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POSTURAL CONTROL AND GAIT ALTERATIONS IN YOUNG ADULT TOBACCO AND E-CIGARETTE USERS: A COMPARATIVE STABILOMETRIC AND TREADMILL-BASED ANALYSIS

The research investigates how tobacco and electronic cigarette (e-cigarette) consumption affects postural control and walking patterns in young adult populations. The study included 60 participants who were divided into three groups of 20 each: non-smokers and traditional smokers and e-cigarette users. The participants completed stabilometric tests under static conditions with eyes open and closed while undergoing treadmill-based dynamic gait analysis. The researchers used parametric or non-parametric statistical tests together with Spearman's correlation and principal component analysis (PCA) and supervised machine learning classifiers to analyze biomechanical features. The study revealed substantial differences between non-smokers and e-cigarette users regarding body mass index (BMI) and foot force distribution and walking speed and step length measurements. Correlation analyses revealed strong associations between center of pressure dynamics and plantar pressure distribution, with group-specific interaction patterns. PCA demonstrated partial group separation, especially for non-smokers versus e-cigarette users. Machine learning models, especially logistic regression, achieved the highest classification accuracy (up to 82.8%) in distinguishing non-smokers from e-cigarette users. These findings suggest that habitual use of tobacco or e-cigarettes may influence balance and locomotor control in subtle but measurable ways, with potential implications for neuromuscular health monitoring in young populations.

Keywords: postural stability, e-cigarettes, tobacco use, gait analysis, stabilometry, young adults, machine learning, PCA.

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КОНТРОЛЬ ПОЗИ ТА ЗМІНИ ХОДИ У МОЛОДИХ ДОРОСЛИХ КОРИСТУВАЧІВ ТЮТЮНУ ТА ЕЛЕКТРОННИХ СИГАРЕТ: ПОРІВНЯЛЬНИЙ АНАЛІЗ СТАБІЛОМЕТРІЇ ТА ХОДИ НА БІГОВІЙ ДОРОЖЦІ

Дослідження вивчає, як вживання тютюну та електронних сигарет (е-сигарет) впливає на контроль пози та особливості ходи у молодих дорослих. У дослідженні взяли участь 60 осіб, яких розподілили на три групи по 20: некурці, курці традиційних сигарет та користувачі електронних сигарет.

Учасники виконували стабілометричні тести у статичних умовах з відкритими та закритими очима, а також проходили динамічний аналіз ходи на біговій доріжці. Для аналізу біомеханічних показників дослідники застосовували параметричні та непараметричні статистичні тести, кореляцію Спірмена, метод головних компонент (PCA) та контрольовані класифікатори машинного навчання. Дослідження виявило значні відмінності між некурцями та користувачами електронних сигарет за індексом маси тіла (ІМТ), розподілом сили стопи, швидкістю ходьби та довжиною кроку. Кореляційний аналіз *показав тісні зв'язки між динамікою центру тиску та розподілом плантарного тиску, з характерними для кожної групи моделями взаємодії. PCA продемонстрував часткове розділення груп, особливо між некурцями та користувачами е-сигарет.*

Моделі машинного навчання, зокрема логістична регресія, досягли найвищої точності класифікації (до 82,8%) у розмежуванні некурців та користувачів електронних сигарет. Ці результати свідчать, що регулярне вживання тютюну або е-сигарет може впливати на баланс та контроль рухів у тонкий, але вимірюваний спосіб, що має потенційне значення для моніторингу нейром'язового здоров'я молоді.

Ключові слова: постуральна стабільність, електронні сигарети, вживання тютюну, аналіз ходи, стабілометрія, молоді дорослі, машинне навчання, PCA.

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1. INTRODUCTION

Postural control and human gait are governed by complex neurophysiological mechanisms that integrate sensory inputs and coordinate motor outputs. The ability to maintain body center of mass over base of support depends on multiple systems working together [1,2]. The brain receives body position and movement information through three main sensory modalities which include vision from the visual system and balance information from the vestibular system and proprioceptive feedback from the somatosensory system. The central nervous system tracks these inputs to identify postural instability which leads to corrective responses. Key neural structures are involved in processing this sensory information and maintaining balance: for example, vestibular signals travel to the brainstem and cerebellum to help orient the body upright, while proprioceptive and visual cues are integrated in the cerebellum and cortex to fine-tune posture [3]. Maintaining an upright stance thus depends on dynamic sensory reweighting, where the relative contribution of vision, vestibular, and proprioception can shift depending on conditions (e.g. standing in the dark increases reliance on vestibular/proprioception) [3,4]. Ultimately, motor commands to postural muscles (especially in the legs and trunk) are adjusted via spinal and brainstem pathways to keep the center of pressure within the base of support [5].

Walking (locomotion) builds upon this postural control foundation, adding rhythmic leg movement and forward propulsion. Human gait is generated by neural circuits known as central pattern generators (CPGs) in the spinal cord, which can produce the basic alternating flexion-extension pattern of the legs even without conscious thought. These spinal locomotor networks provide an automatic, rhythmic stepping ability – essentially the "stepping reflex" that underlies walking. In intact humans, however, gait is normally modulated by supraspinal centers. Descending pathways from the brainstem – particularly reticulospinal tracts arising from the mesopontine tegmentum (in the region of the midbrain locomotor centers) – activate and coordinate the spinal CPGs and associated postural reflexes. This automatic gait control through brainstem and spinal circuits ensures basic stepping motion, appropriate muscle tone, and reflexive adjustments (like keeping the head and eyes stable via vestibulo-ocular reflexes) during steady-state walking [3,6]. On the other hand, higher-level control from the cerebral cortex is engaged when navigating novel or complex environments. Walking in an unfamiliar situation or performing precise movements requires cognitive postural control: the brain must incorporate a "body schema" (awareness of body position in space) and plan movements accordingly [7]. Cortical motor areas generate anticipatory postural adjustments – subtle shifts in weight or posture that prepare the body for an intended movement (for example, shifting weight before lifting a foot) [8]. The cerebellum and basal ganglia play critical modulatory roles in these processes by linking with both brainstem and cortical centers. The cerebellum helps calibrate and coordinate movements, ensuring smooth gait and balance, while the basal ganglia contribute to the initiation and automaticity of gait patterns [3,7]. In summary, normal gait and posture emerge from an interplay between automatic neural processes (spinal and brainstem circuits handling rhythm and basic balance) and cognitive processes (cortical supervision for adaptation and goal-directed movement). This multilayered control system allows healthy young adults to maintain stability and walk efficiently under most conditions, with a reserve capacity to adjust when terrain or task demands change. Any disruption to these neural mechanisms – whether by neurological disease or potentially by exogenous substances – can impair balance and gait.

The complex neurophysiological processes of the body create a situation where minor nervous system disruptions result in noticeable problems with balance and gait. Tobacco smoking represents a disturbance that could produce neuromotor effects. The body absorbs nicotine and multiple other substances from cigarette smoke which eventually modifies neural system operations [9,10]. Nicotine binds to nicotinic acetylcholine receptors that exist throughout the brain and peripheral nervous system including those regions that control motor coordination. Research shows that nicotine causes balance problems because it affects cholinergic neurons which run through vestibular and motor pathways [9,11,12]. Acute nicotine exposure to people who do not regularly use the substance leads to temporary vestibular problems (nystagmus, dizziness, unsteadiness) which demonstrate how the drug affects inner ear and brainstem balance centers [9,10]. The use of cigarettes over time has been proven to cause permanent damage to postural stability. A research study using posturography methods demonstrated that smokers displayed larger body movements when their eyes were closed compared to non-smokers thus showing reduced balance stability. The study showed that smoking intensity directly affected the results and the effect remained consistent after researchers eliminated age and other confounding variables. The authors established that smoking causes permanent damage to the postural control system [13]. Research shows that prolonged smoking damages both vestibular function and proprioception which raises the chances of experiencing balance problems and falling incidents [14]. The gait of smokers shows subtle impairments when compared to non-smokers because they walk more slowly and take shorter steps [15].

