15.5	1466.25	5.875	88

Table 2: Normalization of Decision Matrix (Equation 23 and Equation 24)

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
Vuzix M4000	0.2304	1.0000	0.2703	0.4000	0.3350	0.2667	1.0000	0.3750	0.2500
Rokid Glass 2 Wifi	0.1931	0.4448	0.5714	0.5714	1.0000	0.1667	0.3600	0.1250	0.1250
RealWear Navigator 500	0.2622	0.9650	0.2222	0.2857	0.2600	1.0000	0.0900	0.2500	0.2500
Magic Leap 2 Developer Pro	0.0896	0.1617	0.2308	1.0000	0.0590	0.2625	0.4000	1.0000	1.0000
Lenovo ThinkReality A3	0.3257	0.1977	0.4615	0.6429	0.0590	0.1667	0.0400	0.1875	0.1250
Nreal Light Developer Kit	0.3668	0.1977	0.5660	0.7429	0.7100	0.1042	0.0560	0.3750	0.2500
TCL RayNeo X2	1.0000	0.1977	1.0000	0.3571	0.0590	0.3333	0.2000	0.3750	0.5000
Epson Moverio BT-45C	0.2655	0.1977	0.3243	0.4857	0.3400	0.1667	0.2000	0.2500	0.2500

Table 3: Weighted Decision Matrix (Eq. 25) and Negative Ideal Solution Value (Eq. 26 and Eq. 27)

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**
Vuzix M4000	0.0247	0.1272	0.0349	0.0437	0.0386	0.0292	0.0995	0.0368	0.0263
Rokid Glass 2 Wifi	0.0207	0.0566	0.0737	0.0624	0.1152	0.0182	0.0358	0.0123	0.0132
RealWear Navigator 500	0.0281	0.1228	0.0287	0.0312	0.0299	0.1093	0.0090	0.0245	0.0263
Magic Leap 2 Developer Pro	0.0096	0.0206	0.0298	0.1092	0.0068	0.0287	0.0398	0.0981	0.1052
Lenovo ThinkReality A3	0.0349	0.0252	0.0596	0.0702	0.0068	0.0182	0.0040	0.0184	0.0132
Nreal Light Developer Kit	0.0393	0.0252	0.0730	0.0811	0.0818	0.0114	0.0056	0.0368	0.0263
TCL RayNeo X2	0.1072	0.0252	0.1290	0.0390	0.0068	0.0364	0.0199	0.0368	0.0526
Epson Moverio BT-45C	0.0285	0.0252	0.0418	0.0530	0.0392	0.0182	0.0199	0.0245	0.0263
Negative Ideal Solution Value	0.0096	0.0206	0.0287	0.0312	0.0068	0.0114	0.0040	0.0123	0.0132

Table 4: Determination of Eukledian (Eq. 28) (E_i), Taxicab Distances (T_i) (Eq. 29), Evaluation Scores (H_i) (Eq. 33) and Ranking

	E_i	T_i	H_i	**Ranking**
Vuzix M4000	0.1517	0.3232	0.7915	**1**
Rokid Glass 2 Wifi	0.1312	0.2704	0.3241	**5**
RealWear Navigator 500	0.1458	0.2722	0.5385	**4**
Magic Leap 2 Developer Pro	0.1534	0.3102	0.7527	**2**
Lenovo ThinkReality A3	0.0568	0.1127	-1.5536	**8**
Nreal Light Developer Kit	0.1085	0.2428	-0.1256	**6**
TCL RayNeo X2	0.1507	0.3153	0.7070	**3**
Epson Moverio BT-45C	0.0519	0.1390	-1.4347	**7**