DEVELOPMENT OF A RANKING MODEL OF HUMAN STRESS MEASUREMENT USING A HYBRID MCDM METHOD

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Abstract
Stress is a response to mental/emotional or physical aspects that are encountered in daily life. In order to manage stress, it is required to monitor the stress levels on a continuous basis. Individual physiological parameters such as Heart Rate (HR) and Blood Pressure (BP) and respiration activity can be used as a measure to determine stress. But, the accuracy of determination is limited by using individual parameters. Usage of multiple parameters aids in the better determination of stress. The process of stress measurement is still not automated. The physician has to manually diagnose this using several parameters. There is a strong need to find out an automatic approach through which the stress level of multiple patients may be assessed automatically. Multi criterion Decision-Making (MCDM) is one of the efficient approaches that is generally applied in arriving at an optimum decision when face with multiple alternatives having multi conflicting and non-commensurable decision criteria. This approach is a well-known tool for solving complex real-life problems due to its intrinsic ability to judge diverse alternatives with reference to various decision criteria in order to choose the best alternative. To solve this problem weighted Combined Distance-based Assessment (W-CODAS) MCDM method is proposed. This approach has been implemented on the manually collected medical data of a total of 60 patients from Dr. Suresh Kumar Pundir at Alfla Hospital, Faridabad. This data includes Age, Body Temperature (Fahrenheit) BP systolic, BP diastolic, and Heart Rate of each patient. The proposed method bolsters the doctor's community to calculate the patient stress, automatically. Two existing MCDM methods Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), and Distance-Based Approach (DBA) has also been implemented to evaluate the effectiveness of the proposed method.

Keywords: *Stress measurement, MCDM, W-CODAS, TOPSIS, DBA, Ranking*

Introduction
When it comes to improving health, managing chronic illnesses, and preventing illness, monitoring human health is crucial. Many of today's health monitoring tools require invasive procedures like drawing blood or inserting a catheter. As a response to this issue, non-invasive gadgets that can monitor many physiological parameters without requiring invasive procedures have been created.There are several processes involved in developing a non-invasive device for human health care monitoring, including research, design, prototype production, and testing. Heart rate, blood pressure, oxygen saturation, breathing rate, and temperature are just some of the biometrics that may be monitored by this handy device. The device may also keep track of your workouts, sleep cycles, and food intake. The device might be made to be worn or handheld depending on the intended use. The portable device may be a tiny, lightweight gadget that can be carried in the user's pocket, while the wearable device can be sewed into a piece of clothing or an item like a bracelet or necklace. Technology such as sensors, wireless connection, and data processing algorithms are all used in the creation of a non-invasive health monitoring gadget. Physiological characteristics may be detected using sensors, and then sent to a smartphone or computer through wireless connection for analysis. Algorithms designed for analyzing data can take this information and apply it to better people's health.Overall, creating a non-invasive device for monitoring human health is a difficult process that calls for input from many

different fields of study. The advantages of such a device, however, are substantial, since it may aid in the early diagnosis and treatment of diseases and enhance the quality of life for those who suffer from chronic conditions. There are several potential uses for this non-invasive health monitoring equipment in healthcare facilities including hospitals and clinics. Patients with diabetes, hypertension, and heart disease may all benefit from using the gadget to monitor their health and spot any changes that may need treatment. Patients having surgery or other medical operations may be monitored using the gadget to guarantee their safety and well-being.The physiological measure for relevance to stress analysis is explained in table 1

I. **Table 1:**Physiological Measure for Relevance to Stress Analysis

Physiological Measure	**Description**	**Relevance to Stress Analysis**
Galvanic Skin Response (GSR)	Measures the electrical conductivity of the skin, which is influenced by sweat secretion, and can provide an indication of emotional arousal and stress levels.	Identifies patterns and trends in stress levels over time and serves as a gauge of emotional arousal and response.
Blood Pressure (BP)	Determines the force exerted on the heart and blood vessels by measuring arterial blood pressure.	Provides a quantitative assessment of the body's reaction to stress
Heart Rate Variability (HRV)	An indicator of the autonomic nervous system's reaction to stress, measuring the interval between heartbeats. Reduced HRV is linked to greater vulnerability to cardiovascular disease and chronic stress.	Helps detect chronic stress and its associated health concerns by measuring the autonomic nervous system's reaction to stress.
Respiration Rate	A person's respiratory reaction to stress may be gauged by monitoring their respiration rate. Breathing patterns, such as deep, slow, or irregular breathing, may vary in response to stress.	Helps the user understand how their breathing changes in reaction to stress and suggests exercises that might help them calm down and breathe more normally.
Electroencephalography (EEG)	A stress test that measures electrical brain activity may reveal how you're feeling mentally and emotionally. Stress-related patterns of brain activity, such as elevated amygdala activity and depressed frontal cortex activity, may be detected by EEG.	Identifies stress-relieving activities and gives the user insight into how they affect the user's emotional and cognitive responses to stress.
Skin Temperature	Takes a reading from the skin's surface to reveal how the body is reacting to stress. Reduced peripheral blood flow and vasoconstriction, both of which may affect skin temperature, are two effects that stress can have.	Learn how your body reacts to stress, and use that information to choose activities that will help you relax and feel better.

