An examination of prolonged sitting ergonomic challenges in digital learning using TOPSIS and machine learning

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Abstract

The objective of the presented work is the examination of ergonomic challenges of prolonged sitting in digital learning using an instrumental multi-criteria decision-making technique named 'TOPSIS' (Technique for Order of Preference by Similarity to Ideal Solution). A total of sixteen ergonomic challenges of prolonged sitting in digital learning have been identified by a group dialogue with laptop, tablet, smartphone users, academicians, and students. The study compares equal weight ages and variable weight ages, finding that eye strain, neck pain, and mental tiredness are the most close to ideal solutions, while leg pain is the least. Linear Reggression, a machine learning approach, is the best-performing model, with Neural Network and SVM showing marginal improvement. The outcomes of the experiment demonstrate that the suggested model functions well in terms of accuracy, and techniques have been used to raise the diagnostic rate and solve the issue. The outcomes can be very helpful in finding and applying measures to deal with ergonomic challenges of prolonged sitting in digital learning. Policymakers may use the output of this study regarding the relative importance and productivity influencing tendency of these chosen sixteen ergonomic challenges, for creating mechanisms for the betterment of human-computer interface.

Keywords: TOPSIS; Ergonomics ; Machine Learning ; Digital learning; Optimization

1. Introduction

Ergonomics is the domain of the study of population to the situation of the study environment [46]. The definition of ergonomics is 'the design of work with optimum possible usage of human competencies without overcoming human restrictions'. While using electronic gadgets, people keep ignoring health by neglecting the rules of ergonomics. Ergonomics is the scientific study of the working man, taking into account the many psychosocial and medical aspects of human labour [42]. A significant rise in quantity of people suffering from disorders is seen as the result of prolonged

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screen duration on monitor of tablet, laptop or PC.

The practical aim of ergonomics is to condition and justify the adaptation of labor to man [42]. Several studies had explored the relationship between enhanced use time with electronic gadgets and musculoskeletal system disorders [46]. Improper posture of the people using PC or laptop along with inappropriate ergonomic position might result in musculoskeletal system disorders [47]. A prolonged lifestyle is connected with an enhanced probability of cardiovascular disease, obesity and diabetes[33]. A research work focused on technological growth along with ergonomics consideration in the productivity with optimized use of computer is demand of hour [40]. Recent advancements in machine learning have resolved numerous challenging problems and instilled renewed optimism among scholars.

The presented paper suggests the Analysis of ergonomic challenges of prolonged sitting in digital learning and showcases the ability of application of multi-criteria decision-making based on MCDM approach- TOPSIS. Section 2 outlines reviewing of recent past work and relevant literature.

2. Review of relevant Literature

It is noteworthy that the environment for digital learning is created and examined according to academic patterns [20]. The unprecedented expansion of digital learning has sparked the development of several strategies for the issue of academic viability in the virtual academic environment [31]. Healthcare applications have not had a significant impact on helping users practice behavioral adjustments with electronic devices used in virtual schooling [30]. The human computer interface is trying to produce 'healthcare' technologies to improve users' interactions with technological breakthroughs [48]. The goal of using digital learning method is to change the conventional teaching pedagogy in academic institutions and replace it with one that is more participative and interactive[32]. The authors have developed a framework for healthcare which accounts for the complex and dynamic nature of man interactive mechanism with emerging technologies [48]. The writers may take into account a number of challenges while creating healthcare systems to lessen the impact that digital technology causes to users' lives [52].

Earlier research has contrasted a number of supervised learning strategies. Asri et al. [4] studied to investigate the efficacy of support vector machines and k-nearest neighbor. The study's objective was to detect each algorithm's overall effectiveness by data classification with specificity, overall efficacy. The inquiry used the 10-fold cross-validation re-sampling method. As a result, bias and computation time were decreased and all data points were verified with precision. Subsequently, the model has been fit to the dataset, and the model's efficacy has been assessed on the basis of accuracy, model development time, and properly and incorrectly classified occurrences. Bayrak et al. [8] did the comparison support vector machines and artificial neural networks for early illness prediction of breast cancer cases. Ultimately, the models were assessed using the following criteria: ROC area, accuracy, precision, recall, and SMO (sequential). The literature indicates that little to no study on the combined use of TOPSIS and machine learning has been published [1]. Therefore an integrated ML–TOSPSIS strategy has been employed in the current investigation. Table 1 sums up the relevant work regarding ergonomic challenges because of prolonged sitting of academicians and students.

Table 1: Latest relevant research work

S. No.	Authors	Their Work	Research Gap/ Future Scope
1	Ayça Aytar et al., (2020)	They investigated how ergonomic instruction for virtual learners, in COVID years, affected their musculoskeletal discomfort [47].	They analyzed the data obtained using statistical software. This might be done using any MCDM technique.
2	Muna A. Salameh et al., (2022)	For purpose of examining the relationships between musculoskeletal pain and various cause factors, authors looked at the incidence of musculoskeletal pain in scholars enrolled in virtual training [46].	Musculoskeletal pain is not significantly correlated with the use of digital gadgets or prolonged sitting.
3	Michailid	They conducted a cross sectional survey with more	The study is focused on

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	ou et al., (2022)	than three hundred university academicians and students and studied the sedaentrtary sitting influences on bodyache and stiffness among the students in middle east and balkan region [33].	chronic musculoskeletal problems only but not other ergonomic disorders.
4	Nsolo et al. (2019)	They evaluated a set of machine learning algorithms in terms of the predictive performance of individuals in soccer matches [36].	Any MCDM technique might have been used as an integrated approach along with machine learning.

Ergonomic challenges of prolonged sitting in digital learning have been discussed in section 3.

