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The Impact of Cell Phone Usage on Fall Risk and Postural Control During Free-Standing

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Abstract: Smartphone use raises concerns about forward head posture, and the high cognitive load and reduced situational awareness involved increase fall risk. This study aimed to assess the impact of smartphone usage (both holding and texting) on fall risk and postural control in healthy young adults. Thirty-three young adults completed three identical 20-s trials in static (AMTI platform) and dynamic (Balance Biodex platform) conditions, including (1) the baseline (eyes open and standing still), (2) passive phone use (holding and looking at the phone with the screen off), and (3) a dual task (texting while standing). Postural control was assessed using linear measures (CoP path length and the Fall Risk Test index) and nonlinear metrics (sample entropy, fractal dimension, and the Lyapunov exponent). The results indicated that smartphone use, especially texting, significantly increased CoP variability in the anteroposterior direction and Fall Risk Test values, highlighting reduced stability. A nonlinear analysis revealed decreased adaptability and the complexity of postural control during phone use. These findings suggest that mobile phone interactions impair balance and increase fall risk due to cognitive and physical distractions.

Keywords: balance assessment; mobile phone distraction; nonlinear measures; linear measures

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1. Introduction

Postural control is a key biomechanical mechanism that enables humans to maintain stability and balance in static and dynamic situations [1]. It depends on the intricate cooperation of the visual, vestibular, and proprioceptive systems, whose synchronization is essential for the body to respond quickly and accurately to changing environmental conditions [2]. Postural control is typically assessed using specialized tools such as force platforms, which record changes in the displacement of the center of pressure (CoP) of the feet on the ground. These measurements enable the analysis of body-movement variability in the anterior–posterior (AP) and mediolateral (ML) directions, serving as important indicators of postural stability. By analyzing the variability of the CoP trajectory, it is possible to monitor the effectiveness of the mechanisms responsible for maintaining balance [3]. Linear indicators such as the CoP sway range, CoP velocity, and the ellipse sway area are often used to quantify body sway. However, these linear measures alone cannot fully capture the complexity of dynamic postural sway. Kedziorek and Blazkiewicz [4] emphasize the importance of nonlinear measures when analyzing CoP signals, particularly concerning temporal variations in CoP displacement across the AP and ML directions. These nonlinear metrics provide insight into the regularity, adaptability, stability, and complexity of the postural control system. One widely used nonlinear metric is sample entropy (SampEn), which assesses the regularity of the CoP time series. Higher SampEn values reflect a more irregular CoP time series, indicative of a healthy and adaptive system, while lower values suggest greater regularity, which may signal rigidity and potential pathology [5]. Another nonlinear measure, fractal dimension (FD), evaluates the complexity of the CoP signal. An FD value of 1 would theoretically represent an entirely still stance, which is practically impossible due to natural postural sway [6]. Finally, the Lyapunov exponent (LyE) measures the system's resistance to external perturbations. A higher LyE value indicates greater adaptability and faster response to stimuli, whereas a lower LyE suggests difficulties in adjusting to environmental changes and potential rigidity in the system [7].

Fall risk is closely linked to the body's dynamic and static stability, which determine the ability to maintain balance under different conditions [8]. Static stability refers to the body's ability to maintain equilibrium at rest, whereas dynamic stability refers to movement control and the ability to restore equilibrium after disturbances [9]. The two aspects are interrelated—better static stability promotes a more effective response to changes in position, which influences dynamic stability. In the context of fall risk, static instability can lead to difficulty maintaining a standing position without additional support. At the same time, impaired dynamic stability can result in problems with movement control, especially during sudden changes in direction, braking, or moving over uneven ground. Research has shown that people prone to falls have poorer dynamic stability compared to healthy individuals of a similar age and younger adults [10].