The following sections comprise this paper: section II summarizes previous work by various authors, section III defines the proposed stress measurement methodology, section IV describes the experimental results, and section V concludes the paper by summarizing the conclusion and future scope.

Literature

Over the world, stress is the most common mental health issue that causes people to act and feel differently. There are a wide variety of serious human illnesses that may be brought on by prolonged exposure to stress explained by Sharma et al. (2021)In order Selecting manuscripts, synthesising data, and analysing results are the three phases of the review process. There has been much research on the problems with SL tactics and the possible use of hybrid approaches in stress diagnosis. To better understand these optimisation methods, the benefits and drawbacks of several SL (Bayesian classifier, random forest, support vector machine, and closest neighbours) and SC (fuzzy logic, nature-inspired, and deep learning) methods have been described. Stresses of many kinds—social, behavioural, and biological—have been recognised for their deleterious consequences. Stress's effects on the mind, body, and behaviour have been briefly discussed [1]. Lee et al. (2020)offered an overview of the literature on the use of wearable sensors to measure employee health and safety in the workplace, with a focus on how this technology may be used to monitoring workplace safety. A variety of sensors, such as those that can detect falls, fatigue, and heat stress, are investigated by the authors. The article goes on to highlight how wearable sensors have several applications, including alarm systems and remote monitoring, that might enhance the effectiveness of safety monitoring in the workplace [2].

According to reports by Wu et al. (2019), the effects of stress on a person's body are said to vary greatly depending on the individual because of the variety of circumstances that surround individuals. So, in order to be effective, a monitoring system for stress must evaluate, on an individual basis, not only the physiological but also the psychological effects of stress, and then transform these evaluations into an objective quantitative measure that is of importance to the user. Because of this, the authors of this study envisioned a system that relies on regression analysis and company is fully equipped from the cognitions (Nervous System Inspection, SRI), biochemical (tests of epithelial glucocorticoid), and biological (initiatives of HRV) domains by using the idea of triangle in order to reach a high degree of dependability and solidity throughout the process of assessing stress on a person. The mental stress index, also known as the MSI, was developed with the assistance of the proposed model [3]. Faurholt-Jepsen and Munkholm, (2019)presented a comprehensive review of the current crop of wearable sensors designed to track mental health. The authors discuss a wide variety of sensors, including those used to measure electroencephalography, heart rate, and skin conductance. The article goes on to describe how wearable sensors may enhance the accuracy of mood monitoring thanks to features like real-time feedback and data processing. The report suggests that mood monitoring with wearable sensors has the potential to be both accurate and unbiased [4]. Stuart et al.(2020)also investigated whether or not users are able to successfully use the approaches for stress management that are presented during a simulation. We used a series of virtual patients and the Simple Triage and Rapid Treatment (START) system to carry out a pilot experiment using a within-subjects design (n=12), an exploratory mixed-method design, and an exploratory mixed-method design. According to the findings of this study, there is a pressing need to investigate how stress might be caused by realistic situations involving virtual individuals and which strategies are the most successful in mitigating the effects of stress on users participating in virtual simulations [5].