3. Ergonomic challenges of prolonged sitting in digital learning

For the attainment of the chief objective of our work is the Analysis of ergonomic challenges [37] of prolonged sitting in digital learning, total 16 challenges have been identified (with the help of group dialogue with experts of different age group and professional positions with different roles in digital learning like university faculty members, college undergraduate students, school teachers, research scholars from diversified localities as metropolitan regions, urban areas, small towns) as mentioned in Table 2.

Table 2: The ergonomic challenges of prolonged sitting in digital learning

S. No.	Ergonomic Challenges
1	Back Pain
2	Neck Stiffness
3	Shoulder Pain
4	Asthenopia (Eye Strain)
5	Hearing Impairment/ Hearing Loss
6	Median Nerve Compression (Hand And Wrist Challenges)
7	Mental Exertion
8	Physical Exhaustion
9	Depression
10	Corpulence (Obesity)
11	High Blood Pressure
12	High Blood Sugar

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13	Legs Pain (Hip, Thigh, Ankle, Knee)
14	Cardiovascular Disease (CVD)
15	Osteoporosis (Weakened Bones)
16	Arthralgia (Joint Pain)

Studies on the risks of laptops in ergonomic based Internet of Things related medical difficulties have found their impact on wellbeing and health. From an ergonomics perspective, new technological developments have unintended effects on workers and computer users. The literature review pointed to an inadequacy from the viewpoints of ergonomics challenges [42].

3.1 Back Pain:

Users of PCs who must operate the keyboard passively complain of back pain [29]. The effects of a backache also affect other muscles, causing pain [44]. Because of incorrect postures, using a PC and stationary sitting may have an impact on users' backaches [25].

3.2 Neck Stiffness:

A greater lowering slope is present for the link along the modest risk of neck stiffness [28]. A powerful correlation between passive posture and neck discomfort, with neck flexion establishes a positive correlation with neck stiffness [3].

3.3 Shoulder Pain:

Ergonomic concerns are the basis for offensive shoulder postures [38]. Marcus et al. [28] noted that the postural variable that demonstrated an increased threat for Issue is the inner elbow angle. According to Lozano et al., interactions with electronic gadgets have an impact on the entire shoulder system [26].

3.4 Asthenopia (Eye Strain):

According to Hayes et al. [21], environment variance is typically on the basis of eye strain, which predominately influences personal compatability.

3.5 Hearing Impairment/ Hearing Loss:

There is a high possibility that internal ear reflexes will develop [12]. According to ongoing studies, more than one billion students are facing a risk of hearing losses because of unsafe listening practices [50].

3.6 Median Nerve Compression (Hand And Wrist Challenges) :

Thomsen et al. [12] investigated how biological and mechanical factors, such as recurrent strange postures, increase the risk of Median Nerve Compression with increased carpal tunnel stress. While typing, keyboard users choose a variety of comfortable postures that involve less movement [6]. In situations where there is an issue with nerve compression, Median Nerve Compression frequently manifests as numbness and pain in the affected area of the body [24].

3.7 Mental Exertion:

A few studies demonstrate the predominance of mental exertion [17]. The meaning of the word stress could refer to a generalized physiological reaction to a thing or person that causes stress. A couple of the structures demonstrate how unfavorable psychosocial situations might cause distress, that is intended to enhance the risks of musculoskeletal adverse effects [28].

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3.8 Physical Exhaustion:

Physical exhaustion associated with passive sitting may reduce spinal stability [51]. A survey had been conducted to identify the portion of the human body where PC users suffer signs of weakness in order to identify the signs of ergonomic challenges [43].

3.9 Depression:

The risk of depression can be significantly increased by spending several hours each day sitting sedentarily in front of a computer screen [19].

3.10 Corpulence (Obesity):

Any individual's BMI defines the condition. Body mass index, or BMI, is the product of weight in kilograms and height in square meters. Regular prolonged sitting is part of daily routine and is directly related with corpulence [22]. Long hours of sitting leads to Obesity [34].

3.11 High Blood Pressure:

Screen time and high blood pressure are clearly linked, regardless of a person's physical makeup. Critical online use and health challenges including high blood pressure have been linked in a number of studies. Blood pressure can be reduced by avoiding passive computer use [13]. Consequences of prolonged sitting along with continuous screen time disturbs the body and at times leads to Hypertension [15].

3.12 High Blood Sugar :

Sitting at a computer for an extended period of time each day may have negative health effects for people with high blood sugar. [14] showed a link between high blood sugar and passive computer use. In a statement from 2016 [10], the American Hyperglycemia Association advocated for less passive computer use.

3.13 Legs Pain (Hip, Thigh, Ankle, Knee):

Undue pain felt in both knees, calves, feet caused by prolonged work posture. Painful category is found in thighs due to work posture and non-ergonomic facilities [2].

3.14 Cardiovascular Disease (CVD):

Cardiovascular disease is becoming more prevalent thus consideration is needed for the consideration of ergonomic design infrastructure for digital learning [7]. Relevant work investigating the relationship between computer use (screen time) with prolonged sitting and cardiovascular disease (CVD) has been recognized [18]. Prolonged duration is linked with an enhanced risks of cardiovascular diseases. The authors conducted a systemized study for investigation the relation between prolonged duration and cardiovascular diseases [49].

3.15 Osteoporosis (Weakened Bones):

Effects of a prolonged sitting has been poorly investigated and has been the reason behind adverse ergonomic challenges like Osteoporosis. Other ergonomic challenges like Diabetes leads to weakening of bones [27].

3.16 Arthralgia (Joint Pain):

Ergonomic challenges like restricted joint motion and joint pain are affected by the posture especially prolonged sitting related with digital learning [45].

Multi criteria decision making technique 'TOPSIS' (Technique for Order of Preference by Similarity to Ideal Solution) and Machine Learning has been explained in Section 4.

