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Behavioural Predictors of Forward Head Posture Risk: A Correlation, Machine Learning, and Clustering Analysis

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ABSTRACT

Forward Head Posture (FHP) has become increasingly common among university students due to prolonged digital device use and inadequate ergonomic behaviour. This study aims to identify the behavioural factors that most strongly predict neck tension, which is used as an indicator of FHP risk, among laptop users at Universitas Ciputra. A total of 141 survey responses were collected, capturing digital lifestyle patterns that include screen exposure, posture habits, ergonomic awareness, physical activity, and screen-related symptoms. The analysis followed a complete methodological sequence that involved data preprocessing, correlation testing, supervised machine-learning modelling, and K-Means clustering. The results show that headache after screen use, frequency of head-down posture, ergonomic knowledge, and weekly exercise emerged as the most influential behavioural predictors of neck tension, with head-down posture demonstrating the strongest association ($r = 0.437$). Correlation testing supported three of the four hypotheses, while the Random Forest model achieved the highest predictive performance (71.01% cross-validated accuracy). The clustering analysis revealed two distinct behavioural subgroups with different ergonomic risk profiles. These findings highlight specific behavioural targets that can support ergonomic-awareness efforts and help reduce the likelihood of FHP development in academic environments.

I. Introduction

The rapid growth of digital technology has completely changed how people work, study, and interact in their daily lives. Many academic and professional activities now depend on digital devices that make daily tasks faster and more connected. However, this convenience comes with health consequences. Longer screen time and reduced movement are known to cause musculoskeletal strain and postural problems [1], [2]. A 2025 cross-sectional study among desk-job employees reported that more than one-third of participants spent over eight hours a day in front of screens and experienced a high rate of neck and shoulder discomfort [3]. Likewise, research on university students revealed that spending over five hours daily on digital devices was closely associated with a higher incidence of neck and upper-back pain compared with shorter usage durations [4]. Recent investigations have also shown that prolonged smartphone or laptop use alters cervical posture and contributes to neck-muscle fatigue even in young adults [5], reinforcing concerns about the cumulative impact of screen-based activities on musculoskeletal health [6].

In academic environments, digital reliance continues to increase, especially among university students and lecturers who depend on laptops for coursework, teaching preparation, and administrative work. In Indonesia, the use of digital devices among students expanded rapidly since the post-pandemic era, but many still show limited awareness of ergonomic posture and healthy screen habits. Many people work from non-ergonomic positions, like couches or beds, and spend five to seven hours a day in front of screens [7], [8]. While several local studies have documented extended laptop use among students, most have measured only usage duration without examining its relationship to postural health outcomes. International findings similarly indicate that poor device-use habits, combined with sedentary routines, are associated with increased neck discomfort and heightened risk of Forward Head Posture (FHP) [5], [9], [10]. This gap underscores the need for campus-based research that connects digital behaviours with posture-related symptoms in Indonesian student populations.

One of the most common posture deviations associated with long-term device use is Forward Head Posture (FHP), a condition in which the head shifts forward relative to the vertical shoulder line [11]. This posture increases the mechanical load on the cervical spine and often leads to neck pain, shoulder tightness, and fatigue [11], [12]. Biomechanical research has shown that maintaining a bent neck while using a laptop or smartphone alters the activation of neck extensor and trapezius muscles, reducing postural control [11]. Visual problems such as myopia can also make users lean their heads forward when focusing on nearby screens, which further increase strain on the neck and shoulders [13]. Prolonged sitting without regular movement breaks contributes to muscle fatigue and reinforces the cycle of postural stress [14]. Evidence from recent studies also indicates that these posture deviations can lead to functional limitations and increased neck-pain intensity among frequent digital-device users [5], [9], supporting the relevance of early behavioural detection.

Lifestyle factors also play an important role in shaping postural health. Recent research has shown that individuals who spend more than six and a half per day sitting have a 3.3-times greater likelihood of developing Forward Head Posture (FHP), especially when they engage in limited physical activity and rarely perform stretching exercises [15]. Other studies have reported that students who frequently use smartphones in bed or study without proper ergonomic adjustments experience higher levels of postural discomfort [4], [14]. Systematic reviews also highlight sedentary behaviour as a consistent predictor of neck and shoulder pain in young adults [10]. Moreover, recent analyses suggest that behavioural patterns such as device use, posture habits, and physical activity can even predict neck-pain severity through machine-learning approaches [16], emphasising the complex interplay between digital lifestyle and musculoskeletal outcomes.