The construction of an internet of things system for the control of students' stress is shown by Rodic-Trmcic et al. in 2018. An open architecture was used in the development of the Internet of Things system, and it is an essential component of the educational environment. The system is made up of two components: the first of which allows for the assessment of critical characteristics that may be used to detect stress in pupils, and the second of which is for the regulation of stress. A mobile health application that features relaxation material is the component of the stress management system that you will use. A method like this should reduce the amount of excitement and have an effect on making the future less stressful [6]. On the other hand, Kassymova et al.(2018)addressed stress and the biological responses to it, which is a significant issue that affects students all over the contemporary world. It discussed and offered ways for stress management that are simple to perform for students and instructors even while classes are in session. Some examples of these techniques include yoga

pranayama and Japanese finger stress release techniques. People's mental and physical health might suffer as a direct result of the effects of stress, which is a big issue in our current day [7].
Flatt et al., (2018)reviewed the latest studies on the topic of using wearable sensors to monitor athletes' stats. The authors discussed a wide variety of sensors, including those used to track movement, heart rate, and oxygen levels. Advantages of wearable sensors that might enhance the effectiveness of performance monitoring in sports are discussed, including real-time feedback and personalised goal setting. A more objective and practical method of monitoring athlete performance is required, as stated in the report [8]. Vahedian-Azimi et al., (2018**)** Wearable sensors for cardiovascular disease monitoring: Wearable sensors for monitoring cardiovascular disorders are discussed in this article. Sensors like those used to record electrocardiograms, blood pressure, and heart rate variability are discussed by the writers. Features of wearable sensors, such as wireless communication and remote monitoring, are discussed, along with their potential to improve the efficacy of monitoring cardiovascular disease. The paper implies that monitoring cardiovascular illness using wearable sensors may be an efficient and non-invasive option [9]. Zhang et al., (2021) reviewed recent developments in eye-tracking wearables. Infrared cameras, eye-tracking devices, and electrooculography sensors are only few of the numerous that are discussed. The article continues to address the potential benefits of using wearable sensors for eye health monitoring, including real-time feedback and data analysis. Wearable sensors, as shown in this article, may make monitoring eye health easy and effective [10].
Xu et al., (2021) reviewed the current status of wearable brain health monitors This article reviews the latest studies that have investigated the feasibility of using wearable sensors to monitor psychological well-being. This book covers a wide range of sensors, including those used in electroencephalography, functional magnetic resonance imaging, and magnetoencephalography. The study claimed that it is possible to use wearable sensors to conduct objective and efficient monitoring of brain health [11].
Srinivasanetal.(2006)utilised photos of the thumb before and after occlusion, have devised a method for testing Hb levels in blood in a non-invasive manner. As a consequence of the blockage, the blood begins to pool in the thumb, which causes a change in the colour of the blood. The degree to which the colour changes is directly proportional to the amount of Hb present in the blood. They had taken images of all 200 people while concurrently measuring the Hb levels of each subject using a procedure that is considered to be conventional. They came up with an equation for multiple regressions between the variations in the R, G, and B colour values before and after blockage of the blood and the Hb value as measured by the usual approach. They claimed that r2 was equal to 0.71 [12]. Kanashima et al. (2005)contrasted the effectiveness of a non-invasive Hb monitor that uses NIR imaging (AstrimTMSysmex) to that of an automated haemotogyanalyser (K-4500). The noninvasive gadget works by transmitting several NIR wavelength bands via the user's fingertip, which are then utilised to scan blood vessels. Hb concentration may be calculated by using the information and then doing the following computation [13]. Osterberg and Blaschke, (2005)reviewed the research on the effectiveness of using wearable sensors to monitor patients' adherence to prescribed medications. The authors discussed several sensors, including ingestible ones like smart pill bottles and medication event monitoring systems. The report goes on to talk about how wearable sensors, with their wireless connections and data processing capability, might make drug adherence monitoring systems more effective. The research suggests that unobtrusive and effective monitoring of medication adherence may be possible via the use of wearable sensors [14].

PROPOSED METHODOLOGY

THE METHODOLOGY: W-CODAS

In this paper, the W-CODAS technique, an effective combination of the Shannon Entropy approach and the CODAS method, is proposed to optimize e-learning websites. For a better understanding, the process is outlined below.

3.1 Shannon Entropy Approach

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The weight computation of the performance indices utilized in any decision-making situation is prioritized in Shannon's Entropy method [20-22]. After the performance ratings of the alternatives are collected for all performance indices, a decision matrix is created, which serves as the foundation for the weight computation. This method's implementation procedure is as follows:

Let $[A_{ij}]_{mxn}$ be the decision matrix of size $[m \text{ x } n]$, where 'm' and 'n' denotes the number of alternatives and performance indexes, respectively.

$$[A_{ij}]_{mxn} = \begin{array}{c c} & \begin{array}{cccc} n_1 & n_2 & \dots & n_n \end{array} \\ \begin{array}{c} m_1 \\ m_2 \\ \vdots \\ m_n \end{array} & \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \dots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mn} \end{bmatrix} \end{array}$$

