European Journal of Artificial Intelligence and Machine Learning
Vol 5 | Issue 2 | April 2026
ISSN 2796-0072

RESEARCH ARTICLE

Machine Learning-Based Analysis of Occupational Cervical Pain in Bangladesh: Integrating Clinical and Non-clinical Determinants

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ABSTRACT

Using machine learning methods, data obtained from 2815 Bangladeshi subjects indicated that approximately 42.5% of all participants experienced at least one type of musculoskeletal complaint. The rates of these complaints were significantly higher among female participants and those with a body mass index (BMI) classified as overweight and/or obese. Using principal component analysis (PCA) with a 3-dimensional biplot reduced the total number of variables and explained approximately 98% of the cumulative variance in the data. Among the different analytical prediction model types evaluated, the support vector machine (SVM) had the highest structural reliability (R^2 = 0.82–0.90). As determined by SHAP interpretability analysis, BMI (20.3%) and age (18.1%) were significant clinical and non-clinical predictors, respectively. The use of random forest regression (RFR) demonstrated that individuals following either bioactive-rich or bioactive-poor standard diets, would experience significant reductions in cervical pain levels; however, individuals following a bioactive-rich diet were more likely to achieve these significant reductions than those following standard diets ($p < 0.0001$), and those men and women who included dietary sources of omega-3 (fatty acids) in their diet were associated with approximately a 55% reduction in cervical pain. In addition, individuals following a daily regimen of natural products containing flavonoids experienced an approximate 52% reduction in cervical pain levels, while those who consumed daily products containing probiotics had approximately a 51% reduction. Therefore, utilizing metabolic and nutritional optimization strategies provides a non-pharmacological and evidence-based method to effectively manage cervical pain.

Keywords: Bioactive compounds and dietary supplements, machine learning analysis, occupational cervical pain, SHAP-based feature optimization.

Submitted: February 10, 2026

Published: April 12, 2026

10.24018/ejai.2026.5.2.70180

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1. Introduction

Neck pain (NP) is a widespread musculoskeletal disorder characterized by chronic pain, stiffness, and loss of function in the upper spine, and is often attributed to sustained mechanical stress and/or improper posturing over a prolonged period. Whereas NP was historically defined as being due to a biomechanical breakdown of cervical intervertebral discs and/or facet joints, an increasing number of studies have recognized that NP can be defined from a bio-psycho-social perspective. The causes of NP include clinical triggers (e.g., degenerative disc disease [DDD] and nerve root impingement) and an extensive range of non-clinical triggers [1]. Workers with sedentary jobs and manual laborers are disproportionately affected, with research in developed nations indicating that nearly 70% of the population will experience NP in their lifetime [2]. There is mounting evidence suggesting that physical ergonomic factors (i.e., ergonomics) and psychosocial stressors (i.e., high job strain and low levels of social support) interact to primarily contribute to chronic neck pain, changing the treatment paradigm from using simple analgesic medications to more complex, multifactorial approaches [3].

The epidemiological picture of chronic pain (CP) in the context of Bangladesh is incredibly concerning; however, very few reports have analyzed the situation, indicating that it remains a largely under-reported problem. Available studies demonstrate that there are very high prevalence rates for musculoskeletal disorders (MSDs) among the growing urban workforce, with rates ranging from 42% to 58% within certain sectors, including ready-made garments (RMG), corporations, and young athletes [4], [5]. In addition to high prevalence rates for MSDs, an emerging trend shows that the Bangladeshi working population faces what is referred to as the "triple burden": a lack of standardized ergonomic regulations, reliance on self-medication (in part due to a lack of disposable income to seek healthcare services) and a cultural stigma associated with reported symptoms early in their course until they have reached debilitating levels. While researchers in Western countries frequently report high recovery rates for patients who participate in organized physiotherapy programs, Bangladeshi patients frequently present with more advanced stages of vertebral degeneration than those who participate in physiotherapy programs outside of Bangladesh; this is likely attributable to significantly higher rates (approximately 30%) of poor workstation ergonomics and higher rates of systemic nutritional deficiencies than those in other developed countries [6]. A lack of available data on cervical health has resulted in inadequate public health policies specific to the needs of this vulnerable population.