4. Methodology Used

4.1 Introduction to TOPSIS Method

Problems involving Multi Criteria Decision Making may be computed by numerous techniques available. Among several Multi Criteria Decision Making methodologies, TOPSIS (created by Hwang and Yoon) is very instrumental. The TOPSIS method's graphical model was created by Zulqarnain et al. [57]. The TOPSIS approach aids in ranking

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options according to how closely they adhere to the ideal solution and achieve the highest level from all potential options [58]. TOPSIS is a methodology that can construct possible ideal set of solutions and possible minus ideal set of solutions for numerous attributes problem. Out of a set of options, TOPSIS selects solutions. In particular, the selected option is closest to the positive ideal solution and farthest from the negative ideal solution [41].

4.1.1 The fundamental steps in TOPSIS methodology:

The TOPSIS approach assume a decision matrix consisting of n criteria and m choices.

Step 1:Criteria Selection:

Deciding the standards for assessing the options. Decided standards ought to be quantifiable and pertinent to the decision-making process. Let's denote the decision matrix as R , with dimensions m x n.

$$R = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1J} \\ r_{21} & r_{22} & \cdots & r_{2J} \\ \cdots & \cdots & \cdots & \cdots \\ r_{I1} & r_{I2} & \cdots & r_{IJ} \end{bmatrix} \qquad \text{..................(1)}$$

Each element [57] in matrix denotes performance or valuation of alternative i on criterion j.

Step 2: Normalization of the decision matrix: Normalization of every element of the decision matrix R for ensuring that all criteria are given equal weight. If all criteria are same type then no need to normalized **the matrix, decision matrix is equal to the normalized matrix.** Decision matrix that consists of rows representing alternatives and columns representing criteria. Normalized decision matrix, and its attributes expressed as

$$s_{ij} = r_{ij} \qquad \text{...................(2)}$$

$$\text{i.e .}\ S_{ij} = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1J} \\ s_{21} & s_{22} & \cdots & s_{2J} \\ \cdots & \cdots & \cdots & \cdots \\ s_{I1} & s_{I2} & \cdots & s_{IJ} \end{bmatrix} \quad [11]$$

Step 3: Compute the weighted normal decision matrix:

Assign weight ages for every criterion for reflecting their comparative importance.

Let's denote the weights as $P = [p_1, p_2, p_3, \dots \dots p_n]$ . ...(3)

Multiply every column of the normal decision matrix Y_{ij} by its corresponding weight age:

$$v_{ij} = P_j * s_{ij}; (i = 1,2, \dots, I; j = 1,2, \dots, J) \qquad \text{..................(4)}$$

Step 4: **Calculate the ideal and anti ideal copmutations:**

For every criterion, identification of the worst and best values among all alternatives. For cost criteria, the ideal solution is the least value while For benefit criteria, the ideal solution is the greatest value. For each criterion, identify the best (ideal) and worst (anti-ideal) values among all alternatives.

The ideal solution (T^{+J}) and ($q^{-\mathrm{J}}$) are expressed as the positive and negative ideal solution sets respectively that may be computed for each criterion is given by:

$$T^{+J} = \left[v_1^+, v_2^+, \dots, v_J^+\right] \ \&\ q^{-\mathrm{J}} = \left[v_1^-, v_2^-, \dots, v_J^-\right] \qquad \text{...................(5)}$$

$$\text{Where,} T^{+J} = \begin{cases} \max v_{ij}, & \text{if } j \text{ is a benefit attribute} \\ \min v_{ij}, & \text{if } j \text{ is a cost attribute} \end{cases}$$

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$$q^{-J} = \begin{cases} \min v_{ij}, & \text{if } j \text{ is a benefit attribute} \\ \max v_{ij}, & \text{if } j \text{ is a cost attribute} \end{cases} \quad [54]$$

Step 5: Calculate the Euclidean distances: Determine H ow Close we are to the Ideal Solution: The division of the distance to the negative ideal solution by the total of the distance to the ideal solution and the distance to the negative-ideal solution, we can compute how near each option is to the ideal answer.

$$M_i^+ = \sqrt{\sum_{j=1}^{J}\left(v_{ij} - v_j^+\right)^2} \quad , \; N_i^- = \sqrt{\sum_{j=1}^{J}\left(v_{ij} - v_j^-\right)^2} \quad \text{.............................}(6)$$

Measure the distance between each option and the ideal and anti ideal solution as per the Euclidean distance rule. The Euclidean distance from ideal solution (M_i^+) and Euclidean distance from the anti ideal solution (N_i^-) may be determined for each choice.

Step 6: Computation of the relative closeness: Compute the relative closeness of each option with the help of division of the distance to the anti-ideal solution by the summation of the distance to the anti ideal and ideal solutions

$$C_i = \frac{N_i^-}{N_i^- + M_i^+} \quad \text{...............................}(7)$$

For each option i determine the relative closeness C_i [9]

Step 7: Ranking of the alternatives: Ranking of the alternatives as per their comparative closeness C_i. The option with the nearest closeness value is desirable**.** TOPSIS Model is demonstrated in Figure 1.