Eq. 1 normalizes the decision matrix.

$$norm[A_{ij}]_{mxn} = \frac{A_{ij}}{\sum_{i=1}^{m} A_{ij}} \quad (1)$$

Once the decision matrix is normalized, eq. (2) calculates the entropy value for each performance index.

$$E_{ij} = -k \sum_{j=1}^{n} norm[A_{ij}]\left(ln\left(norm[A_{ij}]\right)\right) \quad (2)$$

Where $k = \frac{1}{ln\,(n)}$

After obtaining the entropy values, eq. (3) estimates the priority weights of all the performance indexes.

$$[w_i]_{mx1} = \frac{E_i}{\sum_{i=1}^{m} E_i} \quad (3)$$

3.2 CODAS

Ghorabaee et al. [23-24] created the CODAS approach to successfully tackle the decision-making problem in 2016. It primarily calculates two types of distances: Euclidean distance and taxicab distance. The concept behind the taxicab distance is that there are instances when two options are not simply comparable in terms of Euclidean distance. The CODAS approach is implemented in a step-by-step manner:

1) The CODAS method formulates the decision matrix $[A_{ij}]_{mxn}$ consisting of performance ratings of the alternatives w.r.t. all performance indexes.

$$[A_{ij}]_{mxn} = \begin{array}{c c} & \begin{array}{cccc} n_1 & n_2 & \dots & n_n \end{array} \\ \begin{array}{c} m_1 \\ m_2 \\ \vdots \\ m_n \end{array} & \begin{bmatrix} A_{11} & A_{12} & \dots & A_{1n} \\ A_{21} & A_{22} & \dots & A_{2n} \\ \vdots & \vdots & \dots & \vdots \\ A_{m1} & A_{m2} & \dots & A_{mn} \end{bmatrix} \end{array} \quad (4)$$

2) The decision matrix is now normalized using the linear normalization method as given below:

$$norm[A_{ij}]_{mxn} = \begin{cases} \frac{A_{ij}}{\max_i A_{ij}} & if\ j \in N_b \\ \frac{\min_i A_{ij}}{A_{ij}} & if\ j \in N_c \end{cases} \quad (5)$$

3) Multiply the weight matrix $[w_i]_{mx1}$ obtained using Shanon entropy approach with the $norm[A_{ij}]_{mxn}$ obtained in the previous step as follows:

$$weighted[A_{ij}]_{mxn} = [w_i]_{mx1} * norm[A_{ij}]_{mxn} \quad (6)$$

4) Identify the negative ideal solution following step 3.

$$[ns_j]_{1xn} = \min_i(weighted[A_{ij}]_{mxn}) \quad (7)$$

5) Now, calculate the Euclidean and taxicab distance for each of the alternatives as given below:

$$ED_i = \sqrt{\sum_{j=1}^{n} weighted[A_{ij}] - [ns_j]} \quad (8)$$

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$TD_i = \sum_{j=1}^{n} \left| weighted\left[A_{ij}\right] - \left[ns_j\right] \right|$ (9)

6) Formulate the relative preference matrix as given below:

$$R_p = [R_{ik}]_{mxn}$$

Where $R_{ik} = (ED_i - ED_k) + (\varphi(ED_i - ED_k) * (TD_i - TD_k))$

Here $k \in 1 \dots m$ and φ show a threshold function used to analyze the Euclidean distance equality of two alternatives. The threshold function is:

$$\varphi(y) = \begin{cases} 1 & if\ |y| \geq \tau \\ 0 & if\ |y| < \tau \end{cases} \quad (10)$$

Here τ ranges from 0.02 – 0.05.

7) Calculate the final preference index value for all alternatives as given below:

$P = \sum_{k=1}^{m} R_{ik}$ (11)

8) Now the alternatives are ranked based on the calculated preference index value in step 7.

EXPERIMENTAL RESULTS

To evaluate the physical stress level from the acquired patient data, all three MCDM techniques have been used in this study. Tables and graphs have been used to compare the results of all three methods. To demonstrate, the suggested approaches, TOPSIS, DBA and W-CODAS, are applied to comprehensive data sets while considering three different selection criteria. The data set is obtained at the Alfla Hospital in Faridabad under the direction of Dr. Suresh Kumar Pundir. The medical data of 60 male and female individuals were gathered, including age, body temperature (Fahrenheit), blood pressure systolic, diastolic, and heart rate. These 60 patients' data is divided into seven datasets, each having 20 patients. To understand the data division, a table is given below.