The relationship between fall risk and static/dynamic stability requires further clarification. While both aspects contribute to balance control, their distinct roles and interplay in increasing fall susceptibility remain an area of ongoing investigation. Providing additional explanations in the introduction would enhance the reader's understanding by outlining how different stability components contribute to fall risk. Furthermore, external factors such as environmental conditions (e.g., slippery pavement and uneven ground) and cognitive load due to dual-tasking influence the risk of falling [11,12]. Using the phone while walking, talking, or having to focus on another task at the same time can impair balance control, as attention resources are split between different activities. Research indicates that performing dual tasks, such as using a smartphone while walking, can negatively affect dynamics [13].

Contemporary research on postural control increasingly highlights the impact of technology, particularly mobile phones, on body stability [14]. Smartphone use during movement, such as walking, reduces lower limb stability, restricts arm motion, and shifts focus toward phone interactions at the expense of balance [15]. Mobile phone use in daily activities increases cognitive load, visual distraction, and manual demands, which collectively elevate the risk of falls, one of the leading causes of unintentional injury among young adults [13,16]. Additionally, smartphone use is a dual-task activity that divides attention and negatively affects postural stability and motor coordination [17,18]. A particularly important factor is the alignment of the head and neck while using a phone. Smartphone users often hold devices below eye level, leading to forward head tilt, cervical flexion, and compensatory curvature of the upper thorax. This disrupts the biomechanical balance of the cervical spine [14,19]. Research shows that, while standing, the C0–C1 joint (at the skull base) experiences significant flexion of approximately $27.50 \pm 14.05°$, while the lower cervical vertebrae (C2–C7) remain almost immobile [20]. Phone use typically results in a head tilt of 30–35 degrees, increasing cervical spine strain. At 30 degrees, the head's effective weight increases from 5 kg in a neutral position to 18 kg; at 45 degrees, it rises to 22 kg, and at 60 degrees, it reaches 27 kg [20,21]. Prolonged strain can lead to neck pain, poor posture, and permanent spinal changes, emphasizing the need for the awareness of ergonomic posture during phone use [22,23].

In addition to head and neck positioning, the way a phone is held also influences postural control and body stability. Using a phone often requires the involvement of one or both hands, which can significantly affect balance. Holding the phone with one hand is usually associated with asymmetric weight distribution and limited compensatory arm movement, leading to increased instability in the lateral plane. While static conditions allow users to maintain a relatively stable posture, even holding a phone in one hand can introduce slight imbalances. Texting with both hands, on the other hand, requires greater upper limb involvement, altering the body's center of gravity and restricting free balancing movements. Furthermore, using both hands leads to a higher degree of visual fixation on the screen, reducing environmental awareness and the ability to react quickly to changes in balance conditions [24,25]. Together, these factors underscore the importance of informed smartphone use to mitigate its impact on postural stability and musculoskeletal health.

The aim of this study was to assess the impact of smartphone usage (both holding and texting) on fall risk and postural control in healthy young adults. The following hypothesis was formulated: mobile phone use during standing impairs postural control by increasing CoP variability, reducing adaptive control (SampEn), and decreasing postural complexity (FD, LyE), thereby increasing the risk of falls.

2. Materials and Methods

2.1. Participants and Measurement Protocol

Thirty-three young, healthy individuals took part in the study, comprising 17 women and 16 men (Table 1). The inclusion criteria required participants to have no history of muscular or neurological disorders, no lower limb injuries in the past six months, right lower limb dominance (preferred leg for kicking a ball [26]), and right-handedness. The exclusion criteria included balance impairments, treatment with medications affecting the nervous system, and the dominance of the left lower or upper limb for writing.

Table 1. Characteristics of the participants (mean ± SD).

Group	Age [Years]	Body Mass [kg]	Body Height [cm]
Females (n = 17)	22.76 ± 1.2	61.94 ± 7.59	166.71 ± 5.10
Males (n = 16)	22.13 ± 1.71	77.63 ± 9.23	181.31 ± 4.38
All (n = 33)	22.45 ± 1.48	69.55 ± 11.49	173.79 ± 8.82

This study was approved by the University Institutional Review Board (Reference No. SKE01-15/2023) and conducted following the ethical guidelines of the Declaration of Helsinki. All participants were fully informed about the study's objectives and procedures before participation.