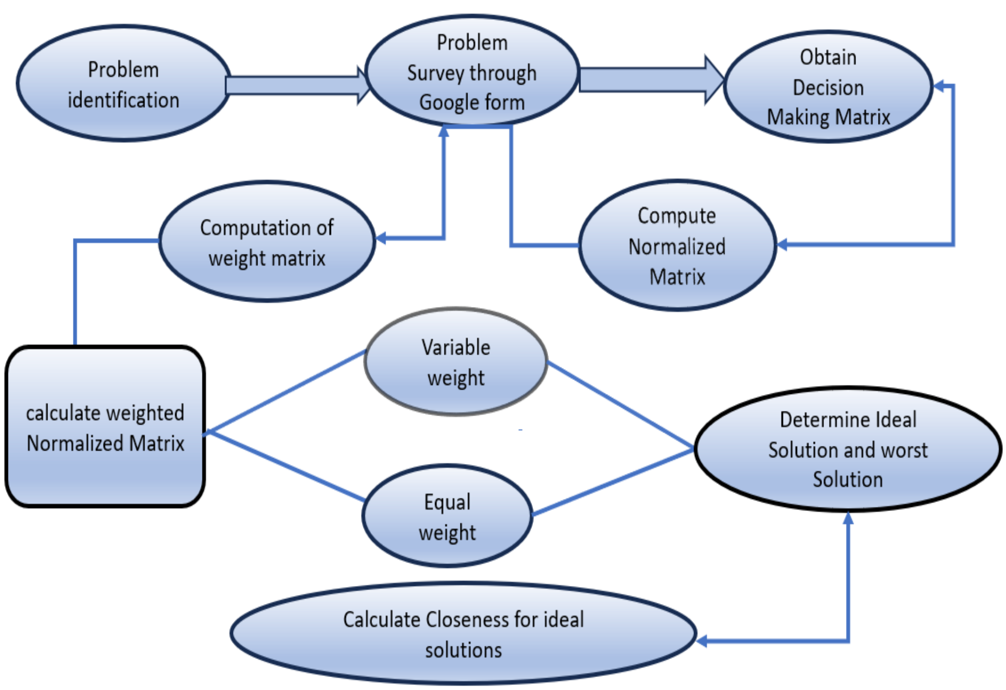

Figure 1. TOPSIS Method

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4.2 Machine Learning:

Real world applications of machine learning algorithm are significant [55]. In the last few years, multi-criteria decision-making techniques have gained a lot of traction in fields like healthcare, transportation, and environmental challenges. Decision-makers benefit from MCDM techniques, which produce more number of objective decisions. In combination with machine learning, multi-criteria decision-making techniques are invaluable. Researchers are investigating novel approaches for creating decision support systems that integrate machine learning with numerous criteria [55].

When neural networks and random forest models are used, large machine-learning datasets can be of great benefit [5]. With integrated machine learning and multicriteria decision-making models, researchers in the present period look for workable solutions to challenging challenges [55]. Machine learning is competent enough to have its applications in an IoT environment. The Internet of Things and social networking exploration offer vast datasets. Since there are so many options available with a wide range of criteria, choosing a decision might be challenging given the availability of an infinite number of datasets. Research scholars are proposing mixed models of multi-criteria decision making and machine learning ways to circumvent such scenarios [56]. People can choose how to apply machine learning. The researchers look at integrating a machine learning approach with several criteria for creating a decision support system. Machine learning researchers are paying attention to problems related to multi criteria decision making. The goal of the project is to create a highly effective multi-criteria decision framework that incorporates machine learning algorithm solutions [55]. The development of machine learning applications along with the plenty of data in recent years and its considerable results have sorted out several complex problems. Several researchers have been presenting new approaches combining Machine Learning and MCDM techniques, enabling the evaluating ability of machine learning models in the last couple of years [35]. Machine learning is growing its importance in various fields of studies.

The aim of machine learning classification, a form of supervised learning, is to forecast the categorical class labels of novel occurrences by utilizing historical data. In classification, the algorithm generates predictions on unseen data after learning from labeled training data. A categorical label, such as "spam" or "not spam" for email classification or "fraudulent" or "legitimate" for credit card transaction classification, is the result of a classification algorithm. Classification Methodologies The most basic type of classification is called binary classification, and its result is a binary label, such as true or false, yes or no, or 0 or 1. The sort of categorization known as "multi-class classification" allows the result to fall under multiple classes. Multi-label classification allows for the assignment of numerous labels to each instance, for instance, when categorizing animal photographs into categories such as cat, dog, or horse. A news story, for instance, can be divided into several categories, such as politics, sports, and entertainment. Popular Classification Algorithms are used here. Despite its name, logistic regression is utilized to solve classification-related challenges. It forecasts the likelihood that an instance will fall into a specific class[35].

Decision trees are structures that resemble trees, with each branch standing in for a decision rule and each node for a feature. Support Vector Machines (SVMs) with the supervised learning models are applied to regression analysis and classification tasks. The Naive Bayes classifier is the probabilistic algorithm that utilizes the Bayes theory and makes strong assumptions about the independence of its features.

Neural network models mimic the way the brain processes information by being organized into a number of layers. The fully connected, feed forward neural network classifiers that are accessible in the Statistics and Machine Learning allow us to modify the activation functions and size of the fully connected layers.

5. Results and Discussion

5.1 TOPSIS Calculation

Collected raw data has been made appropriate for TOPSIS calculation by taking Arithmetic mean of all the values and it has been put in Table 3.

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Table 3: Matrix with arithmetic means values of collected data for sixteen ergonomic challenges of prolonged sitting in digital learning.