Table 2: Input test data division

Data Set	Age	Category	Number of Patients
1	30 - 42	Male	20 (1-20)
2	30 – 42	Female	20 (21-40)
3	25 - 37	Pregnant Women	20 (41-60)

Only the BP systolic, BP diastolic, and Heart Rate parameters are considered selection criteria for all three MCDM approaches for experimental purposes. This medical information has been separated into all the groups. A conventional hypertension level (adapted from AV Chobanian et al., JAMA 289:2560, 2003) is used to better comprehend the physical stress level, as shown in Table 3 below. Each category has been given a score (ranging from 1 to 5) based on the recommendation of a doctor or physician, with a score of 1 indicating a patient with normal systolic and diastolic BP, i.e., least physical Stress, and a score of 5 indicating a patient with systolic BP above 140 mmHg and diastolic BP above 90 mmHg, i.e., highest physical Stress.

Table 3: Blood Pressure Classification (Adapted from AV Chobanian et al.: JAMA 289:2560, 2003)

S. No.	Blood Pressure Classification	Systolic, mmHg	Diastolic, mmHg	Score from the Doctor
1.	Normal	<120	<80	1
2.	Prehypertension	120 - 139	80 – 89	2
3.	Stage 1 hypertension	140 - 159	90 - 99	3
4.	Stage 2 hypertension	≥ 160	or ≥ 100	4
5.	Stage 3 hypertension	≥ 140	and < 90	5

The Doctor's review scores are used as a basis for comparison. This review score will be compared to the outcome rank from each MCDM approach. This procedure will support the suggested data validation techniques. The doctor evaluation score and the scores from the three techniques are contrasted in Table 4. Additionally, the first 20 instances (dataset 1) display the most critical ranking of the MCDM approach. This comparison compares the effectiveness of each MCDM technique concerning the Doctor's review score.

Table 4: Comparative analysis of Score from the Doctor, TOPSIS, DBA &W-CODAS Score for the patient from dataset 1

	Score from the Doctor	TOPSIS Score	TOPSIS Rank	DBA Score	DBA Rank	W-CODAS score	W-CODAS Rank
PATIENT 1	1	0.894151	20	441.6401	16	-4.04859	20
PATIENT 2	2	0.522048	13	335.523	11	-0.75604	13
PATIENT 3	5	0.317694	6	263.4438	4	1.130339	6
PATIENT 4	1	0.717685	18	368.0497	13	-2.49407	18
PATIENT 5	3	0.457106	11	294.2004	8	0.20657	10
PATIENT 6	1	0.653934	17	468.0362	18	-2.39987	17
PATIENT 7	3	0.352164	9	562.2071	20	0.641225	9
PATIENT 8	1	0.849246	19	417.9426	15	-3.48738	19
PATIENT 9	4	0.290378	5	277.2741	7	1.340481	5
PATIENT 10	3	0.498896	12	324.5505	10	-0.00382	11
PATIENT 11	5	0.281483	4	253.5197	3	1.7333	4
PATIENT 12	3	0.416115	10	396.2092	14	-0.16887	12
PATIENT 13	4	0.338962	8	364.4244	12	0.846982	8
PATIENT 14	2	0.57559	15	453.8446	17	-1.81707	16
PATIENT 15	4	0.338773	7	264.8756	5	0.882879	7
PATIENT 16	2	0.650578	16	514.3946	19	-1.31388	15
PATIENT 17	5	0.195615	2	94.90841	1	3.021176	2
PATIENT 18	2	0.524974	14	235.9059	2	-0.79491	14
PATIENT 19	5	0.220474	3	277.0127	6	2.795084	3
PATIENT 20	5	0.122295	1	313.3173	9	4.686458	1

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According to the W-CODAS statistics, Table 4 shows that Patient 1 has the least physical Stress and Patient 20 has the greatest. Patient 1, who experienced the least physical stress, received a review score of 1, while Patient 20, who had the most, received a review score of 5. These results agree with the doctor's evaluation. For the dataset 3 patients, W-CODAS performs better than TOPSIS and DBA. let's visualize this to better understand Figure 1 also includes a graph to aid in understanding the rank attained by various strategies. For dataset 1 patients, the graph contrasts TOPSIS, DBA, and W-CODAS Rank.