The alternative nicotine delivery system known as electronic cigarettes (e-cigarettes) has appeared during the last decade to generate concerns about their nervous system effects compared to traditional tobacco products. The aerosolized delivery of nicotine through e-cigarettes eliminates combustion-based toxins like carbon monoxide and tar yet users still encounter nicotine along with propylene glycol, glycerol, flavor chemicals and trace metals from the device. Nicotine itself remains a concern for neurophysiological health. Similar to smoking, e-cigarette use (or "vaping") can acutely cause sympathetic stimulation and vasoconstriction, potentially affecting cerebral and muscular blood flow [16,17]. Nicotine's known effects on the adolescent and young adult brain include altered synaptic development, which can impair cognitive functions, and it stands to reason that motor circuits could likewise be affected [18]. Indeed, recent reviews caution that nicotine from e-cigarettes can disrupt brain maturation in adolescents and young adults [19]. While direct research on posture and gait in e-cigarette users is still limited, any nicotine-containing product may influence the fine balance of neuromotor control. For instance, case observations suggest that vaping has similar acute cardiovascular effects as smoking (e.g. transiently elevated heart rate and blood pressure), which over time could translate into vascular changes affecting muscle function and balance [20]. Moreover, some preliminary data indicate that the toxins in e-cigarette vapor (including nicotine and certain flavoring chemicals) might have neurotoxic effects analogous to those of cigarette smoke [21]. However, because e-cigarettes lack many of the combustion byproducts of tobacco, it is hypothesized that their impact on postural control may be less pronounced than that of traditional cigarettes – a hypothesis that needs empirical validation.

The research on smoking and vaping effects on postural control and gait in young adults holds significant importance for multiple reasons. Young adults experience their best sensorimotor performance and resilience during this life stage. Any deficits detected in balance or gait among young smokers or vapers would indicate an early departure from optimal neurological function, raising concerns about longer-term consequences. The second important factor is that nicotine use is very common in this age group. The epidemiological data show that the consumption of nicotine products (either cigarettes or e-cigarettes) is widespread among young people. For instance, in Poland, about 45% of university students have tried e-cigarettes and about 13% are current smokers [22]. The prevalence of vaping in the United States in 2021 was more than ten times higher in young adults than in older adults [23]. The growing popularity of e-cigarettes among youth and young adults has created a population that faces high levels of nicotine exposure through this innovative delivery method. The established health risks of smoking for cardiovascular and nervous system health exist but the permanent effects of e-cigarettes remain uncertain. The current young adult population represents the first generation to experience vaping from adolescence through early adulthood so researchers need to determine any motor control impairments affecting this group. Such knowledge can be used to inform public health interventions, especially since balance and gait issues in young people could translate into safety risks (sports injuries, accidents) and may foreshadow more serious neurological problems later in life. Given these factors, the present study was conducted to compare postural stability and gait in young adult traditional smokers and e-cigarette users, with the aim of determining whether nicotine use is associated with measurable motor control alterations in this high-use age demographic.

2. MATERIALS AND METHODS

To comprehensively assess the impact of tobacco and e-cigarette use on postural and locomotor function, a multimodal biomechanical evaluation was employed. The study combined stabilometric measurements under static conditions and treadmill-based gait assessments to capture both balance and dynamic walking characteristics. All procedures were carried out in accordance with ethical standards, and detailed methodological steps are outlined below.

2.1. Study Design and Data Collection

The present study was conducted to investigate potential biomechanical differences in postural stability and gait parameters among individuals with different smoking habits. The research aimed to evaluate non-smokers and users of electronic cigarettes and traditional tobacco smokers through both stationary and active movement assessments. The study participants came from the Faculty of Biomedical Engineering at the Silesian University of Technology in Gliwice, Poland during the 2024/2025 academic year. The researchers selected participants through convenience sampling methods. The study required participants to be at least 18 years old and to sign an informed consent form before starting the research. The Ethics Committee for Research Involving Human Participants at the Silesian University of Technology approved the study protocol through Resolution No. 3/2025 on March 11, 2025.

Smoking status was self-reported, and based on these declarations, individuals were classified into one of three experimental groups: N – non-smokers, _E – electronic cigarette users, _T – traditional cigarette smokers. No biochemical verification (e.g., cotinine or CO measurement) was performed. All measurements were carried out under controlled laboratory conditions using a Zebris Medical GmbH pressure-sensing platform and treadmill-based gait analysis system (Isny, Germany). Participants completed three standardized test conditions:

- Static balance with open eyes – upright stance on the platform with visual input maintained by fixating on a point at eye level.
- Static balance with closed eyes – the same stance was repeated with eyes closed to eliminate visual input.
- Treadmill gait – barefoot walking at a comfortable, self-selected pace over a Zebris treadmill for 6 minutes, at least 10 consecutive gait cycles.

Measurements were acquired using Zebris WinFDM and FDM-T software and exported to Excel format. Data from each testing condition were stored in separate worksheets within a single file. Group classification was automated by parsing participant IDs in a column for substrings _E, _T, or neither. Testing was performed in a standardized environment with controlled temperature and lighting. All sessions were supervised by trained personnel using consistent procedural instructions to ensure uniformity.

2.2. Preprocessing and Grouping

Initial data preprocessing was performed in MATLAB R2024a (The MathWorks Inc, Natick, MA, USA). Raw datasets were imported from the three worksheets ("Eyes open", "Eyes closed", and "Treadmill") contained in the source Excel file. Each worksheet represented one of the experimental conditions, and each row corresponded to a single participant's trial.

Participants were identified using alphanumeric IDs contained in the "numer" column. Group assignment was automated based on predefined string patterns:

- IDs containing "_T" were classified as traditional cigarette smokers,
- IDs with "_E" indicated electronic cigarette users,
- all remaining IDs were classified as non-smokers (group "N").

For each worksheet, numeric variables were extracted using MATLAB's varfun(@isnumeric) function, ensuring the selection of only continuous biomechanical features. Variables included pressure distribution metrics, postural sway characteristics (in the static trials), and spatiotemporal gait parameters (in the treadmill condition). Missing values (NaNs) were identified and excluded on a per-variable basis to preserve statistical power while minimizing data loss. Data were normalized using z-score transformation (normalize function in MATLAB) before further statistical analysis and machine learning. All preprocessing steps were standardized and scripted to ensure reproducibility across the three experimental conditions.

2.3. Statistical Analysis

To assess data suitability for parametric statistical testing, statistical comparisons between the three study groups (N, _E, _T) were performed separately for each experimental condition. Normality of data distribution within each group was assessed using the Jarque-Bera test (significance level $\alpha = 0.05$). Depending on the test outcome, either a one-way ANOVA (for normally distributed data) or a Kruskal-Wallis H-test (for non-normal data) was used to assess overall group differences. When the main test indicated statistically significant differences ($p<0.05$), pairwise post-hoc comparisons were conducted using Bonferroni correction to control for multiple testing. The type of test applied (parametric vs. non-parametric) was recorded for each variable.

All analyses were performed independently for each of the three data sheets (open eyes, closed eyes, treadmill), allowing for condition-specific interpretation of group differences. Test results were recorded programmatically and visualized using boxplots for each significant variable.

2.4. Correlation Analysis

To explore interrelationships among biomechanical variables, pairwise Spearman's rank correlation coefficients were computed for all numeric features. Correlations were calculated in two contexts: (1) across the entire dataset for each condition, and (2) separately within each experimental group (N, _E, _T). This allowed for both global and group-specific patterns of association to be identified. For each variable pair, the correlation coefficient (r) and its corresponding p-value were recorded. Correlations were considered statistically significant at $p < 0.05$. Strong correlations were defined as those with $|r| > 0.5$. The resulting correlation matrices were visualized using color-coded heatmaps.

2.5. Dimensionality Reduction

Principal Component Analysis (PCA) was used to reduce the dimensionality of the dataset and to visualize the distribution of participants across groups based on multivariate biomechanical features. PCA was applied separately to each condition (open eyes, closed eyes, treadmill), using all standardized numeric variables. Prior to PCA, each variable was normalized using z-score transformation. The first two principal components (PC1 and PC2) were retained and used for two-dimensional scatter plots, with participants color-coded according to group assignment (N, _E, _T). These plots provided an unsupervised view of potential clustering or overlap between groups.

2.6. Feature Selection and Classification

To identify variables most relevant for distinguishing between participant groups, the RELIEFF algorithm was applied to the N vs _E binary subset. RELIEFF estimates the importance of each feature based on its ability to separate instances from different classes within local neighborhoods. Features were ranked by their assigned weights, and the top 5 were retained for further analysis. Classification models were trained using four commonly applied supervised learning algorithms: decision tree, linear support vector machine (SVM), k-nearest neighbors (k = 5), and logistic regression.