Recently, machine learning (ML) methods have been increasingly used to identify risk factors in musculoskeletal health. Models such as Decision Tree, Random Forest, and Support Vector Machine have shown high accuracy in detecting posture-related disorders and ranking key risk variables [2], [17]. For instance, previous studies have successfully employed ML models to predict Forward Head Posture (FHP) based on physical and behavioural features, while others have used explainable ML approaches to reveal occupational and lifestyle predictors of neck and shoulder pain [17]. More recent work has demonstrated the effectiveness of ML in identifying the dominant predictors of mechanical neck pain in computer-intensive populations [16], further supporting its relevance for analysing digital-behavioural datasets. Despite growing interest, most ML research still relies primarily on clinical rather than behavioural data, leaving a gap in understanding how everyday digital habits contribute to postural symptoms.

II. METHODOLOGY

This study adopted a quantitative cross-sectional design to investigate how everyday digital behaviours relate to neck tension, a symptom commonly associated with Forward Head Posture (FHP). Neck tension was used as a functional proxy indicator of Forward Head Posture (FHP) risk rather than a clinical diagnosis. Previous musculoskeletal studies have shown that sustained cervical flexion and poor head posture significantly increase muscle activation imbalance and subjective neck tension, particularly in populations with prolonged digital-device use [11], [12], [14]. Although objective postural measurements such as the craniovertebral angle provide higher diagnostic precision, self-reported neck tension remains a widely accepted early indicator of posture-related musculoskeletal strain in large-scale behavioural surveys [9], [14]. Cross-sectional approaches are widely applied in musculoskeletal and digital-device research because they allow behavioural exposure and symptom data to be captured simultaneously within a single time frame, a method frequently used in studies involving university students and office workers who engage in prolonged screen use [1], [4], [8]. This design is particularly appropriate for FHP-related research because posture deviations and neck discomfort typically emerge gradually from repeated daily behaviours rather than acute events. Accordingly, focusing on behavioural indicators enables early identification of lifestyle factors that may contribute to postural strain in academic settings. The present study focused on behavioural indicators commonly observed among laptop users, including daily screen exposure, sitting posture, cervical flexion, ergonomic awareness, and physical activity, to better understand how modern digital habits contribute to postural strain in academic settings.

Participants were recruited voluntarily from a university environment and were eligible if they routinely used a laptop for academic or professional activities. The online questionnaire collected demographic information such as age, gender, and academic role; however, no personal identifiers were used during analysis to preserve confidentiality. The instrument was adapted from validated ergonomic and musculoskeletal studies, particularly research examining poor sitting posture [8], prolonged laptop behaviour [7], visual strain linked to near-work screen tasks [13], and lifestyle contributors to Forward Head Posture [15]. Recent findings further show that neck-pain severity among computer users is strongly influenced by behavioural and ergonomic factors, which supports the inclusion of these variables in the current study [16]. The final survey consisted of thirteen behavioural questions assessing sitting duration, device distance, cervical flexion habits, ergonomic awareness, physical activity levels, and symptoms such as headache after extended screen exposure. A pilot test was completed beforehand to ensure clarity of wording and comprehension. This step ensured that respondents consistently interpreted each behavioural item, thereby strengthening measurement validity.

All behavioural variables were numerically encoded following ergonomic thresholds identified in previous literature. Screen-time duration, posture type, device distance, and the frequency of head-down posture were encoded in ascending order of ergonomic risk, reflecting musculoskeletal modelling practices used in studies of digital-device users [1], [14], [15]. Protective factors such as ergonomic knowledge and weekly exercise were encoded so that higher values represented lower behavioural risk, consistent with findings that greater ergonomic understanding promotes healthier posture choices [7], [17] and that regular physical activity reduces the severity of neck-related musculoskeletal symptoms [15]. The dependent variable, neck tension, was initially collected as a five-point Likert score but later converted into a binary classification representing low- and high-tension levels, following symptom-severity categorisation approaches used in musculoskeletal and digital health studies [14]. To contextualise these analytical steps, a visual overview of the methodological procedure is presented in Figure 1. The diagram summarises the sequential stages involved in data collection, preprocessing, construct validity testing, machine-learning modelling, and clustering analysis, which together form the analytical workflow used to identify behavioural predictors of neck tension among laptop users.