S. No.	Ergonomic Challenges	CITY AREA			METROPOLITAN REGION			SMALL TOWN		
		CF	CS	RS	CF	CS	RS	CF	CS	RS
1	Back Pain	7.00	6.14	8.00	9.00	6.33	6.50	7.00	4.70	6.00
2	Neck Pain	7.29	6.37	8.00	8.50	6.22	7.00	7.00	4.80	8.00
3	Shoulder Pain	7.43	5.14	8.00	8.50	4.67	5.50	6.50	3.65	5.50
4	Eye Strain	8.57	7.29	9.00	8.50	6.67	8.00	7.00	6.05	7.00
5	Hearing Loss	5.29	5.94	7.00	7.50	5.00	6.50	6.00	4.10	5.50
6	Hand And Wrist Challenges	5.29	4.57	7.00	7.00	5.78	5.00	5.50	3.80	6.00
7	Mental Tiredness	6.86	6.96	7.00	7.50	6.56	7.00	6.00	5.65	7.00
8	Physical Tiredness	7.29	6.33	7.00	7.50	6.22	8.00	6.00	5.55	4.00
9	Depression	6.43	6.18	6.00	6.50	4.56	1.50	5.00	5.50	6.00
10	Obesity	7.71	5.98	7.00	8.00	5.89	6.00	5.00	5.30	5.50
11	High B. P.	6.14	4.90	5.00	7.00	3.67	7.50	3.00	4.60	5.50
12	High Blood Sugar	6.29	4.22	6.00	6.50	3.56	6.00	5.50	4.10	5.00
13	Legs Pain	5.71	4.25	6.00	5.50	4.00	4.00	5.50	4.60	2.00
14	Heart Disease	5.00	4.53	5.00	6.00	3.44	5.50	6.00	3.85	3.50
15	Weakened Bones	5.00	4.75	6.00	6.50	3.33	6.00	6.50	4.15	4.00
16	Joint Pain	6.29	4.67	6.00	7.00	4.00	4.50	7.00	4.25	1.50

A web based Google-form questionnaire had been circulated among variety of respondents who are stake holders in digital learning. Our group of respondents are from different age groups and experts with different roles in digital learning as professional positions like college faculty members (CF), college undergraduate students (CS), research scholars (RS) from diversified localities as metropolitan regions, urban (city) areas, small towns (rural regions) for getting raw input data collected regarding ergonomic challenges of prolonged sitting in digital learning. Respondents have been asked to rate (on the scale of one to nine) the potential of dangers of identified sixteen ergonomic challenges of prolonged sitting in digital learning. We have created an average matrix having sixteen rows for all sixteen ergonomic challenges of prolonged sitting in digital learning.

Giving each consideration the right weight during the decision-making process is essential to evaluating ergonomic concerns. To do this, a normalized decision matrix must be created, with each column standing for a distinct ergonomic consideration. Equal weighting and variable weighting are the two main weighting strategies. The equal weighting approach offers a balanced viewpoint by treating each component equally. However, the effects of various ergonomic issues on employee efficiency, safety and health vary in real world situations. Factors that present serious risks to employee productivity and well being are given more weight in the variable weighting approach. A more data driven approach to decision making is made possible for organizations by this comparison, which offers insightful information about the efficacy of various weighting techniques in ergonomic assessments.

Normalized decision matrix and decision matrix are same as all criteria are same type.

Case 1: The 16 ergonomic issue are given equal weights of 0.0625 each. Euclidean distance from ideal solution (M_i^+) and Euclidean distance from the anti ideal solution (N_i^-)for all sixteen ergonomic challenges (equal weights case)

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have been computed and tabulated in Table 4. Further, the relative closeness of all sixteen ergonomic challenges C_i has been calculated and tabulated in Table 4.

Table 4: Euclidean distances & Relative Closeness to the Ideal Solution (Case1: equal weights)

Ergonomic challenges	M_i^+	N_i^-	C_i	**Rank**
Back Pain	0.23	0.63	0.74	13
Neck Pain	0.16	0.70	0.81	15
Shoulder Pain	0.34	0.53	0.61	10
Eye Strain	0.07	0.77	0.92	16
Hearing Loss	0.37	0.50	0.58	9
Hand And Wrist Challenges	0.43	0.45	0.51	8
Mental Tiredness	0.22	0.63	0.74	14
Physical Tiredness	0.32	0.58	0.65	12
Depression	0.55	0.38	0.41	4
Obesity	0.30	0.52	0.64	11
High B. P.	0.50	0.47	0.48	7
High Blood Sugar	0.48	0.41	0.46	6
Legs Pain	0.63	0.25	0.28	1
Heart Disease	0.59	0.34	0.37	2
Weakened Bones	0.52	0.40	0.44	5
Joint Pain	0.59	0.35	0.37	3

As shown in Table 4, 'Eye Strain' has got the most relative closeness to the ideal solution '0.92' followed by 'Neck Pain' '0.81' and 'Mental Tiredness' '0.74'. These values of comparative closeness to ideal solution have been demonstrated in Figure 2. As shown in Figure 2, 'Legs Pain' has got the least comparative closeness to the ideal solution followed by 'heart disease' and 'Joint Pain'.

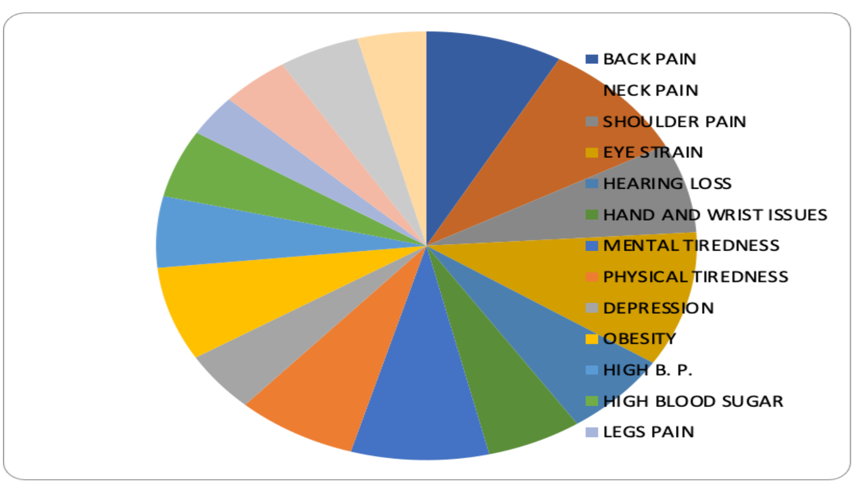

Figure 2. Relative Closeness of all sixteen ergonomic challenges (Case 1 : equal weights)

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Case 2: The 16 ergonomic challenges are given different variable weights as shown in Table 5 below.