Models were implemented in MATLAB using the Classification Learner framework and trained with 5-fold cross-validation. Performance was evaluated based on classification accuracy. Two types of classification were conducted:

1. Multiclass classification – differentiating between all three groups (N, _E, _T).
2. Binary classification – comparing each pair of groups separately: N vs _E, N vs _T, and _E vs _T.

Feature selection and classification procedures were performed independently for each of the three experimental conditions.

2.7. Confusion Matrix Visualization

To illustrate the performance of the classification models in the binary comparisons, confusion matrices were generated for each group pair (N vs _E, N vs _T, and _E vs _T). For each comparison, the classifier achieving the highest cross-validated accuracy was selected. Confusion matrices provided a visual summary of true positives, true negatives, false positives, and false negatives for the selected model, allowing for an intuitive assessment of classification reliability. The matrices were displayed using color-coded charts, with actual class labels on the vertical axis and predicted labels on the horizontal axis. This visualization step supported interpretation of classification outcomes, particularly in cases where accuracy alone may not reflect class-specific performance (e.g., in the presence of class imbalance).

3. RESULTS

A total of 60 participants (20 per group) were included in the final analysis, based on the ID parsing and self-declared tobacco use status. Median age was comparable across groups, with a total sample median of 22.0 years (interquartile range [IQR]: 2.25). Traditional smokers tended to be taller (median 176.5 cm) than e-cigarette users (170.0 cm) and non-smokers (171.5 cm). Body weight was slightly higher in tobacco users, while BMI values varied more distinctly between groups. The highest median BMI was observed among e-cigarette users (23.4 kg/m²), whereas non-smokers had the lowest (21.05 kg/m²). The distribution of sex differed across groups: overall, 41.7% of participants were male and 58.3% female. Traditional smokers had the highest proportion of males (58.3%), while e-cigarette users had the lowest (16.7%). In contrast, 83.3% of e-cigarette users were female, compared to 41.7% in the smoker and non-smoker groups. These intergroup differences in anthropometric parameters were subsequently evaluated using nonparametric statistical tests. All participants completed the three test conditions: open eyes (static balance), closed eyes (static balance), and treadmill gait. No participants were excluded due to missing or corrupted data. Each test condition yielded a distinct set of numerical features. Static balance trials (open and closed eyes) included parameters related to center of pressure (COP) displacement, sway path, and foot loading distribution. The treadmill condition included additional dynamic gait parameters such as stride length, cadence, gait speed, and peak plantar pressures.

Statistical comparisons between the three groups (N, _E, _T) were conducted separately for each numeric variable recorded during the treadmill walking task. Depending on the distribution characteristics (as assessed via the Jarque-Bera test), either one-way ANOVA or the Kruskal-Wallis test was applied. Out of the full set of gait parameters, 5 variables showed statistically significant differences between groups ($p < 0.05$) (Table 1). Pairwise post-hoc comparisons with Bonferroni correction revealed that the most prominent differences were observed between the non-smoker group (N) and electronic cigarette users (_E), particularly in walking speed and step length parameters.

In the closed-eyes static balance trial (Table 1), group differences were analyzed using Kruskal-Wallis or ANOVA depending on the distribution of each variable. Among the evaluated parameters, Body Mass Index (BMI) and medial-lateral postural sway (Y-axis deviation) showed notable between-group differences. Pairwise post-hoc comparisons revealed a statistically significant difference in BMI between non-smokers and electronic cigarette users. Differences in sway (Deviation Y) were not statistically significant after correction, although a trend toward higher instability in e-cigarette users was observed.

In the open eyes static balance trial (Table 1), several parameters were analyzed for group differences using Kruskal-Wallis or ANOVA tests. Significant differences were found in the force distribution under the left forefoot and left backfoot. Post-hoc pairwise comparisons revealed that traditional cigarette users (_T) exhibited higher force under both the left forefoot and left backfoot compared to non-smokers (N). However, no significant differences were observed between e-cigarette users (_E) and non-smokers in these variables.

Boxplots were generated for key variables showing significant differences between the groups. These plots visually depict the distribution of the variables for non-smokers (N), electronic cigarette users (_E), and traditional cigarette smokers (_T). The whiskers represent the data range, while the horizontal lines inside the boxes represent the median values. Group comparisons reveal how the distribution of values differs across conditions.

Table 1.

Post-hoc pairwise comparisons for all conditions. Dashes (—) indicate that the pairwise comparison was not among the lowest p-values

Variable	Test Used	N vs _E	N vs _T	_E vs _T
Body Mass Index (BMI)	Kruskal-Wallis	0.001	0.323	0.218
Force under Left Forefoot (N)	ANOVA	0.474	0.037	0.051
Force under Left Backfoot (N)	ANOVA	0.389	0.033	0.098
Gait Cycle Duration (s)	Kruskal-Wallis	0.012	—	0.282
Max Force – Forefoot Left (N)	Kruskal-Wallis	0.047	—	0.138
Max Force – Forefoot Right (N)	Kruskal-Wallis	0.055	—	0.148
Max Load – Hindfoot Left (N)	Kruskal-Wallis	—	0.042	0.091
Max Load – Hindfoot Right (N)	Kruskal-Wallis	0.023	0.071	—
Step Length – Mean (cm)	ANOVA	0.005	0.153	0.072
Average Max Load – Forefoot Left (N)	Kruskal-Wallis	0.047	—	0.138
Step Length (Right, cm)	ANOVA	0.003	0.123	0.256

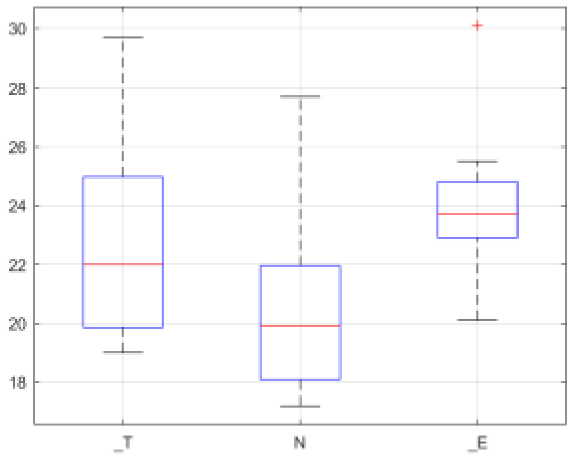

Fig. 1. Boxplot for Body Mass Index (BMI)