The study involved a total of six trials conducted across two distinct platforms, with three trials performed under static conditions and three under dynamic conditions. The static trials were conducted using an AMTI AccuSway force platform (Advanced Mechanical Technology Inc., Watertown, MA, USA) paired with Balance Clinic 2.02.01 software, sampling data at 100 Hz. Dynamic trials were performed on the Biodex Balance System SD (BBS) platform (Biodex Medical Systems, Shirley, NY, USA), which features a circular platform capable of moving freely along both the AP and ML axes. During testing, the BBS platform operated in Fall Risk Test (FRT) mode, for which the level of stability progressively decreased from level 6 (high instability) to level 2 (low instability).

Each trial, under both static and dynamic conditions, lasted 20 s and followed the same sequence: (1) the baseline trial (EO)—standing with both feet, with the hands resting along the trunk and the eyes open while looking straight ahead; (2) the visual distraction trial with passive phone use (EP)—standing with both feet while holding a phone and looking at its turned-off screen; and (3) the cognitive–motor dual-task trial (SMS), which involved participants standing with both feet on the ground while holding a phone and typing a text message. The text messages used for this task were typical of real-life scenarios, such as informing someone that the participant would be late for an appointment due to circumstances like traffic. Examples included messages like "Sorry, I'm going to be late, there's a terrible traffic jam in the city" or "Mum, I'm going to be late. I'll be there in 20 min." During the study, the lab environment did not maintain conditions of silence, allowing participants to engage in the task in a more natural, less controlled manner. Participants could hold the phone however they preferred, and the research team recorded whether they used one or both hands. The method of holding the phone was not specified, reflecting real-world flexibility.

2.2. Parmeters—Linear and Nonlinear Measures

From the AMTI platform (static conditions), the total center of the pressure path length, as well as the path length in the AP and ML directions (linear parameters), were extracted for each individual across EO, EP, and SM trials. Additionally, a 20 s time series of CoP displacements in the AP and ML directions was exported separately, each consisting of 2000 data points per direction.

The analysis of the relationship between the total CoP path length and its components allows for a better understanding of the body's stabilization strategies and the compensatory mechanisms used to maintain balance. The value of the total CoP path length is derived from the summed displacement in both axes, which means that both dynamic changes in AP direction and adjustments in ML have a direct impact on this parameter. Movements in the AP axis tend to be more pronounced and related to the control of the equilibrium as a result of dynamic changes, such as rocking the body forward and backward. Movements in the ML axis, on the other hand, are more pronounced, as human lateral stability is more controlled due to the widening of the support plane and the activity of the stabilizing muscles. The interplay between the AP and ML components may reflect the body's adaptive strategies. For example, an increase in the movement of the center of pressure towards the AP may compensatively restrict the movement of the ML to prevent a fall. The relationship between the total CoP path length and its AP and ML components reflects the complexity of balance mechanisms and adaptive strategies under different conditions. An increase in the total CoP path length may result from an excessive overshoot of either or both axes.

Non-linear measures were then calculated for these time series, including SampEn, FD, and LyE, using MATLAB R2021a (MathWorks, Natick, MA, USA).

For the same trials (EO, EP, and SM) conducted on the Biodex platform (dynamic conditions), a Fall Risk Test index (FRTi) was derived for each individual.

2.2.1. Sample Entropy (SampEn)

Sample entropy quantifies the complexity of a time series by measuring the likelihood that similar patterns remain similar over an increased sequence length. It was defined as $\text{SampEn}(N, m, r) = -ln\left[\frac{B^{m+1}(r)}{B^{m}(r)}\right]$, where the following applies:

$B^m(r)$ represents the average number of repeated sequence counts of length m that remain within a tolerance, r.

$B^{m+1}(r)$ represents the same measure for sequences of length $m + 1$.