Table 5: Variable weights assigned to ergonomic challenges

Ergonomic Challenges	**Variable Weight**	**Ergonomic Challenges**	**Variable Weight**
Back Pain	0.069	Depression	0.066
Neck Pain	0.071	Obesity	0.069
Shoulder Pain	0.060	High B. P.	0.057
Eye Strain	0.080	High Blood Sugar	0.052
Hearing Loss	0.063	Legs Pain	0.053
Hand And Wrist Challenges	0.055	Heart Disease	0.052
Mental Tiredness	0.074	Weakened Bones	0.054
Physical Tiredness	0.070	Joint Pain	0.055

Euclidean distance from ideal solution (M_i^+) and Euclidean distance from the anti ideal solution (N_i^-) for all sixteen ergonomic challenges (variable weights case) have been computed and tabulated in Table 6. Further, the relative closeness of all sixteen ergonomic challenges C_i has been calculated and tabulated in Table 6.

Table 6: Euclidean distances& Relative Closeness to the Ideal Solution (Variable weights)

Ergonomic challenges	M_i^+	N_i^-	C_i	**Rank**
Back Pain	0.44	0.84	0.66	13
Neck Pain	0.36	0.95	0.73	15
Shoulder Pain	0.74	0.55	0.43	9
Eye Strain	0.01	1.25	0.99	16
Hearing Loss	0.73	0.57	0.44	10
Hand And Wrist Challenges	0.92	0.39	0.30	6
Mental Tiredness	0.36	0.94	0.72	14
Physical Tiredness	0.51	0.79	0.61	12
Depression	0.85	0.51	0.37	8
Obesity	0.55	0.72	0.57	11
High B. P.	0.94	0.44	0.32	7
High Blood Sugar	1.01	0.32	0.24	4
Legs Pain	1.11	0.19	0.14	1
Heart Disease	1.09	0.26	0.19	2
Weakened Bones	1.00	0.34	0.25	5
Joint Pain	1.02	0.31	0.23	3

As shown in Table 6, 'Eye Strain' has got the most relative closeness to the ideal solution '0.99' followed by 'Neck Pain' '0.73' and 'Mental Tiredness' '0.73'.

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These values of comparative closeness to the ideal solution have been demonstrated in Figure 3. As shown in Figure 3, 'Legs Pain' has got the least comparative closeness to ideal solution '0.14' followed by 'Heart Disease' '0.19' and 'Joint Pain' '0.23'.

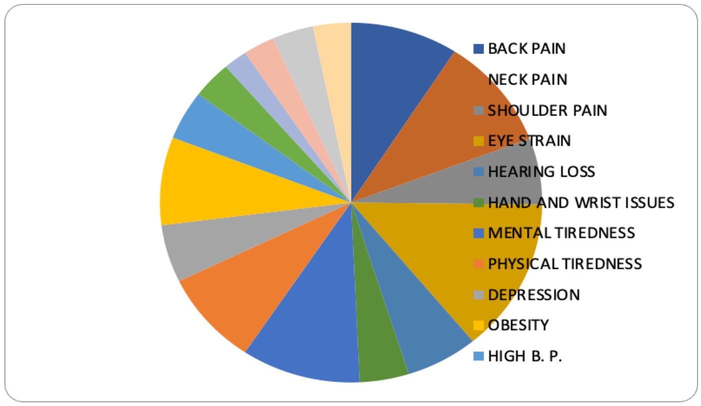

Figure 3. Relative Closeness of all sixteen ergonomic challenges (Case 2: Variable weights)

Table 7 include the correlation between them (e.g., Rank by TOPSIS Method – equal weights vs. Rank by variable weights.) using Spearman's ranking correlation coefficient to determine the level of agreement between the rankings obtained from the two different case consideration. The calculated correlation coefficient will help us to understand how closely the rankings from the two methods align.

Table 7: Comparison of ranking between equal and variable weights & correlation

Ergonomic challenges	Rank (Variable weights)	Rank (equal weights)	Difference
Back Pain	13	13	0
Neck Pain	15	15	0
Shoulder Pain	9	10	1
Eye Strain	16	16	0
Hearing Loss	10	9	-1
Hand And Wrist Challenges	6	8	2
Mental Tiredness	14	14	0
Physical Tiredness	12	12	0
Depression	8	4	-4
Obesity	11	11	0
High B. P.	7	7	0
High Blood Sugar	4	6	2
Legs Pain	1	1	0
Heart Disease	2	2	0
Weakened Bones	5	5	1
Joint Pain	3	3	0

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Calculate Rank correlation by the formula $r = 1 - \frac{6\sum d_i^2}{n(n^2-1)}$, we get r=0.961764706.According to value of r from both cases are strongly correlated.   Rank Comparision between equal and variable weights has been shown in Figure 4.