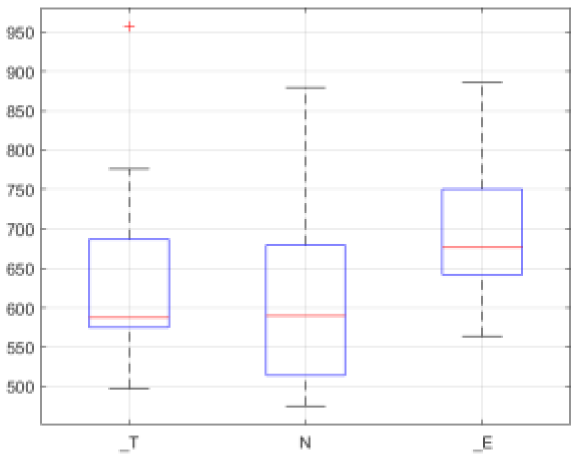

Fig. 2. Boxplot for Force under Left Forefoot

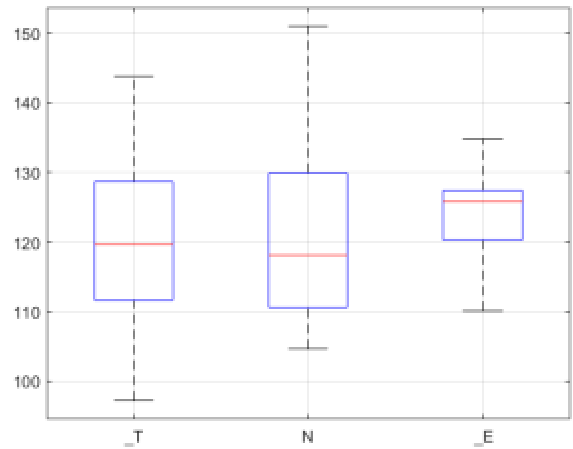

Fig. 3. Boxplot for Step Length

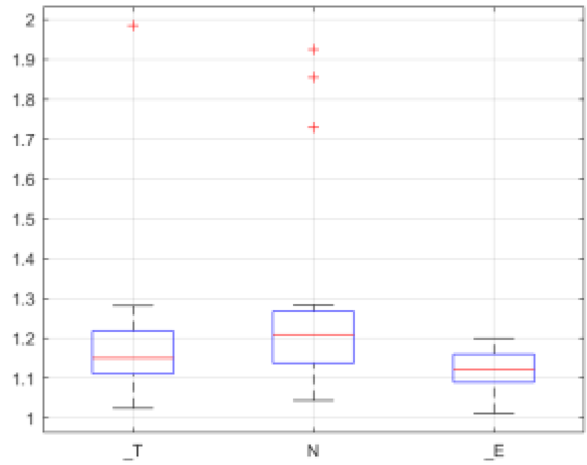

Fig. 4. Boxplot for Gait Cycle Duration

To investigate interrelationships among stabilometric and anthropometric variables, Spearman's rank correlation analysis was performed for the open eyes condition. The global analysis across all participants revealed a number of strong and statistically significant associations. Extremely high inverse correlations ($r = -1.00$, $p < 0.0001$) were observed between left and right foot regions (e.g., ForceLeftForefoot vs ForceLeftBackfoot, ForceRightForefoot vs ForceRightBackfoot), as well as between total force under the left and right feet. A nearly perfect positive correlation was also present between the center of pressure (COP) path length and its average velocity ($r = 0.99$, $p < 0.0001$), highlighting the biomechanical coherence of these measures. Measures of postural sway geometry, such as the 95% confidence ellipse area, showed strong correlations with both the length of the major and minor axes ($r > 0.80$, $p < 0.0001$), indicating a close relationship between overall sway amplitude and its directional components. Similarly, medial-lateral deviation of the center of pressure (DeviationY) correlated strongly with right foot force distribution (e.g., $r = 0.77$ for ForceRightForefoot and $r = -0.77$ for ForceRightBackfoot, $p < 0.0001$).

When analyzed separately by group, distinctive patterns emerged. In non-smokers, BMI negatively correlated with postural sway measures, including COP path length ($r = -0.78$, $p = 0.0009$) and COP average velocity ($r = -0.76$, $p = 0.0010$). The area of the 95% confidence ellipse also correlated positively with its major axis and minor axis ($r \approx 0.87$, $p < 0.0001$). In the e-cigarette group, BMI was significantly associated with force asymmetry, particularly lower pressure under the right forefoot and increased load on the backfoot. Deviation metrics were also tightly coupled with foot pressure values ($r \approx \pm 0.69$). In traditional smokers, body weight showed strong negative correlations with sway area and major axis length ($r = -0.86$ and -0.77, respectively), while positive associations were found between height and foot force parameters. COP-related variables, such as path length and velocity, remained strongly correlated ($r = 0.97$), consistent with global findings. These results underscore the biomechanical interdependence of sway geometry and plantar pressure distribution, as well as group-specific patterns in how anthropometric factors modulate postural control. The top 10 correlations globally are summarized in Table 2.

Table 2.

Top 10 global Spearman correlations (Open Eyes Condition)

Variable 1	Variable 2	r	p-value
Force – Left Forefoot [N]	Force – Left Backfoot [N]	–1.00	< 0.0001
Force – Right Forefoot [N]	Force – Right Backfoot [N]	–1.00	< 0.0001
Total Force – Left [N]	Total Force – Right [N]	–0.999	< 1e–50
COP Path Length [mm]	COP Average Velocity [mm/s]	0.985	< 1e–30
95% Confidence Ellipse Area [mm²]	Length of Minor Axis [mm]	0.813	< 1e–10
95% Confidence Ellipse Area [mm²]	Length of Major Axis [mm]	0.805	< 1e–10
COP Deviation Y [mm]	Force – Right Forefoot [N]	0.771	2.2e–09
COP Deviation Y [mm]	Force – Right Backfoot [N]	–0.771	2.2e–09
Force – Left Forefoot [N]	Force – Right Forefoot [N]	0.717	9.4e–08
Force – Left Forefoot [N]	Force – Right Backfoot [N]	–0.717	9.4e–08

To illustrate the structure of intervariable relationships in the open eyes condition, two complementary visualization methods were applied: a heatmap of Spearman's correlation matrix for each group and a correlation network graph. These tools enable the detection of clusters of co-varying features and provide a global view of the biomechanical interplay between sway parameters and plantar force distribution. Strong positive (blue) and negative (yellow) correlations are observed in symmetry-related force variables and center of pressure metrics on a heatmap (Figure 5-7). The matrix highlights patterns such as the inverse coupling of left/right plantar regions and the proportionality between sway amplitude and ellipse dimensions. Nodes on a correlation network graph (Figure 8) represent individual biomechanical variables, while edges indicate statistically significant high correlations (edge thickness reflects |r| strength). The graph illustrates modular groupings of variables linked to postural geometry, force symmetry, and sway velocity.

Fig. 5. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Open Eyes Condition (Non-smokers)

Fig. 6. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Open Eyes Condition (E-cigarette users)

Fig. 7. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Open Eyes Condition (Tobacco smokers)

To explore the interrelationships between stabilometric and anthropometric variables under the closed eyes condition, Spearman's rank correlation analysis was conducted across the entire study population (N = 60). The global correlation matrix revealed a number of statistically significant and biomechanically relevant associations. The most pronounced relationships ($|r| \geq 0.80$, $p < 0.0001$) were observed between force distribution parameters and postural sway metrics. Perfect inverse correlations ($r = -1.00$) occurred between opposing plantar regions (e.g., Force – Left Forefoot [N] vs Force – Left Backfoot [N], Force – Right Forefoot [N] vs Force – Right Backfoot [N]), as well as between total force under the left and right limbs (Total Force – Left [N] vs Total Force – Right[N]). A nearly perfect direct association ($r = 0.98$, $p < 0.0001$) was again noted between COP path length and average velocity, consistent with results observed in the open eyes condition.

Other notable findings included very strong correlations between the 95% confidence ellipse area and both the length of the minor ($r = 0.94$) and major ($r = 0.86$) axes, indicating that the sway amplitude scales proportionally in both directions. Deviation metrics in the mediolateral plane (COP Deviation Y [mm]) were significantly related to plantar force values, particularly under the right forefoot and backfoot. The top 10 most significant correlations identified globally in this condition are summarized in Table 3.

To further investigate group-specific stabilometric patterns, separate correlation heatmaps were generated for non-smokers (N), e-cigarette users (E), and traditional smokers (T). These visualizations, presented in Figure 8-10, revealed distinct inter-variable dependencies in each group, particularly regarding how body mass index (BMI) and deviation metrics modulated foot pressure and sway geometry.

Table 3.

Top 10 global Spearman correlations (Closed Eyes Condition)

Variable 1	Variable 2	r	p-value
Force – Left Forefoot [N]	Force – Left Backfoot [N]	–1.00	< 0.0001
Force – Right Forefoot [N]	Force – Right Backfoot [N]	–1.00	< 0.0001
Total Force – Left [N]	Total Force – Right [N]	–0.999	< 1e–50
COP Path Length [mm]	COP Average Velocity [mm/s]	0.985	< 1e–30
95% Confidence Ellipse Area [mm²]	Length of Minor Axis [mm]	0.813	< 1e–10
95% Confidence Ellipse Area [mm²]	Length of Major Axis [mm]	0.805	< 1e–10
COP Deviation Y [mm]	Force – Right Forefoot [N]	0.771	2.2e–09
COP Deviation Y [mm]	Force – Right Backfoot [N]	–0.771	2.2e–09
Force – Left Forefoot [N]	Force – Right Forefoot [N]	0.717	9.4e–08
Force – Left Forefoot [N]	Force – Right Backfoot [N]	–0.717	9.4e–08