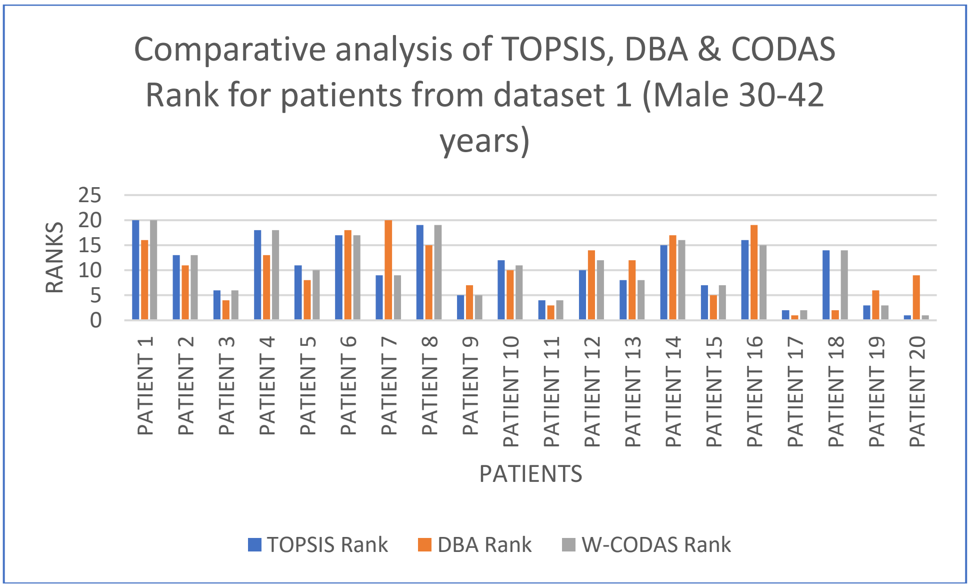

Figure 1: Comparative analysis of TOPSIS, DBA &W-CODAS Rank for patients from dataset 1

Now, let's jump directly to the comparative analysis of all three methods for rest of the datasets one by one. Let's move on to the comparison analysis for dataset 2 after analyzing the results of all three methods and the doctor's assessment for dataset 1. Table 5 displays a study of the patient's Score from the Doctor, TOPSIS, DBA, and W-CODAS Scores in comparison for dataset 2.

Table 5: Comparative analysis of Score from the Doctor, TOPSIS, DBA &W-CODAS Score for the patient from dataset 2 (Female 30 – 42 years)

	Score from the Doctor	**TOPSIS Score**	**TOPSIS Rank**	**DBA Score**	**DBA Rank**	**W-CODAS score**	**W-CODAS Rank**
PATIENT 21	2	0.433808	12	327.4449	12	-1.5725	13
PATIENT 22	1	0.808609	20	523.9612	20	-1.57855	20
PATIENT 23	5	0.266826	1	159.898	1	-1.56842	1
PATIENT24	3	0.448675	13	405.3295	16	-1.57014	9
PATIENT 25	3	0.294457	2	168.6593	2	-1.57096	11
PATIENT 26	5	0.346201	7	307.8539	9	-1.56829	4
PATIENT 27	4	0.38647	9	345.0864	14	-1.56862	6
PATIENT 28	4	0.326365	5	276.9334	6	-1.56868	7

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PATIENT 29	5	0.316701	4	284.5558	7	-1.56739	2
PATIENT 30	4	0.477735	14	271.4408	5	-1.5734	5
PATIENT 31	2	0.556823	17	498.2159	19	-1.57304	14
PATIENT 32	2	0.683368	19	412.2165	17	-1.57683	15
PATIENT 33	1	0.533939	16	324.4875	11	-1.57528	18
PATIENT 34	5	0.34966	8	308.3536	10	-1.56816	3
PATIENT 35	1	0.620059	18	431.4546	18	-1.57645	19
PATIENT 36	4	0.337673	6	288.6157	8	-1.5688	8
PATIENT 37	3	0.311452	3	231.6485	3	-1.57017	10
PATIENT 38	2	0.425195	10	257.838	4	-1.57356	16
PATIENT 39	3	0.428675	11	369.4074	15	-1.57102	12
PATIENT 40	1	0.487614	15	338.5489	13	-1.57421	17

According to the results of all three approaches, Patient 22 has the lowest physical Stress, whereas Patient 23 has the highest physical Stress, as shown in Table 5. The results are consistent with the Doctor's assessment, with patient 22 having the lowest physical Stress and a review score of 1 and patient 23 having the most significant physical Stress and a review score of 5. It is also evident from the chart that all three approaches perform nearly identically for the dataset 2 patients.
To understand the figures better, Figure 2 includes a graph to help understand the rating produced by various approaches. TOPSIS, DBA, and W-CODAS Rank are compared for patients in dataset 2.