The results of this study reveal a data-driven approach to understanding the causes of cephalic palsy (CP) in Bangladesh. The main goal of this project is to use advanced machine learning (ML) technologies, such as support vector machines (SVM) and SHAP interpretability, to identify and quantify the most impactful clinical (diseases or disabilities) and non-clinical factors (socioeconomic status) contributing to CP. Using this information, we hope to progress from prediction to "elucidation." In addition, this study explores a new area for the treatment of CP in the rehabilitation of patients through the use of functional foods and dietary supplements/targeted nutrition to reduce inflammation related to cervical pain. By combining the analysis of multi-dimensional data through computation with nutritional science, this study aims to create a model that can be applied broadly to reduce the burden of cervical occupational pain in the context of Bangladesh.

2. Materials and Methods

2.1. *Sample Sizing and Data Collection*

The integrated multifactorial profiling strategy of the investigative framework combined clinical parameters and socio-demographic/non-clinical characteristics as two broad analytical areas. The clinical parameters included physiological and comorbid indicators, such as body mass index (BMI), tobacco use, and systemic conditions (hypertension, diabetes, bronchial asthma, and chronic kidney disease) that were evaluated with a large number of non-clinical variables (occupational tenure, daily work intensity, gross monthly income [GMI], etc.) and other data that were specific to family/household members or their relationship with others. Sequentially, an Excel file was populated with the 2815 participants and all relevant details regarding their occupations. The sample size was determined by using the formula defined in (1):

$$n = \frac{Z^2.p.(1-p)}{e^2} \tag{1}$$

where n is the population size (285), Z is 95% confidence, p is the expected prevalence, e is the margin of error/precision (degree of accuracy).

2.2. *Machine Learning Driven Data Analysis*

2.2.1. *PCA Analysis*

To better understand the underlying multi-dimensional patterns in the dataset of 2815 public health observations, the authors constructed and implemented a sophisticated predictive modelling process. Principal component analysis (PCA) was performed using the OriginPro software platform [7]–[9]. By removing related variables from the 2815 records, PCA converted these into a smaller number of orthogonal principal components and thus resolved the multicollinearity issues. PCA produced a set of eigenvectors (the highest variance explaining) that removed a large amount of the "noise" associated with both clinical and non-clinical markers. The resulting structure of the data was suitable for replicating the training and validation of the models with improved performance.

2.2.2. *ANN, SVM, and GBR-Based Non-Linear Relationship Study of the Single Factors*

This study used machine learning (ML) ensembles built on support vector machines (SVM), gradient boosting regression (GBR), and artificial neural networks (ANN) to overcome the limitations of frequentist statistics, which notoriously overlook the stochastic variability of epidemiologic data [10], [11]. SVM uses hyperplanes to create optimal classifications of selected health outcomes in a high-dimensional feature space. GBR allows the use of boosting via a series of weak learners to minimize loss functions through repeated iterations, thus providing a means for robust rank-ordering of predictor variables as well as increased resilience to sparse datasets. ANNs were used to develop a multi-layer deep neural network that could model complex non-linear relationships within population metrics to capture hierarchical levels of detail and provide a more sophisticated approach for predicting future developments in public health trends. All data processing and validation for all ML algorithms were performed using optimally constructed Python environments [12], [13]; validation of the data and algorithms was accomplished via secondary comparison with GraphPad Prism 8.0.1 [14]–[16].

2.2.3. *SHAP-Based Feature Optimization*

The SHAP library in Python was used to optimize features and provide interpretability through a game-theoretical approach to deconstruct the logic behind the

SVM's predicted values [10]. The marginal contribution of each clinical/nonclinical attribute was computed across all 2815 records, thus ensuring that the model's high dimensionality would be transparent. This layer of analysis allowed for an unbiased ranking of features based on their mean absolute impact to remove redundant variables while preserving important signals of epidemiological impact. Therefore, a reduced feature set was developed that reflected the most important contributors to health disparities in the population studied [17].