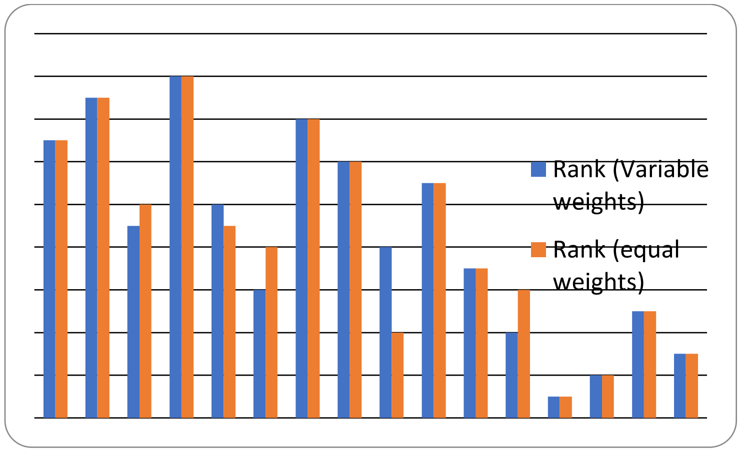

Figure 4. Rank Comparision between equal and variable weights

5.2 Machine learning calculation:

To assess gathered ergonomic challenges many scholars are interested in applying data mining and machine learning techniques. The diagnosis rate has been raised using machine learning techniques and training models for classifying the data by the use of classification machine learning.To increase the propensity of the created rules for ergonomic challenges by using Statistics and Machine Learning using python and after cleaning and normalizing data illustrated by Linear Regression,SVM ,KNN ,Random Forest ,XGBoost, Polynomial Regression, SVR and Neural Networks.It tends to predict the more accurate model. Figure 5 below gives an overview of the workflow from data collection to the final model [40].

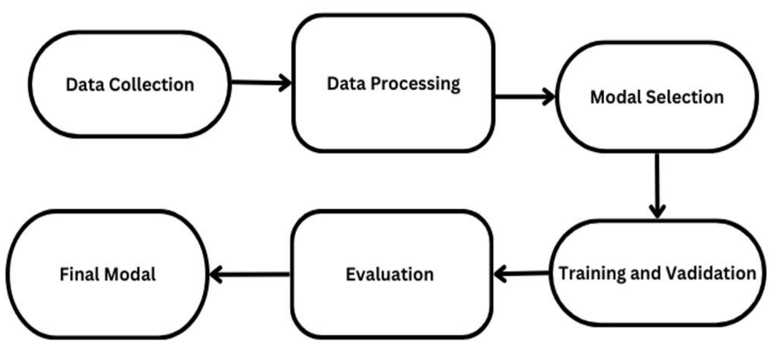

Figure 5. Working procedure from data collection to final model

The dataset is loaded from an Excel file and feature variables (X) are extracted .The target variable (y), representing the severity score, is taken from the last column.The dataset is then split into 80% training data and 20% for testing data .Eight regression models are trained to predict the severity score.In Linear Regression a simple linear model is fitted to the training data.The model predicts the test data.In Support Vector Regression (SVR) and Support Vector Machine with an RBF kernel is used for trained .In K-Nearest Neighbors (KNN) Predictions are generated, and MSE & R^2 are computed.Random Forest Regression is trained with bagging method.Polynomial Regression (Degree 2) polynomial features are generated. A linear model is applied to the transformed features and Extreme Gradient

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Boosting (XGBoost) is implemented .Fully connected deep neural network is created with 64 neurons in the first hidden layer (ReLU activation) 32 neurons in the second hidden layer (ReLU activation).1 neuron in the output layer (for regression).The network is trained with the Adam optimizer for 50 epochs and Predictions are made using the trained model. To determine the best-performing model, the TOPSIS method is used, which ranks models based on their closeness to an ideal solution. Addionally we added TOPSIS scores for each model as shown in Table 8. Rankings of models based on their performance have been tabulated in Table 8.

Table-8: TOPSIS Scores and rankings of each model

Model	**TOPSIS Score**	**TOPSIS Ranking**
Linear Regression	1	1
Random Forest	0.99981	2
Neural Network	0.96297	3
XGBoost	0.95614	4
SVR	0.75956	5
SVM	0.6345	6
KNN	0.5	7
Polynomial Regression	0.5	8

To train and validate classification models for binary or multiclass problems, select from a variety of algorithms. Compare the validation errors of each model side by side once it has been trained, and then select the best model. Different Models for computation have been shown in Table 9.

Table 9: Different Models for computation

Model	**MSE**	**R^2 Score**
Linear Regression	1.592	0.732
SVM	1.957	0.671
KNN	2.260	0.620
Random Forest	1.792	0.699
Polynomial Regression	2.763	0.535
SVR	2.195	0.631
Neural Network	1.727	0.709
XGBoost	1.828	0.692

Following training, testing listed models above best Mean square error for Linear Regression (1.592) and best R^2 Score is (0.732). Figure 6 shows MSE and R^2 scores side by side for each model.

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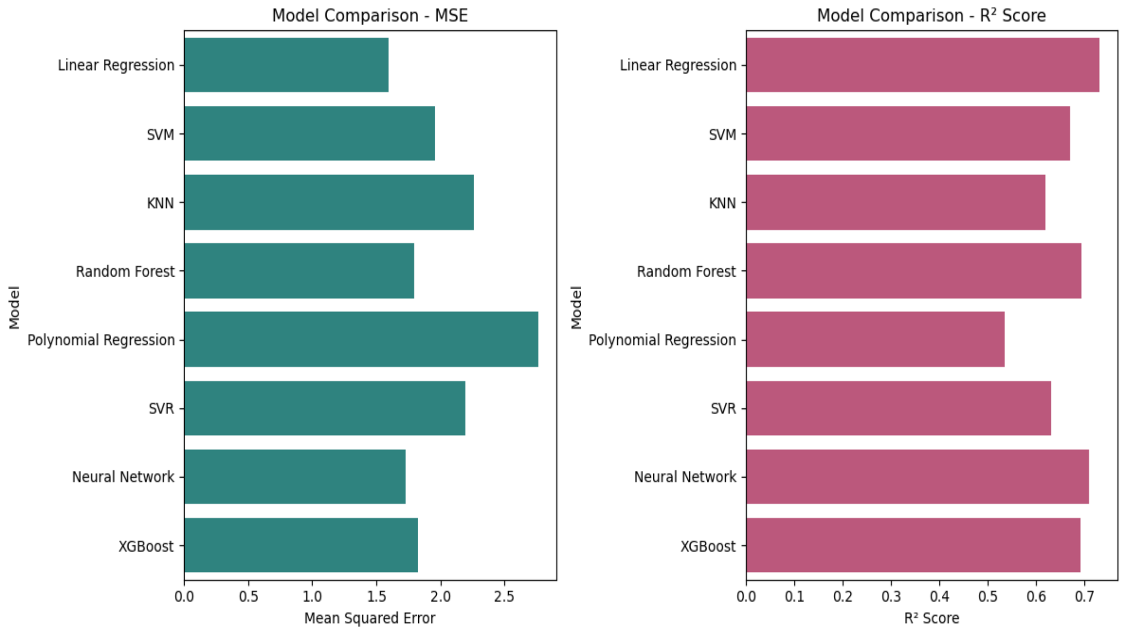