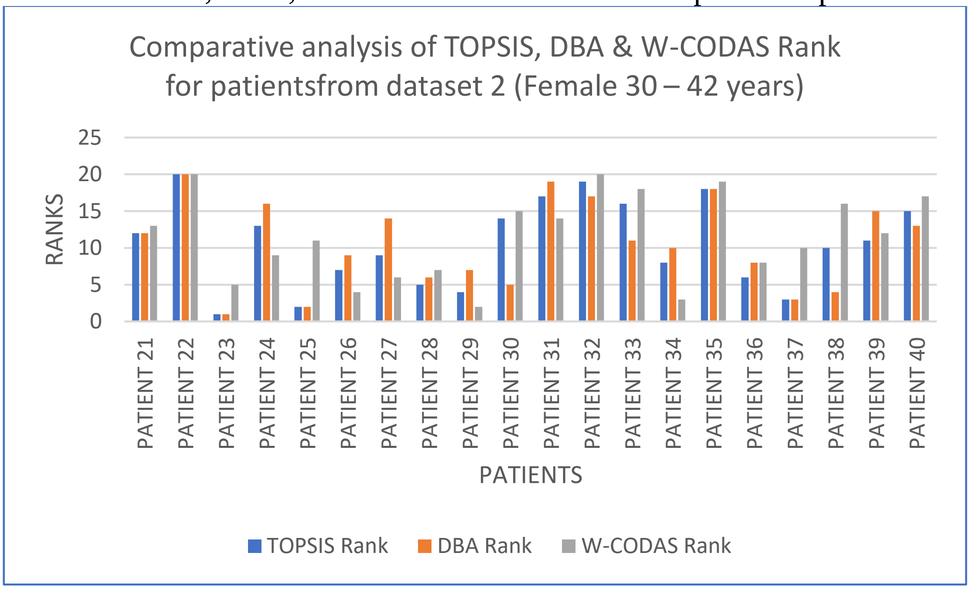

Figure 2: Comparative analysis of TOPSIS, DBA &W-CODAS Rank for patients from dataset 2 (Female 30 – 42 years)

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Let's move on to the comparative analysis for dataset 3 after analyzing the results of all three methods with doctor's review. Table 6 compares the Score from the Doctor, TOPSIS, DBA, and W-CODAS Score for the patient from dataset 3.

Table 6: Comparative analysis of Score from the Doctor, TOPSIS, DBA &W-CODAS Score for the patient from dataset 3 (Pregnant Female)

	Score from the Doctor	TOPSIS Score	TOPSIS Rank	DBA Score	DBA Rank	W-CODAS score	W-CODAS Rank
PATIENT 41	3	0.452748	13	374.7523	17	-0.16178	11
PATIENT 42	1	0.787963	20	421.9914	19	-3.33495	20
PATIENT 43	4	0.262731	6	130.3781	3	1.309519	6
PATIENT 44	4	0.267079	7	400.762	18	1.578741	5
PATIENT 45	2	0.386914	10	167.5977	5	-0.18634	12
PATIENT 46	2	0.541142	15	287.5103	11	-1.62175	15
PATIENT 47	3	0.420486	12	195.8167	7	0.076642	10
PATIENT 48	3	0.269371	8	161.4379	4	1.149413	8
PATIENT 49	1	0.162211	2	256.2827	9	2.445509	3
PATIENT 50	3	0.244991	5	212.5841	8	1.308595	7
PATIENT 51	4	0.455912	14	327.7066	13	-1.05388	14
PATIENT 52	3	0.287022	9	262.5909	10	0.852673	9
PATIENT 53	1	0.193474	3	356.3661	15	2.591849	2
PATIENT 54	3	0.393703	11	192.7505	6	-0.33105	13
PATIENT 55	5	0.04832	1	20.43757	1	3.284777	1
PATIENT 56	4	0.608643	17	292.8417	12	-1.87849	16
PATIENT 57	5	0.720378	19	365.2756	16	-2.96078	19
PATIENT 58	5	0.675079	18	353.0086	14	-2.6981	18
PATIENT 59	4	0.570496	16	426.9095	20	-2.03231	17
PATIENT 60	2	0.218542	4	101.1526	2	1.661706	4

According to W-CODAS statistics, Patient 42 has the lowest physical Stress, whereas Patient 55 has the highest physical Stress, as shown in Table 6. These results align with the Doctor's assessment, with patient 42 having the lowest physical Stress and a review score of 1 and patient 55 having the highest physical Stress and a review score of 5. W-CODAS outperforms TOPSIS and DBA for the dataset of all the patients. To visualize the figures graphically a bar chart is also given. Figure 3 also includes a graph to help understand the rating produced by various approaches. TOPSIS, DBA, and W-CODAS Rank are compared for patients in dataset 3.