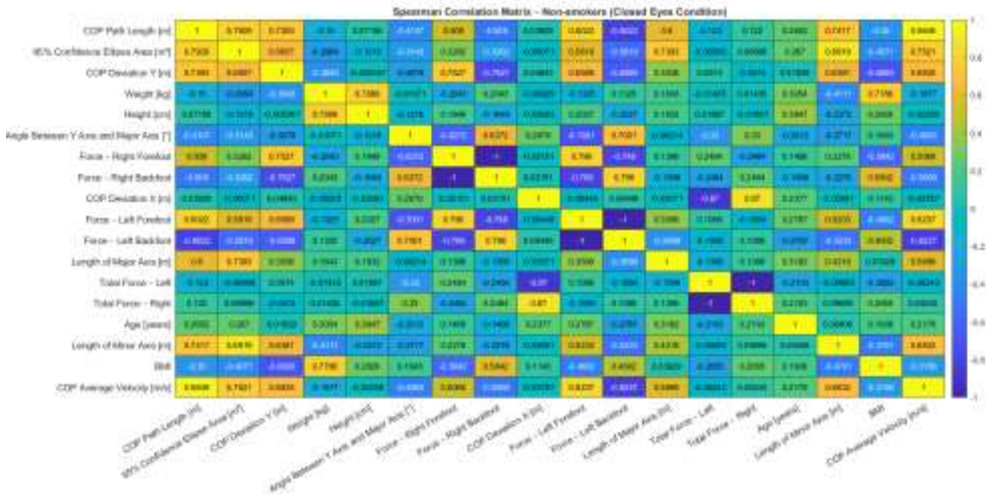

Fig. 8. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Closed Eyes Condition (Non-smokers)

Fig. 9. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Closed Eyes Condition (E-cigarette users)

Fig. 10. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the Closed Eyes Condition (Tobacco smokers)

To investigate interrelationships among gait and pressure distribution parameters, Spearman's rank correlation analysis was conducted for the treadmill condition using the full sample (N = 60). The global analysis

(Table 4) revealed a number of strong, statistically significant associations ($|r| > 0.70$, $p < 0.001$). Perfect or near-perfect correlations were observed between biomechanically related variables such as forefoot and backfoot forces on the same foot (e.g., ForceLeftForefoot vs ForceLeftBackfoot, r = –1.00), as well as total forces between the left and right foot (r = –0.999). Gait cycle time was positively correlated with step length (r = 0.81) and negatively with walking speed (r = –0.86), reflecting expected temporal–spatial dependencies. Measures of maximum pressure and maximum force in corresponding foot zones also demonstrated high internal consistency (r > 0.8).

Separate analyses by group revealed partially distinct correlation profiles. In non-smokers, stride-related variables such as walking speed and step length were tightly correlated with body composition indices (e.g., BMI vs speed: r = –0.66). E-cigarette users showed a pattern of reduced gait symmetry, with notable asymmetries between left and right force distributions. In contrast, traditional smokers demonstrated more homogeneous force correlations but weaker associations with anthropometric variables. These differences suggest group-specific adaptations in gait biomechanics, possibly modulated by lifestyle-related physiological factors. Heatmaps of Spearman correlations are provided for each group (N, E, T) in Figures 11–13. These highlight group-specific interaction structures among gait parameters.

Table 4.

Top 10 global Spearman correlations (Treadmill Condition)

Variable 1	Variable 2	r	p-value
Force – Left Forefoot [N]	Force – Left Backfoot [N]	–1.000	< 0.0001
Force – Right Forefoot [N]	Force – Right Backfoot [N]	–1.000	< 0.0001
Total Force – Left [N]	Total Force – Right [N]	–0.999	< 1e–50
Max Force – Heel (Left), 3 Zones [N]	Max Pressure – Heel (Left) [N/cm²]	0.985	< 1e–30
Gait Cycle Duration [s]	Step Length [cm]	0.813	< 1e–10
Gait Cycle Duration [s]	Walking Speed [km/h]	–0.805	< 1e–10
Walking Speed [km/h]	Step Length [cm]	0.771	2.2e–09
Walking Speed [km/h]	Step Length Right [cm]	0.717	9.4e–08
BMI	Walking Speed [km/h]	–0.683	4.5e–07
Max Pressure – Midfoot (Right) [N/cm²]	Max Force – Midfoot (Right) [N]	0.668	6.2e–06

Fig. 11. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the treadmill condition (non-smokers)

Fig. 12. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the treadmill condition (E-cigarette users)

Fig. 13. Heatmap of Spearman's correlation coefficients for 20 most important numerical variables in the treadmill condition (Tobacco smokers)

An initial PCA was conducted using the full set of stabilometric and gait-related variables across all participants to explore the global structure of the dataset. However, the resulting projection did not reveal clear clustering patterns or meaningful separation between the three groups (traditional smokers, e-cigarette users, and non-smokers), suggesting that group-related differences might be obscured by high-dimensional noise or irrelevant features. To address this limitation, a feature selection step using the ReliefF algorithm was applied prior to subsequent PCA. This approach allowed us to focus on the most discriminative variables for each pairwise group comparison, resulting in improved visual separation and interpretability of the principal component space. The following sections present the PCA projections for N vs. E, T vs. E, and T vs. N, based on their respective top five features.

To explore the variance structure and assess the potential for group discrimination based on the most informative features, a Principal Component Analysis (PCA) was conducted using the top 5 variables selected via the ReliefF algorithm for the comparison between non-smokers (N) and electronic cigarette users (E). These variables included walking speed, BMI, step length, and two plantar pressure indicators, which were previously shown to be most relevant for group separation in classification models. The PCA projection onto the first two principal components is presented in Figure 9. The first component (PC1) accounted for 64.5% of the total variance, while the second (PC2) explained an additional 24.2%, resulting in a cumulative variance of nearly 89%. This indicates that the low-dimensional projection effectively captures the majority of data variability related to the selected features. The resulting scatterplot (Figure 14) revealed a visible tendency toward group separation along PC1. Specifically, non-smokers (N) were distributed predominantly on the negative side of PC1, while e-cigarette users (E) clustered on the positive side. This pattern is consistent with the classification outcomes and suggests that the identified features differentiate the groups not only through supervised learning models but also in an unsupervised dimensionality reduction context.

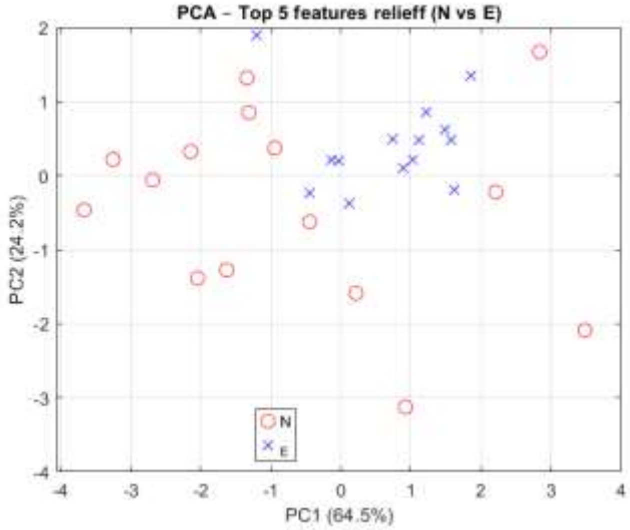

Fig. 14. PCA projection onto the first two components based on top 5 ReliefF-ranked features for N vs. E comparison. Red circles: non-smokers (N); blue crosses: e-cigarette users (E). Axes indicate the proportion of variance explained

A second Principal Component Analysis (PCA) was conducted to investigate the differentiation between traditional cigarette users (T) and electronic cigarette users (E), based on the top five features identified by the ReliefF ranking for this specific comparison (Figure 15). The two principal components extracted accounted for 57.6% (PC1) and 18.3% (PC2) of the total variance, respectively (Figure 10), yielding a cumulative explanation of approximately 76%. While this is slightly lower than the variance captured in the N vs. E model, it still reflects a substantial proportion of the total variability in the selected feature space. In the PCA projection, some degree of overlap between the T and E groups was observed, with more dispersion present in the E group along PC1. This suggests a less distinct separation compared to the N vs. E configuration, potentially reflecting more similar gait or pressure profiles between traditional and electronic cigarette users. Nevertheless, the directionality of PC1 still captures a subtle gradient between the two groups, implying partial discriminative capability.