2.2.4. Correlating Dietary Habits with Cervical Pain Using Machine Learning

Using random forest regression (RFR) and the R programming language script [18], [19], as described in the papers referenced in brackets, the relationship between food interventions and the recovery process from cervical pain was modeled by considering the food interventions that had been determined through research literature. An ensemble was used as an approach to evaluate the predicted impacts of a normal diet, dietary supplements, probiotics, natural products, and functional foods on the frequency of recovery based on research-specific datasets. The use of R's extensive statistical library allowed for the identification and quantification of the exact nonlinear interaction between specified dosages and recovery frequencies [20]–[22].

3. Results and Discussion

3.1. Primary Data Analysis

A summary of the participant characteristics from all 2815 respondents can be found as an Excel spreadsheet in *Supplementary Excel-1*. Among the participants included, 1197 (42.5%) reported experiencing musculoskeletal complaints. Symptomatic frequency was significantly higher for female participants and those in the overweight and obese categories based on body mass index (BMI). Likewise, professional stressors such as working long hours (9–12 h) have been shown to correlate positively with increased levels of pain reported. The heterogeneous distribution of both socioeconomic and clinical variables demonstrates the multifactorial complexity of cervical pain and supports a sound statistical baseline for the integrated principal component analysis (PCA) and machine learning (ML) performance assessments.

3.2. Machine Learning Data Analysis

3.2.1. PCA Analysis

The three-dimensional PCA biplot reduced the disparate clinical and non-clinical variable space with a high level of variance accounted for (98%) in total across the first three principal components (PC1 = 61.9%, PC2 = 23.6%, PC3 = 12.5%). The analysis of the loading vectors showed that R2 and MAE were located in different orthogonal planes confirming that predictive accuracy and error size are two different statistical dimensions within the sample of 2815 records (see Fig. 1). The close clustering of observations within the 95% confidence ellipse indicates a high degree of phenomenological stability of

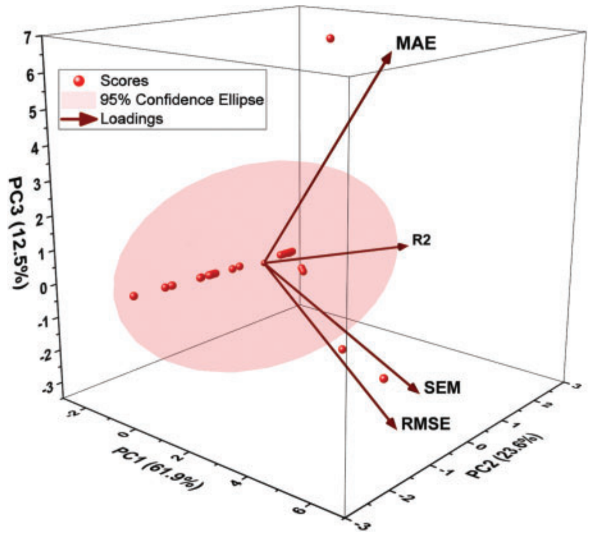

Fig. 1. PCA biplot 3D for distribution of variance for ML models.

these relationships and demonstrates the successful integration of such a wide variety of data sources. Therefore, this dimensionality reduction allowed for the transition to interpretability modelling, supporting the idea that the patterns of variance in this sample were related to systemic health patterns, not random noise [23].

3.2.2. ANN, GBR, and SVM Analysis

Regression comparative analyses revealed that all three model types, GBR and ANN, achieved an almost perfect fit; however, SVM stood out because it utilizes structural risk minimization (SRM) and generalizes better than the other two model types across the same data set of 2815 records. Even with larger MAE and RMSE scores than GBR and ANN, SVM demonstrated a degree of robustness to the adverse effects caused by noise and overfitting from highly complex features such as BMI and hypertension (Table I) with consistently high R^2 (0.82 and up to 0.90) levels over the test dataset. All three model types provide excellent performance and stable clinical results, with SVM providing stronger generalization than GBR or ANN because they demonstrate less sensitivity to fluctuations within the data derived from the literature. Therefore, SVM is the most appropriate framework for generating generalizable conclusions regarding the multifactorial etiology of recovery from cervical pain [24].