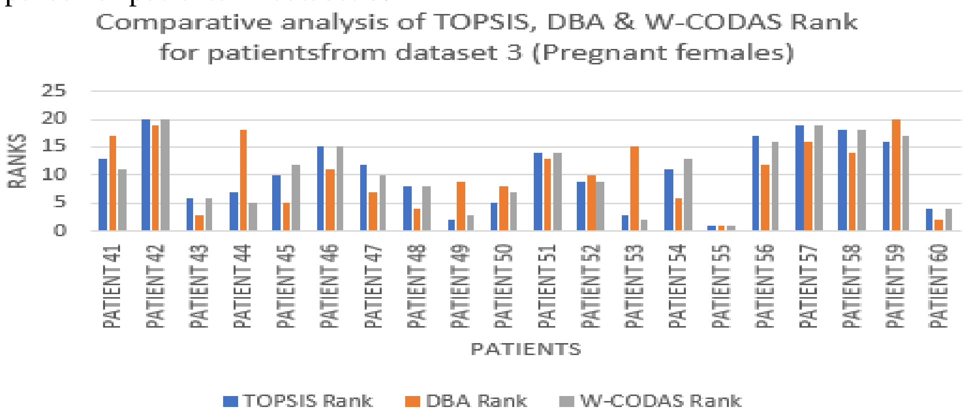

Figure 3: Comparative analysis of TOPSIS, DBA &W-CODAS Rank for patients from dataset 3 (Pregnant females)

It is critical to conclude the effectiveness of the current methodologies, the proposed methodology, and the Doctor's review after examining all seven datasets. Table 7 compares the outcomes matching of all seven datasets using established approaches, a suggested method, and a doctor's opinion.

Table 7: Comparative analysis of all seven datasets for the results matching through existing techniques, proposed technique, and Doctor's review

S.No	Data Set with Gender (age)	The technique's results matched the Doctor's review
1	Male (30 – 42)	TOPSIS &W-CODAS
2	Female (30 – 42)	W-CODAS
3	Pregnant Women (25 – 37)	TOPSIS &W-CODAS

By examining Table 7, it is apparent that the proposed approach W-CODAS, compared to the existing MCDM methods DBA & TOPSIS, performs wholly and efficiently matches the Doctor's review for all datasets.

CONCLUSION AND FUTURE SCOPE

This study used all three MCDM methods to assess patient physical stress. All three strategies were compared using tables and graphs. TOPSIS &W-CODAS work better in the first twenty patients, as patient 20 received the 1st W-CODAS rank with a score of 4.68 and a doctor's evaluation score of 5. Patient 1 was 20th with a -4.04 score and a doctor's evaluation of 1. The doctor recommends patient 1 have the least physical stress and patient 20 the most. Compared to the doctor's views, the proposed method's physical stress results match. This proves the proposed method outperforms. TOPSIS and DBA somewhat reflect the doctor's review. Patient-20, the 1st dataset patient with the TOPSIS method, had the top TOPSIS rank with a score of 0.122 and a doctor's evaluation score of 1. However, Patient 1 was 20th with a 0.894 score and a doctor's grade of 5. According to the doctor, Patient 8 has the second-lowest physical stress and Patient 17 the second-highest. The physical stress outcome is same from both perspectives. The DBA technique ranked Patient 17 first with a score of 94.9 and a doctor's review score of 5. Other than this patient, patient-9 was 15th with a -4.335 and a got score three from the doctor. Per the doctor's directives, patient 16 has the second-lowest physical stress and patient 18 the second-highest. Physical stress is similar from both angles. Comparing DBA and TOPSIS, all three datasets show that the proposed W-CODAS method works efficiently and matches the doctor's review for all datasets. Advanced MCDM techniques like WEDBA, EDAS, and VIKOR can be included and assessed to improve automatic physical stress level determination.

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