Figure 6. Overall Comparison of MSE and R^2 scores for each modal

Consistent with the results, the machine learning modal Linear Regression,Nural Network and SVM performed marginally better than the others. The work's outcome has been compared to various other similar attempts, and it is described in table 10 below.

Table 10: Comparisons of present work with recent studies

S. No.	Author(s)	Outcome	Present Work
1	Negulescu, O. H., & doval, E. (2021)	The authors outlined the benefits and drawbacks of working remotely from home and suggested a structural framework for taking into account specific Internet of Things, ergonomic, time management guidelines [37].	We have identified total sixteen ergonomic challenges of prolonged sitting in digital learning. Then we ranked by applying 'TOPSIS' for two cases as with equal weights and variable weights.
2	Tigli, A., Altintaş, A., & Aytar, A. (2020)	The authors emphasized that specific training programs involving ergonomics will increase ergonomic know-how to reduce musculoskeletal ache with increase in physical activities and contribute to students receiving distance education's attitude of exercise behavior decision-making balance [47].	We analyzed the ergonomic challenges of prolonged sitting in digital learning with the use of an instrumental multi criteria decision making technique named 'Technique for Order of Preference by Similarity to Ideal Solution'. The outcomes can be very helpful in finding and applying measures to deal with ergonomic challenges of prolonged sitting in digital learning.

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3	Clague et al. (2021)	They integrated MCDM and ML techniques in urban flood risks analysis. They compared the ML algorithm for providing urban flood hazards maps by using an integrated ML and TOPSIS [41].	The results of the performance evaluation showed that the SVM quadratic, Ensemble Bagged, and Neural Network models were the best fit for this task.
4	Seh et al. (2021)	They chosen fuzzy ANP to compute the precision of distinctive ML technologies for digital healthcare data security environment [49].	We have identified total sixteen ergonomic challenges of prolonged sitting in digital learning. Then we ranked by applying 'TOPSIS' for two cases as with equal weights and variable weights.
5	Pappalardo et al. (2019)	They developed a machine learning data driven framework for assisting formal soccer scouts the rank soccer players [39].	The SVM quadratic, Ensemble Bagged, Neural Network models consistently achieved great accuracy.

Section 6 also includes the paper's final observations as well as prospects for future study work.

6. Conclusion and Future Scope

The research described here has created a multi criteria decision making system to analyse the ergonomic challenges of prolonged sitting in digital learning using TOPSIS. Back Pain, Neck Stiffness, Shoulder Pain, Asthenopia (Eye Strain), Hearing Impairment/ Hearing Loss, Median Nerve Compression (Hand And Wrist Challenges), Mental Exertion, Physical Exhaustion, Depression, Corpulence (Obesity), High Blood Pressure, High Blood Sugar, Legs Pain (Hip, Thigh, Ankle, Knee), Cardiovascular Disease (CVD), Osteoporosis (Weakened Bones), Arthralgia (Joint Pain) are the sixteen ergonomic challenges that have been identified. Two different cases have been considered as equal weight ages and variable weight ages. In case of equal weight ages and Variable weight ages 'Eye Strain' has got the most comparative closeness to ideal solution followed by 'Neck pain' and 'Mental Tiredness'. On the other side, 'Legs Pain' has got the least comparative closeness to ideal solution followed by 'heart disease' and 'Joint Pain'. And both cases are strongly correlated by the coefficient of correlation. Our machine learning approach using Python, Linear Reggression is the best-performing model among the options, as it balances low error and high explanatory power. It has proved to be highly effective at identifying the best options, indicating its potential for use in ergonomic decision-making after testing and training. Consistent with the results, Neural Network and SVM performed marginally better than the others.

The study suggests practical applications for AI powered ergonomic solutions, including smart ergonomic seating solutions, adaptive e-learning platforms, AI driven virtual ergonomic assistants, workplace ergonomic policy development, wearable posture monitoring devices, gamification of ergonomic practices, and AI powered ergonomic training programs. These solutions can analyze posture, provide real time feedback, integrate machine learning models, and offer personalized recommendations based on user behavior. Additionally, wearable sensors can provide haptic feedback and suggest customized exercise regimens. These solutions can also be implemented in educational institutions and educational institutions.

The future area of study may include the construction of a comparable structure using other approaches like DEMATEL and fuzzy TOPSIS which can be used to cope with complex ergonomic difficulties, to create a similar model. Future research may integrate real-time data collection methods to monitor posture and sitting behaviors during digital learning sessions, develop personalized ergonomic interventions, investigate prolonged sitting's impact on cognitive performance, expand machine learning models. Further ergonomics and educational psychology may be collaboarated. In future, the design of the holistic digital learning environments reducing the physical strain to enhance learning experiences may be developed as interdisciplinary research with health sciences domain. Implementing ergonomic improvements can enhance student well-being and academic performance. The data-driven approach allows for adaptive strategies in dynamic learning environments.

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