3.2.3. Feature Optimization-Using SHAP

Body mass index (20.3%) and age (18.1%) were the most important predictors of cervical pain in clinical and non-clinical settings, respectively, based on a SHAP interpretability analysis (Fig. 2). The clinical panel indicates that BMI has the highest average SHAP value, and the red color of the feature value on the gradient plot indicates that high values of obesity are associated with greater pain severity. The other most significant predictors of pain in this sample were smoking habit (19%) and hypertension (18.4%), suggesting that systemic metabolic stressors and vascular stressors contribute significantly to the deterioration of musculoskeletal tissue (Fig. 2A). For the non-clinical panel, the major predictors of pain

TABLE I: Comparison of ML Models Among Clinical and Non-Clinical Variables

Non-clinical factors						Clinical factors					
Variables	ML models	Regression parameters				Variables	ML models	Regression parameters			
		MAE	SEM	RMSE	R^2			MAE	SEM	RMSE	R^2
Educational attainment	ANN	0.011	0.002	0.044	0.990	BMI	ANN	0.036	0.007	0.082	0.979
	GBR	0.000	1.419	0.000	0.999		GBR	0.002	0.002	0.042	0.994
	SVM	0.097	0.025	0.157	0.878		SVM	0.132	0.039	0.197	0.879
Age (year)	ANN	0.025	0.006	0.080	0.990	Bronchial asthma	ANN	0.009	0.002	0.049	0.980
	GBR	0.005	0.005	0.073	0.992		GBR	6.595	8.517	9.229	0.999
	SVM	0.173	0.061	0.246	0.908		SVM	0.077	0.022	0.148	0.819
Biological sex	ANN	0.009	0.001	0.032	0.995	Diabetes mellitus	ANN	0.014	0.002	0.041	0.989
	GBR	0.000	1.522	0.000	0.999		GBR	0.002	0.002	0.042	0.989
	SVM	0.099	0.025	0.159	0.883		SVM	0.095	0.027	0.165	0.828
Employment status	ANN	0.016	0.002	0.048	0.979	Hypertension	ANN	0.008	0.001	0.029	0.997
	GBR	0.002	0.002	0.042	0.984		GBR	0.000	1.720	0.000	0.999
	SVM	0.072	0.019	0.137	0.827		SVM	0.111	0.029	0.169	0.882
Family composition	ANN	0.010	0.001	0.029	0.996	Kidney disease	ANN	0.031	0.005	0.074	0.919
	GBR	0.000	1.522	0.000	0.999		GBR	3.567	4.764	6.902	0.999
	SVM	0.100	0.025	0.159	0.883		SVM	0.061	0.015	0.122	0.780
GMI (BDT)	ANN	0.041	0.005	0.073	0.987	Smoking habit	ANN	0.009	0.001	0.035	0.995
	GBR	0.004	0.004	0.059	0.991		GBR	0.002	0.002	0.042	0.993
	SVM	0.156	0.051	0.226	0.877		SVM	0.109	0.029	0.169	0.885
Marital status	ANN	0.022	0.003	0.052	0.986	Exercise habit	ANN	0.012	0.002	0.042	0.990
	GBR	0.002	0.002	0.042	0.990		GBR	9.992	1.306	0.000	0.999
	SVM	0.096	0.024	0.156	0.876		SVM	0.096	0.025	0.157	0.866
Workday (h)	ANN	0.011	0.002	0.039	0.993	Musculoskeletal health issues	ANN	0.009	0.002	0.048	0.991
	GBR	0.000	1.635	0.000	0.999		GBR	0.000	1.706	0.000	0.999
	SVM	0.105	0.027	0.165	0.881		SVM	0.107	0.028	0.168	0.883
Residential area	ANN	0.034	0.006	0.079	0.983						
	GBR	0.002	0.002	0.042	0.995						
	SVM	0.154	0.051	0.226	0.864						
Professional years	ANN	0.011	0.001	0.037	0.993						
	GBR	0.002	0.002	0.042	0.992						

were workday hours (11%) and GMI (9.5%), both of which illustrate that the length of time spent working and level of economic support respectively directly predict the frequency of pain experienced (Fig. 2B). The structural hubungan in the gradient, bar, and pie charts was very similar for each of the 2815 records, providing strong evidence that metabolic health and work place life cycle stages have the greatest impact on CP recovery.