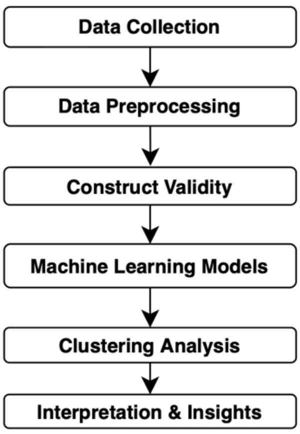

Figure 1. Research workflow diagram used in this study.

Before analysis, the dataset underwent several preprocessing steps. Duplicate submissions, if present, were removed; inconsistent textual responses were cleaned; all categorical variables were transformed into numerical ordinal scales; and Min–Max normalisation was applied to standardise predictor ranges. Because the survey measured a set of multidimensional behavioural constructs, rather than a single psychological trait, internal-consistency measures such as Cronbach's alpha were not appropriate. Recent methodological evaluations emphasise that Cronbach's alpha should not be used when items do not measure a single latent dimension, because the coefficient assumes unidimensionality and tau-equivalence, which do not hold for behavioural surveys like the present study [18]. Instead, construct validity was evaluated using Spearman's and Pearson's correlations, which are widely recommended in ergonomic and musculoskeletal research for assessing relationships between behavioural exposure and physical symptoms [14], [19]. The analytic choice also aligns with statistical guidelines stating that Pearson's r is suitable for normally distributed continuous variables, while Spearman's rho is preferred for ordinal variables or non-linear monotonic associations commonly observed in digital-behaviour datasets [20]. Four hypotheses guided this analysis: headache after using screens was expected to positively predict neck tension, ergonomic knowledge was expected to negatively predict the frequency of head-down posture, frequent cervical flexion was expected to positively predict neck tension, and weekly exercise was expected to negatively predict neck tension. A diagram illustrating these hypothesised relationships should be placed after this paragraph as Figure 2.

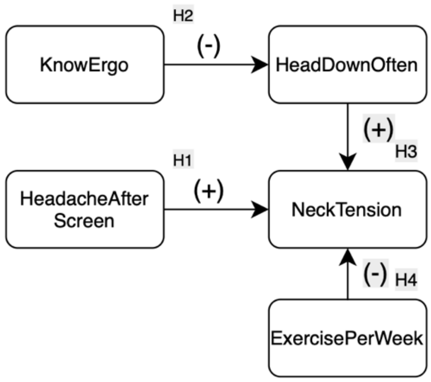

Figure 2. Conceptual model of the hypothesised relationships.

Correlation testing was then performed using Spearman's rho and Pearson's r to evaluate the strength and direction of the hypothesised relationships (H1–H4). Each coefficient was applied according to its statistical suitability as outlined in the methodological section [20].

Supervised machine-learning models were implemented to complement the statistical hypothesis testing and identify which behavioural variables most strongly predicted neck tension. Three algorithms were used: Decision Tree, Random Forest, and Logistic Regression. These models were trained with an eighty–twenty train–test split and evaluated using five-fold cross-validation. The inclusion of multiple algorithms was intended to enable methodological comparison rather than performance optimisation. Although Random Forest was expected to capture non-linear interactions more effectively, simpler models such as Logistic Regression were retained as baseline comparators to evaluate the added value of ensemble learning over linear classification in behavioural health datasets [21]. The Decision Tree model was included for its interpretability and ability to extract feature-importance rankings, Random Forest for improved predictive stability, and Logistic Regression as a linear benchmark. These methodological choices align with comparative ML evaluations showing that Decision Tree provides high model transparency, Random Forest offers superior stability through ensemble averaging, and Logistic Regression serves as a standard linear baseline in classification tasks [21].