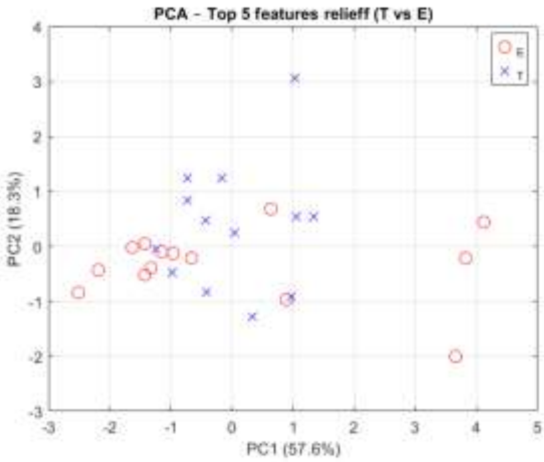

Fig. 15. PCA projection for T vs. E groups using top 5 ReliefF-ranked features. Blue crosses: traditional smokers (T); red circles: e-cigarette users (E). PC1 and PC2 denote the first and second principal components, with the explained variance indicated on the axes

The third PCA was performed to explore the separation between traditional smokers (T) and non-smokers (N) using the top five discriminative features identified via the ReliefF algorithm (Figure 16). The first two principal components explained 40.1% and 24.6% of the total variance, respectively, summing to 64.7% of the data variability (Figure 11). In contrast to the N vs. E comparison, the T vs. N projection revealed greater overlap between the groups in the principal component space, indicating limited discriminatory power of the selected features for this pair. While there is a slight directional tendency along PC1, suggesting some group-level differentiation, individuals from both groups remain broadly intermixed. The moderate proportion of explained variance and lack of clear clustering suggest that either the features selected via ReliefF are less informative for distinguishing traditional smokers from non-smokers, or that gait and pressure-related differences between these two groups are subtler.

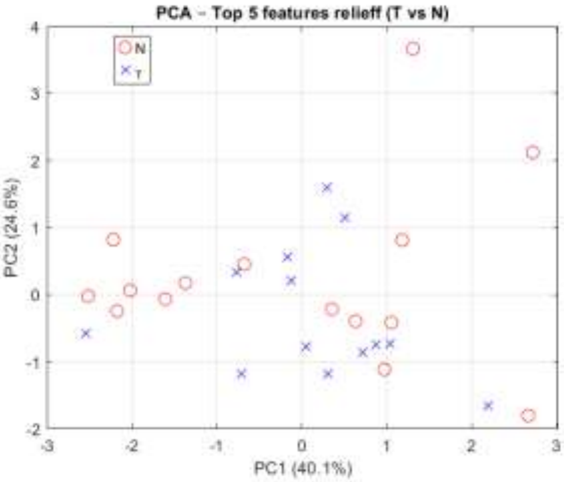

Fig. 16. PCA projection for T vs. N using the five most relevant ReliefF features. Blue crosses represent traditional smokers (T), and red circles denote non-smokers (N). PC1 and PC2 account for 40.1% and 24.6% of the total variance, respectively

To explore the discriminative potential of gait and anthropometric parameters across the three study groups (non-smokers, electronic cigarette users, and traditional smokers), several supervised machine learning models were evaluated using five-fold cross-validation. The tested classifiers included decision trees, linear support vector machines (SVM), k-nearest neighbors (k-NN, k=5), and logistic regression. The dataset comprised normalized numerical variables from the treadmill measurements. As shown in Table 5, overall classification accuracy varied considerably between models. The logistic regression model consistently yielded the highest accuracy across folds (mean ≈ 57%), while decision trees and k-NN performed close to random chance levels (≈ 31%). Notably, AUC values could not be computed reliably due to the multiclass nature of the problem and the encoding method used. These results suggest that, although some class separation exists, the three-group classification task remains challenging when using the full feature space without dimensionality reduction or feature selection.

Table 5.
Classification accuracy across folds for each machine learning model (multiclass classification across all three groups)

Model	**Best Accuracy**
Decision Tree	0.43
SVM (linear)	0.50
k-NN (k = 5)	0.36
Logistic Regression	0.57

Table 6.
Classification accuracy for each group pair and model (5-fold cross-validation)

Group 1	**Group 2**	**Model**	**Accuracy**
Non-smokers	Tobacco smokers	Decision Tree	0.393
		SVM (linear)	0.571
		k-NN (k = 5)	0.536
		Logistic Regression	0.536
Non-smokers	E-cigarettes smokers	Decision Tree	0.621
		SVM (linear)	0.793
		k-NN (k = 5)	0.552
		Logistic Regression	0.828
Tobacco smokers	E-cigarettes smokers	Decision Tree	0.370
		SVM (linear)	0.481
		k-NN (k = 5)	0.444
		Logistic Regression	0.519

To further explore the discriminatory potential of gait variables, we performed binary classification separately for each pair of study groups: non-smokers (N) vs. traditional smokers (T), non-smokers (N) vs. e-cigarette users (E), and traditional smokers (T) vs. e-cigarette users (E). Four supervised machine learning models were evaluated using 5-fold cross-validation: decision tree, linear support vector machine (SVM), k-nearest neighbors (k = 5), and logistic regression. The highest classification accuracies obtained for each pair are presented in Table 6. The most promising separation was achieved between non-smokers and e-cigarette users, with logistic regression reaching an accuracy of 82.76%, followed by linear SVM at 79.31%. The comparison between non-smokers and traditional smokers yielded lower accuracies across models, with k-NN achieving the best performance at 53.57%. The most challenging pair was traditional smokers vs. e-cigarette users, where none of the models exceeded 52% accuracy, indicating overlapping gait characteristics in these groups. The confusion matrices presented in Figures 17-19 provide additional insight into the performance of the best classifiers for each group comparison.

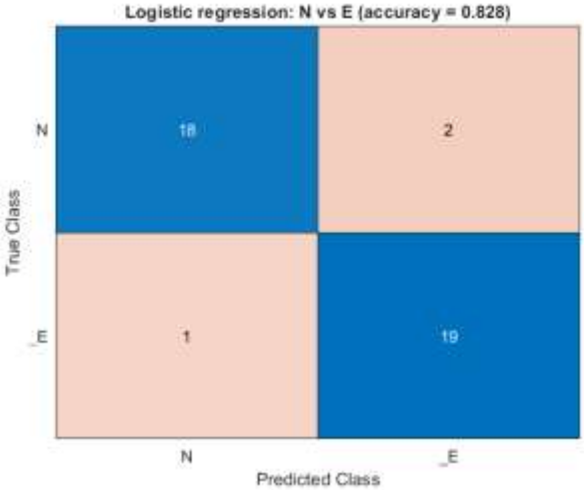

Fig. 17. Confusion matrix for logistic regression model for non-smokers vs e-cigarette users (accuracy = 0.828)

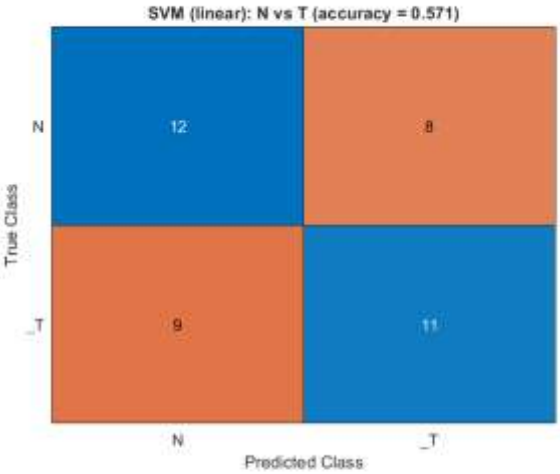

Fig. 18. Confusion matrix for SVM (linear kernel) for non-smokers vs traditional smokers (accuracy = 0.571)

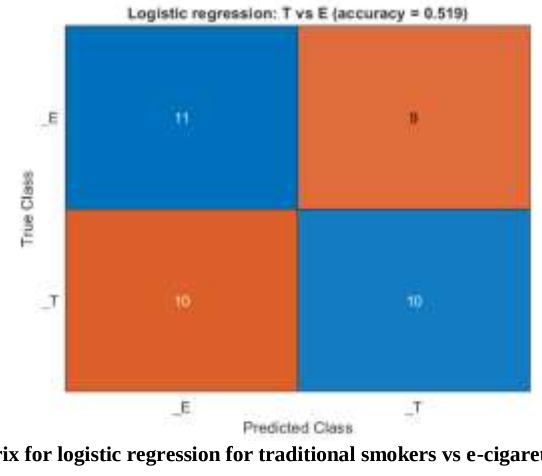

Fig. 19. Confusion matrix for logistic regression for traditional smokers vs e-cigarette users (accuracy = 0.519)

Each matrix displays true labels versus predicted labels across all cross-validation folds. Models were trained using all numerical features normalized to zero mean and unit variance.