3.2.4. Strategic Nutritional Interventions for Suppressing Occupational CP

The results from the RFR model indicate that specific nutrient interventions are far superior to a regular diet for decreasing the intensity of CNP ($p < 0.0001$). Omega-3 fatty acid-rich functional foods provided the most effective (∼55%) reduction, likely via suppression of systemic inflammation due to a high (20.3%) body mass index, as shown by the SHAP analysis (Fig. 3). Natural products containing flavonoids that have bioactive qualities, as well as probiotics from milk, also had a similar level of effectiveness (∼52% and ∼51%, respectively), which indicates that there is a synergistic neuroprotective and anti-inflammatory effect among these three interventions. In addition, bioactive supplementation was found to have a level of approximately 48% in counteracting physiological stressors, such as high blood pressure and smoking. Overall, it has been established that managing metabolic health with targeted hunger nutrition creates a better way to address workplace disparities due to musculoskeletal conditions, such as CNP, without pharmacological means [25].

Targeted dietary supplementation can help reduce the effects of chronic pain (CP) because of the way certain bioactive compounds work together. For example, many phytochemicals (i.e., compounds found naturally in plants) are used as vitamins, minerals, and other healthful substances. Among these phytochemicals are flavonoids (e.g., quercetin, isorhamnetin, apigenin, isovitexin, myricetin, robinetin, etc.), which have excellent antioxidant activity by neutralizing free radicals and inhibiting the production of pro-inflammatory cytokines in musculoskeletal tissue. These phytochemicals are currently used in the development of personalized molecular therapeutics [26]–[28]. Omega-3 fatty acids (i.e., EPA and DHA) also play a role in this process because they generate specialized pro-resolving molecules that help to shut down the inflammatory response [19]. In addition to the benefits of the use of phytochemicals and omega-3 fatty acids as dietary supplements, other methods, such as the use of oleaginous microbes as bio-factories for the production of antimicrobial peptides (i.e., probiotics), are emerging as new approaches to modulating the gut-joint axis and enhancing the body's systemic immune response [29]–[31]. These