To further explore hidden behavioural patterns among respondents, K-Means clustering with two clusters was performed on the encoded predictors. This unsupervised approach enabled the identification of natural groupings, such as respondents with consistently high-risk ergonomic behaviours, offering insights that complement the supervised models. Clustering has been used in musculoskeletal and digital ergonomics studies to reveal behavioural subgroups that are not always visible through classification alone [19]. Previous studies applying unsupervised ML to FHP have shown that clustering can separate individuals into meaningful biomechanical or behavioural subgroups based on craniocervical movement patterns, reinforcing its suitability for identifying distinct ergonomic-risk profiles in this study [22]. A visualisation of the clustering results, along with descriptive comparisons between clusters, should be placed after this paragraph as Figure 4.

All study procedures complied with ethical guidelines for online survey research. Participation was voluntary, no sensitive personal data were collected, and all responses remained anonymous throughout the study.

III. Results and Discussion

The analysis began with an examination of the respondent characteristics obtained through the online survey. After removing one duplicate submission, a total of 141 valid responses were included in the final dataset. Most participants were university students who reported daily laptop use exceeding four hours, a trend consistent with previous findings showing that academic populations frequently experience prolonged screen exposure and an increased susceptibility to musculoskeletal complaints [4], [8]. To provide a clear overview of the sample composition, descriptive statistics including demographic distribution, screen time patterns, and posture-related behavioural frequencies should be presented in Table I.

TABLE I
DESCRIPTIVE STATISTICS OF RESPONDENTS

Variable	Category	n	%
Gender	Male	85	60.28
	Female	56	39.72
Status UC	Student	135	95.74
	Lecturer	6	4.26
Age	Mean ± SD	20.04 ± 3.64	-
Screen Hours	3-5 hours	63	44.68
	6-8 hours	48	34.04
	>8 hours	20	14.18
	<2 hours	10	7.09
Posture	Sitting on a chair at a desk	110	78.01
	Lying on a bed	19	13.47
	Sitting on the floor	7	4.96
	Sitting on a sofa	5	3.54
Screen at Eye Level	No	71	50.35
	Yes	70	49.64
Screen Distance	20-50 cm	109	77.30
	<30 cm	19	13.48
	>50 cm	13	9.22
Exercise Frequency	1-2x	85	60.28
	3-5x	30	21.28
	Never	22	15.60
	Everyday	4	2.84
Likert (Mean ± SD)	HeadDownOften	3.59 ± 1.14	-
	KnowErgo	3.34 ± 1.24	-
	HeadacheAfterScreen	3.08 ± 1.13	-
	ChangePosPerHour	3.70 ± 1.02	-
	TakesBreaks	43.40 ± 1.19	-

Following the descriptive phase, construct validity was examined through correlation testing using Spearman's rho and Pearson's r. These analyses were designed to evaluate four hypothesised relationships derived from ergonomic and musculoskeletal literature: (H1) screen-induced headaches would positively predict neck tension; (H2) ergonomic awareness would negatively predict head-down posture; (H3) frequent cervical flexion would positively predict neck tension; and (H4) weekly physical activity would negatively predict neck tension. The results demonstrated that three of the four hypotheses were statistically supported. Headache after prolonged screen use showed a significant positive correlation with neck tension (Spearman $r = 0.354$, $p < 0.001$), aligning with earlier reports that visual strain and neck discomfort frequently co-occur in digital-device users [13], [14]. Similarly, frequent head-down posture exhibited a moderate positive association with neck tension (Spearman $r = 0.437$, $p < 0.001$), consistent with biomechanical evidence indicating that cervical flexion increases trapezius activation and spinal load [11], [15]. Weekly exercise displayed a significant negative correlation with neck tension (Spearman $r = –0.276$, $p = 0.001$), reinforcing findings that physical activity reduces musculoskeletal symptoms in sedentary populations [15]. In contrast, ergonomic knowledge did not significantly predict head-down posture (Spearman $r = 0.052$, $p > 0.05$), suggesting that awareness alone does not guarantee behavioural implementation, a discrepancy also observed by Visca et al. [8].