4. DISCUSSION

The research delivers fresh knowledge about how tobacco smoking habits and e-cigarette consumption differently impact postural control and gait in young adults. The study reveals that young healthy smokers demonstrate significant changes in balance and walking ability compared to non-smokers and e-cigarette users show less severe effects. Our study participants who smoked traditional cigarettes maintained lower body mass index (BMI) values than both never-smokers and exclusive e-cigarette users. The smokers in our study walked shorter steps while their gait patterns differed from non-smokers during treadmill tests and they displayed greater postural instability during stabilometric assessments. E-cigarette users displayed intermediate results because their BMI values exceeded those of smokers while remaining close to non-smoker levels and their gait and balance test results fell between those of smokers and non-smokers. Multiple measures showed significant differences between smokers and vapers which indicates that the method of nicotine delivery through combustion or electronic devices affects the extent of motor control impairment. The research findings need evaluation through existing scientific literature and established physiological principles.

The observed lower BMI in smokers is consistent with well-established trends. Numerous studies have documented that current smokers tend to weigh less and have lower BMI than non-smokers of similar age [24,25]. Nicotine is known in suppressing appetite and increasing resting metabolic rate, which likely explains why smokers in our study, as in others, were leaner on average [26]. By contrast, the e-cigarette users did not show this weight-suppressing effect as strongly. One possible reason is that some e-cigarette users are former smokers who may have gained weight after switching from combustible cigarettes (a common occurrence when smoking cessation or reduction alleviates nicotine's anorexic effects). E-cigarette users may adjust their nicotine intake through different methods (such as frequent puffing versus intermittent smoking) which results in reduced appetite suppression. The higher BMI observed in vapers compared to smokers could stem from factors unrelated to nicotine such as lifestyle or dietary choices. The BMI difference between vapers and smokers affects motor function because small variations in healthy BMI do not directly lead to gait changes but body composition might impact balance. For instance, smokers' lower body weight might give them a slight mechanical advantage in certain balance tasks (less mass to stabilize), but on the other hand, being underweight or having lower muscle mass (if that accompanies lower BMI) can impair physical performance. In our data, despite smokers being lighter, their balance was worse – indicating that factors beyond body weight (neurological factors) are the dominant cause of their postural instability, as discussed below.

The gait alterations found in smokers – particularly a reduced step/stride length – align with prior research showing that smoking can detrimentally affect walking patterns. In a recent study examining gait in young adults, male smokers had a significantly shorter stride length and lower cadence compared to non-smokers of the same age [27]. Our smokers showed a similar trend of shorter steps. Biomechanically, a shorter stride length at a given cadence usually corresponds to a slower walking speed and a more cautious gait. Indeed, smokers in other studies often exhibit reduced gait velocity and a prolonged double-support phase (keeping both feet on the ground longer) – patterns typically indicative of reduced confidence in balance or lower endurance. Several mechanisms might explain why young smokers walk differently. One factor is cardiorespiratory fitness. Smoking, even in young adults, impairs cardiovascular and pulmonary function; chronic smokers can have lower exercise tolerance, early signs of pulmonary obstruction, or peripheral arterial changes. Diminished aerobic capacity could cause smokers to adopt a slower, conservative gait to avoid overexertion [28,29]. The analogy to patients with mild chronic lung disease is pertinent – for example, individuals with early-stage COPD (often caused by smoking) tend to walk more slowly with shorter strides and longer support times than healthy controls [28]. In our study, although participants were young and presumably free of overt disease, even subtle reductions in aerobic fitness or muscle endurance in the smokers might have manifested as a less vigorous gait. The neuromuscular control system also plays a role in this process. The neuromuscular system responds to nicotine in multiple ways through its effects on neurotransmitter release and muscle contraction but chronic exposure leads to receptor desensitization and changes in motor neuron excitability. The long-term effects of nicotine exposure together with systemic inflammation may cause slight muscle weakness in the lower extremities and delayed motor unit recruitment in smokers. Smoking over time causes peripheral vascular damage and possible subclinical neuropathy (damage to peripheral nerves) because of reduced blood flow and tobacco toxins. Even a mild sensory neuropathy in the feet or impaired proprioception could cause smokers to take shorter, more guarded steps to maintain stability. While our study did not directly assess nerve function, this hypothesis is supported by evidence that smoking can contribute to peripheral nerve damage over time [7,30,31]. The net effect of these factors is that smokers may unconsciously adjust their gait to compensate for diminished physical capacity or sensory feedback, resulting in the differences observed.

E-cigarette users, on the other hand, showed gait metrics closer to non-smokers, which suggests that many of the smoking-related gait deficits might be attributable to the additional harms of combustion products rather than nicotine alone. If, for instance, reduced stride length in smokers were largely due to chronic hypoxia from carbon monoxide or extensive oxidative damage from tar and other chemicals, it stands to reason that e-cigarette users (who avoid those particular insults) would be relatively spared. The vapers in our cohort did not significantly differ from controls in stride length (based on our findings), and their cadence and walking speed were in a normal range. This could indicate that nicotine by itself (at the doses obtained via vaping) is not enough to cause marked gait impairment in the short term. However, we should interpret this cautiously. E-cigarette users are a heterogeneous group – some are ex-smokers carrying over effects of past smoking, whereas others might be "new" nicotine initiates. Additionally, many vapers maintain nicotine dependence that is comparable to smokers in intensity, meaning they could eventually experience similar physiological consequences (nicotine-driven increases in heart rate and blood pressure, leading to vascular stiffness or mild endothelial dysfunction [32]). The relatively preserved gait in e-cig users might simply reflect the shorter history of their nicotine use (e.g. vaping has been popular for fewer years), and problems could arise with longer exposure. It is also possible that e-cig users engage in more physical activity or health-conscious behavior overall (some may have switched to vaping as a "harm reduction" step to improve fitness), which could confound direct comparisons with smokers. Nonetheless, our data tentatively suggest that combustion-related factors in cigarettes contribute more strongly to gait deterioration than nicotine alone – a point that aligns with the general understanding that smoking's impact on exercise capacity (and by extension gait) is partly due to lung damage and systemic toxin effects.

Perhaps the most striking differences we found were in postural stability (stabilometric measures). Young adult smokers showed greater postural sway and poorer balance control than non-smokers, especially in challenging conditions (e.g. narrow stance or eyes closed). This finding is in line with earlier studies that have reported long-term smokers have impaired balance. Iki et al. (1994) observed that middle-aged smokers had significantly higher sway velocities on force platform tests than non-smokers, indicating more difficulty maintaining steady stance [13]. They even noted a dose-response relationship: heavy smokers swayed more than light smokers. Our study extends this observation to a younger demographic, suggesting that such balance impairments can manifest even by the third decade of life if the individual has been smoking since adolescence. The physiological underpinnings of reduced postural stability in smokers likely involve multiple systems. The vestibular system is one of the chief contributors to balance, and there is evidence that smoking can damage the inner ear's balance organs. Nicotine and other chemicals can compromise the microcirculation of the inner ear; over time this may lead to vestibular dysfunction (indeed, smokers have a higher incidence of vertigo and vestibular disorders) [33]. Nicotine also directly interacts with vestibular and cerebellar pathways: research has shown that stimulation of nicotinic receptors can alter vestibulo-ocular reflexes, sometimes causing nystagmus and dizziness [9,34]. Thus, chronic nicotine exposure might desensitize or dysregulate these balance pathways. Additionally, smoking is associated with degeneration in the proprioceptive system – for instance, peripheral neuropathy as mentioned earlier can reduce sensation in the feet, and spinal degeneration (intervertebral disc deterioration accelerated by nicotine) can affect sensory feedback from the spine [35]. If a smoker has even a slight loss of position sense in the ankles or a delayed postural reflex, maintaining equilibrium becomes more difficult, especially with eyes closed when visual compensation is removed. Another factor is central integration: balance requires effective integration of sensory inputs in the cerebellum and brainstem. Chronic smoking has been linked to structural and functional changes in the brain; for example, studies have noted that smokers can have reduced volume in cerebellar regions and other brain areas involved in motor control [36]. It is plausible that long-term smoking leads to microdamage or inflammation in neural networks crucial for balance (perhaps via oxidative stress and small-vessel ischemic effects), thereby degrading the precision of postural adjustments. Our finding that smokers had worse stability even as young adults might be an early sign of such neurodegenerative processes. Importantly, this was a cross-sectional observation – longitudinal studies would be needed to confirm that smoking precedes and contributes to balance decline, but our results align with that interpretation.