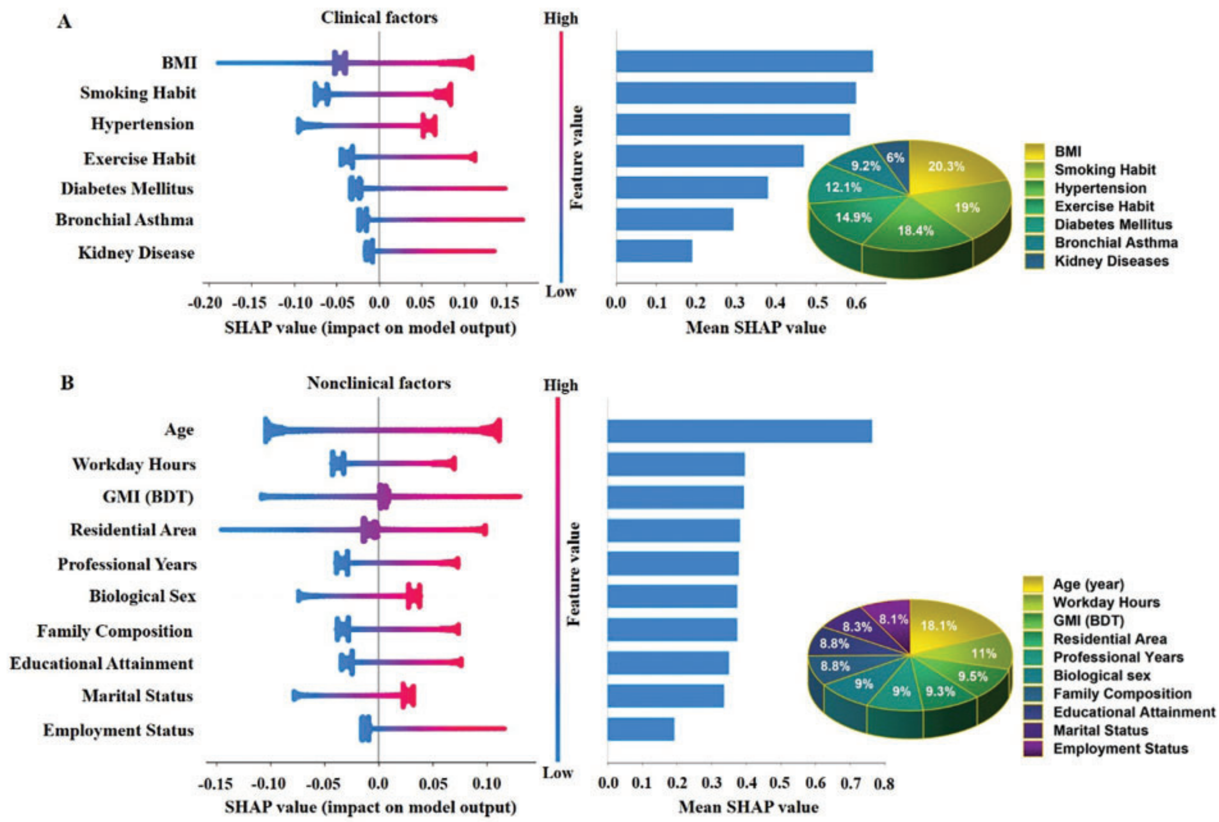

Fig. 2. SHAP analysis of clinical (A) and non-clinical (B) factors in the prediction models. Left panels show the distribution of SHAP values (impact on model output); right panels display mean SHAP values and percentage feature contributions.

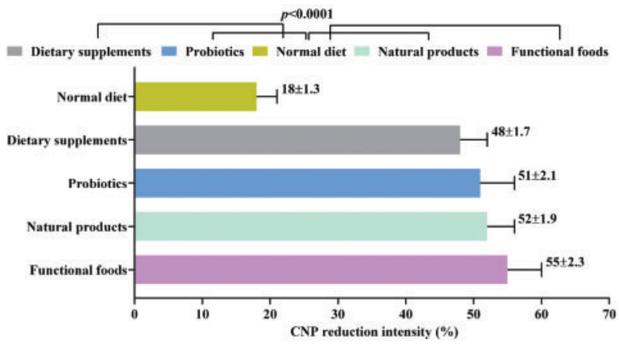

Fig. 3. Comparative efficacy of nutritional treatments on CNP severity.

different classes of high-residual-potency supplements collectively form a multi-tiered biochemical defense that protects cellular function and helps minimize the level of chronic pain stimulated by persistent signals originating from the neck, resulting from occupational injury [32].

4. Conclusion

This study created a multifactorial approach to recognize and reduce work-related chronic pain in Bangladesh. Using SHAP-based data interpretation with a machine-based learning architecture, we found that body mass index (BMI) was the major clinical determinant, whereas age was the major non-clinical determinant. Calculating with random forest regression further confirmed that nutrient interventions high in bioactive content, especially omega-3 fatty acids and certain phytochemicals (e.g., quercetin), had significantly greater pain relief than traditional nutrient interventions. These results provide a scalable, non-medication intervention model for maintaining the health of the neck, with metabolic control being a primary pathway for healing.

Acknowledgment

Tamanna Naznin Shetu from Jiangnan University in China is a CSC Scholar who has contributed all of the relevant technical assistance and provided this information unwaveringly and without exception. The authors would like to express their appreciation to her for all of her contributions and technical assistance.

Funding

No funding was received for this experiment.

Conflict of Interest

The authors have no conflict of interest with the others.

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