This non-significant association suggests a gap between ergonomic knowledge and actual postural behaviour. Previous studies among university populations have similarly reported that awareness of ergonomic principles does not necessarily translate into consistent posture correction during prolonged screen use, particularly when academic demands and sustained laptop engagement override conscious behavioural control [1], [8], [14]. In student settings, prolonged cognitive focus and task continuity often lead individuals to maintain habitual head-down postures despite recognising ergonomic recommendations [4], [12]. This finding indicates that ergonomic knowledge alone may be insufficient to modify postural habits without complementary behavioural reinforcement, environmental adjustment, or structured intervention strategies, a pattern also noted in prior musculoskeletal behaviour studies [14], [19].

Although several statistically significant associations were observed, these findings should be interpreted cautiously. Correlation analysis reflects the strength of relationships between variables but does not establish causal direction. Given the cross-sectional nature of the study, it cannot be determined whether frequent cervical flexion leads to increased neck tension or whether individuals experiencing neck discomfort are more likely to adopt head-down postures. This distinction is important to avoid causal overinterpretation of correlational findings, as emphasised in statistical guidelines for behavioural and health research [20]. The full correlation results, including coefficients and p-values for both Spearman and Pearson tests, should be presented in Table II.

TABLE II
CORRELATION TEST RESULTS FOR H1-H4

Hypotesis	X Variable	Y Variable	Spearman r	Spearman p	Pearson r	Pearson p
H1 (+)	HeadacheAfterScreen	Neck Tension	0.354	0.000	0.354	0.000
H2 (-)	Know Ergo	Head Down Often	0.052	0.543	0.087	0.302
H3 (+)	Head Down Often	Neck Tension	0.437	0.000	0.087	0.302
H4 (-)	ExercisePerWeek	Neck Tension	0.276	0.001	0.276	0.001

To complement the correlation results, supervised machine-learning models were developed to classify respondents into low versus high neck-tension categories. The initial Decision Tree model using all behavioural predictors achieved an accuracy of 68.97%, and performance increased to 72.41% when only eight filtered features were used. However, cross-validation of the full model produced a mean accuracy of 61.75%, indicating limited generalisability. A broader algorithm comparison showed that the Random Forest classifier achieved the highest average cross-validated accuracy at 71.01%, followed by Logistic Regression at 65.96%, whereas the Decision Tree remained the lowest at 61.75%, consistent with previous ergonomic studies reporting that ensemble methods tend to outperform single-tree models due to improved variance reduction [2], [17]. These results indicate that the primary value of the supervised models lies in comparative pattern exploration rather than absolute predictive performance. A summary of these performance results should be outlined in Table III.

TABLE III
MACHINE LEARNING MODEL PERFORMANCE COMPARISON

Model	Mean CV Accuracy (%)
Decision Tree	61.75
Random Forest	71.01
Logistic Regression	65.96

To obtain a more interpretable behavioural model, threshold-based feature selection was performed. A threshold of 0.15 yielded the optimal balance between dimensionality reduction and predictive strength, retaining four key predictors: headache after screen use, ergonomic knowledge, frequency of head-down posture, and weekly exercise. Using only these four variables, the refined Decision Tree achieved a hold-out accuracy of 65.52% and an improved cross-validated accuracy of 70.15%. This indicates that a compact feature set not only preserves predictive performance but also enhances model stability across respondent subsets, an important consideration for behavioural-ergonomics research where overfitting is common due to heterogeneous lifestyle patterns [14], [15].

A supplementary experiment using six behavioural features was also conducted for comparison. Although the six-feature model produced the highest single-test accuracy (72.41%), its cross-validated accuracy reached only 64.53%, suggesting a greater degree of performance fluctuation. Meanwhile, the Random Forest model using the same subset achieved a more stable mean accuracy of 68.87%, reaffirming its robustness across folds [17]. Taken together, these results justify the selection of the four-feature Decision Tree as the final model for interpretation, as it offers the best trade-off between predictive reliability, interpretability, and theoretical alignment with ergonomic predictors of musculoskeletal symptoms [11], [15].