Comparatively, the e-cigarette users in our study showed milder balance impairments. In some stabilometric tests, the e-cig group performed between the smokers and the non-smokers, sometimes not significantly different from the latter. The results indicate that combustible smoking produces greater effects on balance than vaping during the short term. The main reason for this difference could be the hypoxia-inducing components such as carbon monoxide present in cigarette smoke. CO reduces tissue oxygen delivery to the brain and peripheral nerves in a chronic manner. Over years, this could cause subtle diffuse damage (akin to aging-related small vessel disease) that impairs the central processing of balance. E-cigarette aerosol does not contain CO, so e-cig users avoid chronic CO exposure. Additionally, cigarettes contain thousands of chemicals, many of which are neurotoxic (e.g. lead, arsenic, and cadmium have been found in tobacco smoke). Heavy metals like cadmium (abundant in cigarette smoke) can accumulate and cause peripheral neuropathy or vestibular toxicity; e-cig vapor can contain metals from the heating coil (nickel, chromium), but typically in lower amounts than cigarette smoke delivers [37]. Therefore, e-cig users may experience less cumulative neurotoxic burden. Nicotine itself, common to both exposures, undoubtedly can acutely disturb balance – for instance, both smokers and vapers sometimes report dizziness after a large dose of nicotine – but if the chronic balance deficits in smokers were due mostly to non-nicotine factors, it makes sense that vapers fare better. Nonetheless, our e-cigarette group did show a slight trend toward worse balance than pure non-users (though not as bad as smokers), which could mean that nicotine alone does have some chronic impact on postural control. Nicotine's action on the central nervous system might induce subtle changes in reflex timing or muscle tone. There is some evidence from pharmacological studies that nicotine can affect cerebellar function and delay postural reflexes (interestingly, nicotine agonists are being studied for certain balance disorders, indicating the complexity of its effects). Another possibility is that some e-cig users in our study were dual users (both smoking and vaping) or former smokers, which would carry over the balance deficits from smoking. We tried to select exclusive e-cig users, but undisclosed dual use could confound the results. If any dual users were present, their balance would reflect the worse of the two habits, potentially explaining why the e-cig group wasn't entirely "normal" in stability.

Beyond comparing our results with prior studies, it is important to consider the broader implications and possible interpretations of these findings. One interpretation is that the neuromuscular system of young adults is more vulnerable to substance use than traditionally thought. While young people generally have a high physiological reserve, the fact that we detected clear gait and balance differences suggests that nicotine and tobacco are impacting neural control mechanisms relatively early in the exposure timeline. This raises concern that such changes could accumulate and intensify with longer duration of use, potentially leading to clinical balance or gait impairments in mid-life. It also suggests a dose-response relationship: heavy traditional smoking conferred the greatest changes, lighter or non-combustive nicotine use (vaping) showed smaller changes. This mirrors known health gradients, where complete non-use is safest, vaping is intermediate, and smoking is most harmful. Our findings thus support the concept of tobacco harm reduction in one sense (e-cigarettes might pose less risk to balance and gait than cigarettes), but they also serve as a warning that e-cigarettes are not without risk. The presence of any deviation in postural control among e-cig users, even if mild, means that chronic vaping could still have neurologic consequences – possibly via nicotine's effect on the brain or other toxic constituents in the vapor.

5. LIMITATIONS

The study contains multiple limitations which need to be considered when evaluating the research results. The cross-sectional study design prevents researchers from establishing cause-effect relationships between tobacco or e-cigarette use and the observed postural control and gait impairments. The study reveals significant group differences but it remains uncertain whether these changes stem from nicotine exposure or pre-existing differences or a combination of both factors. Research following participants over time would help determine both the sequence of events and whether neuromotor changes can be reversed after people stop using tobacco products. Second, self-reported smoking and vaping status was used to assign participants to groups. Although widely used in behavioral research, self-report introduces a risk of misclassification or underreporting, particularly among dual users or individuals transitioning between products. No biochemical verification (e.g., cotinine testing or carbon monoxide monitoring) was performed to objectively confirm nicotine exposure levels. Third, while efforts were made to control testing conditions, the timing and recency of nicotine intake prior to testing were not standardized. Acute effects of nicotine (e.g., withdrawal or intoxication) may have influenced performance, especially in tasks requiring fine motor coordination or balance. Future research should establish protocols to monitor or document the duration since nicotine consumption to distinguish between persistent and short-term effects. The study used a small participant number (N = 60) from a university-based convenience sample of young adults. The study results might not apply to diverse populations because the participants were evenly distributed between groups but the results could differ from other populations with varying socioeconomic status and physical activity levels and nicotine consumption patterns. The study population consisted mainly of healthy participants which might reduce the observed level of functional impairment in heavier or older users. The study obtained complete biomechanical data but did not include neurophysiological tests such as vestibular testing and proprioceptive thresholds and neuroimaging assessments. The study cannot determine the exact motor impairment source because it lacks neurophysiological and clinical diagnostic measures. Future research should include neurophysiological and clinical diagnostic measures to enhance understanding of how nicotine and tobacco products impact balance and gait through specific pathways. The study delivers important first evidence about early functional effects of tobacco and e-cigarette use in young adults while demonstrating the need for additional focused research.

6. CONCLUSIONS

The present study provides compelling evidence that regular tobacco smoking is associated with measurable impairments in both postural stability and gait parameters among young adults. Despite the relatively short exposure duration typical for this age group, tobacco smokers in our cohort exhibited increased postural sway, shorter step length, and altered gait dynamics compared to non-smokers, suggesting that the deleterious effects of cigarette use on neuromotor control can manifest early in life, long before clinical symptoms or comorbidities become apparent. These findings align with neurophysiological theories indicating that balance and locomotor control are highly sensitive to chronic disruptions in sensory integration, central processing, and peripheral feedback — all of which can be influenced by the neurovascular and toxicological effects of tobacco smoke.

Our comparative study design enabled us to identify the separate effects of traditional smoking versus exclusive e-cigarette use. E-cigarette users showed deviations from non-smokers in some parameters but these deviations were significantly smaller than those found in the smoking group. The absence of combustion-related toxins in vaping appears to reduce some postural and gait impairments that cigarette smoking typically causes. The existence of minimal functional changes in vapers shows that nicotine together with other aerosol components produce small but ongoing effects on neuromuscular function and sensory-motor integration.

The observed differences in BMI, stride characteristics, and stabilometric measures between groups could be attributed to a variety of physiological mechanisms, such as vascular and neurotoxic damage, nicotine-induced modulation of reflexes and proprioception, and other lifestyle factors associated with nicotine product use. The presence of such variations in a young, otherwise healthy population emphasizes the importance of early screening and preventative efforts. It also raises the question of whether stabilometric and gait-based evaluations may be used as early indicators of subclinical impairment or as motivators in clinical smoking cessation programs.

The research findings support public health evidence that tobacco use and e-cigarette use can damage neuromotor integrity in young adults. The study results demonstrate the necessity for additional longitudinal research to study how these impairments develop and whether they can be reversed and to evaluate the effectiveness of cessation and harm-reduction strategies that involve switching from smoking to vaping. Future clinical and epidemiological studies should use objective biomechanical assessments to determine the functional effects of nicotine exposure on younger populations.

In conclusion, this study bridges the gap between neurophysiological research and public health by demonstrating that everyday motor abilities such as balance and walking — often taken for granted in youth — can be subtly but significantly affected by tobacco and nicotine use. These insights should inform not only clinical practice and preventative strategies, but also public discourse surrounding the relative risks of smoking and vaping among young adults.

Future research needs to build upon these results by studying bigger and more diverse groups of people who differ in age, social status and exercise habits. Longitudinal studies are needed to determine the progression and potential reversibility of neuromotor impairments associated with chronic tobacco or e-cigarette use. Objective biochemical verification of nicotine exposure (e.g., cotinine assays, carbon monoxide breath testing) would strengthen group classification and help distinguish between acute and chronic effects of use.

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