The machine-learning models were employed for exploratory and interpretative purposes rather than clinical classification. In behavioural ergonomics research, moderate predictive accuracy is considered acceptable when the primary objective is to identify dominant risk-related features and behavioural patterns instead of producing diagnostic-level predictions [16], [17]. Although Random Forest demonstrated the highest overall performance, simpler models such as Logistic Regression provided a useful baseline for comparison, enabling the evaluation of non-linear ensemble advantages over linear classification in behavioural health data [21]. Machine-learning approaches have been increasingly applied to posture-related predictors in both clinical and occupational contexts, including models designed to detect FHP and other musculoskeletal risk conditions [2], [17]. Recent evidence also demonstrates that ML models can accurately predict neck-pain intensity based on behavioural features, with Decision Tree and Random Forest consistently emerging as the most interpretable and stable algorithms [16]. These findings support the methodological choices adopted in the present study.

Feature-importance analysis was conducted to identify which behavioural variables contributed most strongly to the prediction of neck tension. The results showed that headache after screen use emerged as the most influential predictor, followed by ergonomic knowledge, frequency of head-down posture, and weekly exercise. These variables accounted for most of the model's explanatory power, and their prominence aligns with prior ergonomic and musculoskeletal findings indicating that visual strain, poor cervical posture, and insufficient physical activity are key contributors to neck discomfort in digital-device users [11], [14], [15]. Importantly, the convergence between feature-importance results and correlation findings reinforces the robustness of these variables as consistent behavioural risk indicators rather than model-specific artefacts. A graphical summary of the importance ranking is provided in Figure 3.

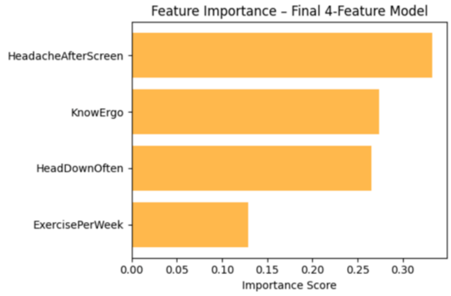

Figure 3. Feature importance ranking from decision tree model

To further explore whether respondents formed natural behavioural subgroups, an unsupervised K-Means clustering analysis (k = 2) was performed using the encoded predictors. The clustering revealed two distinct profiles: one group characterised by higher symptom levels, more frequent head-down posture, and poorer ergonomic habits, and another group displaying generally lower-risk behavioural patterns. These clusters mirrored the supervised-model results and reflect broader ergonomic literature indicating that posture habits and activity levels tend to segment digital-device users into meaningful musculoskeletal risk categories [19]. This finding indicates that behavioural patterns related to digital-device use do not vary randomly across individuals but tend to form consistent risk-oriented groupings. The distribution of respondents across clusters is shown in Figure 4, while the mean values of key behavioural indicators for each cluster are summarised in Table IV.

The clustering analysis using K-Means (k = 2) revealed two behavioural subgroups within the respondent population. The distribution was nearly equal, with both clusters consisting of approximately seventy respondents each, as illustrated in Figure 4.

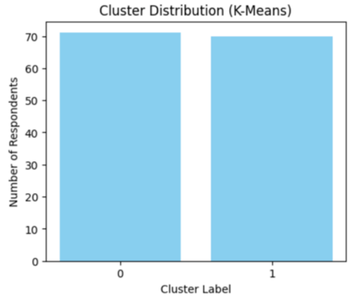

Figure 4. Cluster distribution of respondents (k=2)

TABLE IV
CLUSTER MEANS COMPARISON FOR KEY BEHAVIOURAL VARIABLES

Variable	Cluster 0 (Mean)	Cluster 1 (Mean)
ScreenHours	0.507	0.529
HeadDownOften	0.722	0.571
HeadacheAfter Screen	0.521	0.518
ExercisePerWeek	0.601	0.657
KnowErgo	0.454	0.375
TakeBreaks	0.398	0.404
ScreenDistance	0.535	0.507
NeckTension	3.324	3.171

Although the groups were balanced in size, their behavioural profiles showed meaningful differences. Cluster 0 represents a higher-risk ergonomic behavioural profile, as it exhibited higher mean levels of head-down posture (0.72) and slightly greater headache frequency after screen use (0.52), accompanied by a higher average neck-tension score (3.32). This pattern indicates more pronounced cervical-flexion behaviour and screen-related symptoms, behaviours previously linked to increased musculoskeletal strain during prolonged digital-device use [11], [14]. In contrast, Cluster 1 represents a lower-risk behavioural profile, demonstrating lower head-down posture frequency (0.57), greater weekly exercise participation (0.66), and slightly lower neck tension (3.17), indicating a comparatively lower-risk ergonomic profile. The comparative means for each behavioural variable across clusters are summarised in Table IV.

Taken together, the clustering results reinforce the supervised-model findings by revealing that individuals with higher cervical-flexion tendencies and screen-related symptoms tend to form a distinct high-risk behavioural subgroup. This behavioural distinction enables the clustering results to be interpreted beyond statistical separation, supporting their relevance for identifying ergonomic risk profiles within academic laptop-user populations. This pattern mirrors ergonomic literature showing that posture habits and physical activity levels can segment digital-device users into meaningful musculoskeletal risk categories [19], supporting the robustness of the behavioural distinctions identified in this study.

IV. CONCLUSION

This study examined how digital-lifestyle behaviours relate to neck tension among university laptop users by integrating descriptive analysis, correlation testing, supervised machine-learning models, and clustering. The results show that everyday device-use behaviours such as screen-related symptoms, cervical-flexion habits, ergonomic awareness, and physical-activity levels are meaningfully associated with musculoskeletal discomfort commonly linked to Forward Head Posture.

Correlation testing confirmed three of the four hypotheses. Headache after screen use showed a significant positive association with neck tension, and frequent head-down posture also demonstrated a moderate positive relationship with neck tension. Weekly exercise showed a significant negative association with neck tension, which reflects the protective role of regular physical activity. Ergonomic knowledge did not significantly predict posture behaviour, which suggests that awareness alone does not necessarily translate into correct ergonomic practice.

The machine-learning analysis supported these observations. The Random Forest classifier achieved the highest cross-validated accuracy, while the Decision Tree provided an interpretable model that identified four behavioural variables as the most influential predictors, namely headache after screen use, ergonomic knowledge, head-down posture frequency, and weekly exercise. The alignment between the feature-importance results and the correlation findings indicates that these variables consistently influence neck tension in this population.

The clustering results also revealed two meaningful behavioural subgroups. One subgroup showed higher symptom levels, more frequent cervical flexion, and poorer ergonomic habits. The other subgroup demonstrated lower-risk behavioural characteristics. These patterns mirror the findings from the supervised models and show that digital-behavioural patterns naturally separate users into groups with different levels of musculoskeletal risk.

From a practical perspective, these findings provide evidence-based guidance for ergonomic risk prevention in academic environments. The identified behavioural predictors, particularly screen-related symptoms, frequent head-down posture, and low levels of physical activity, represent actionable targets for campus-level interventions. Universities may use these insights to design ergonomic programs that extend beyond knowledge dissemination by incorporating behavioural reinforcement, workspace adjustment, and physical-activity promotion to reduce early musculoskeletal risk among students.

Several limitations should be acknowledged. First, this study relied on self-reported survey data, which may introduce subjective perception bias and social desirability effects. Second, the cross-sectional design limits causal interpretation of the observed relationships between digital behaviours and neck tension. Third, Forward Head Posture risk was inferred using neck tension as a proxy indicator rather than objective postural measurements such as the craniovertebral angle. Finally, the sample was drawn from a single university, which may restrict the generalisability of the findings to broader student populations. Accordingly, the results should be interpreted as exploratory behavioural insights rather than population-level estimates.

Overall, the findings indicate that neck-tension risk among university laptop users is shaped by a combination of screen-related symptoms, posture behaviour, ergonomic knowledge, and physical-activity patterns. These insights highlight the importance of interventions that focus on strengthening healthy ergonomic habits rather than only improving awareness. Future research may incorporate clinical posture assessments or longitudinal designs to better understand how digital-behavioural patterns influence musculoskeletal outcomes over time.

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