The tolerance, r, was set to 0.2 times the standard deviation of the data to normalize variations.

In the case of this paper, SampEn was calculated using MatLab R2021a codes obtained from the Physionet tool [27]. To calculate this measure, the "default" values $m = 2$ and $r = 0.2 \times$ (standard deviation of the data) were applied [28].

The step-by-step calculation process began by segmenting the time series into overlapping sequences of length m. Then, for each sequence, the number of times another sequence of the same length remained within the tolerance r was counted, and the average count $B^m(r)$ was computed. The process was then repeated for sequences of length $m + 1$ obtaining $B^{m+1}(r)$. Finally, SampEn was calculated by taking the natural logarithm of the ratio $B^m(r)/B^{m+1}(r)$ and negating the result. This method provided an estimate of the regularity and unpredictability of the dataset, where lower SampEn values indicated more predictable patterns, while higher values suggested greater complexity.

2.2.2. Fractal Dimension (FD)

The Higuchi algorithm [29] was used to calculate the fractal dimension (FD) of the time series. The method began by creating sub-series,

$$X_k^m = x[m], x[m+k], x[m+2k], \ldots, x\left[m + int\left(\frac{N-m}{k}\right) \cdot k\right],$$

from the original data, $X = x[1], x[2], \ldots, x[N]$; each sub-series was formed by selecting points at fixed intervals determined by a scaling factor k.

k and m are integers, $int\left(\frac{N-m}{k}\right)$ is the integral part of $\left(\frac{N-m}{k}\right)$, and k indicates the discrete time interval between points, whereas $m = 1, 2, \ldots, k$.

For each sub-series, its length was calculated by measuring the cumulative differences between consecutive points, adjusted for the scale.

$$L(m,k) = \left(\sum_{i=1}^{int\left(\frac{N-m}{k}\right)} |x[m+ik] - x[m+(i-1)k]|\right) \cdot \left(\frac{N-1}{int\left(\frac{N-m}{k}\right)k^2}\right),$$

where N is length of the original time series X.

The average length of the curve for the time interval k was defined as the average of the k values $L(m, k)$, for $m = 1, 2, \ldots, k$:

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L(m,k).$$

Finally, when $L(k)$ was plotted against $1/k$ on a double logarithmic scale, with $k = 1, 2, \ldots, k_{max}$, the data fell on a straight line, with a slope equal to the FD of X. Thus, Higuchi's FD was defined as the slope of the line that best fitted the pairs $\left(ln\left[L(k),\ ln\left(\frac{1}{k}\right)\right]\right)$ in a least-squares sense. To choose an appropriate value for k_{max}, Higuchi's FD values were plotted against a range of k_{max}. The point at which the FD plateaued was considered the saturation point, and the corresponding k_{max} value was selected [30]. A value of $k_{max} = 100$ was chosen for this study.

2.2.3. The Lyapunov Exponent (LyE)

The Lyapunov exponent (LyE) was calculated using an algorithm developed by Wolf et al. [31], which estimated the dominant LyE of a 1D time series by tracking the divergence of nearby trajectories in phase space. The method began by selecting an initial point in the time series and identifying a nearby reference point. The algorithm then tracked both the reference point and the original point over time, measuring how their separation evolved. This divergence was calculated over successive time steps to capture how quickly nearby points in phase space diverged from each other, reflecting the underlying chaotic behavior of the system. The dominant LyE was derived from the rate of this exponential separation. A positive LyE indicated chaos, as it implied that nearby trajectories would diverge exponentially over time, while a negative exponent suggested stability, where trajectories converged. By iterating this process over the time series, the dominant LyE was calculated, providing insight into the system's sensitivity to initial conditions and its overall chaotic nature.

2.3. Statistical Analysis

Statistical analysis was conducted using Statistica v.12 (StatSoft, Tulsa, OK, USA), with the significance level set to $p < 0.05$. The normality of distribution for all parameters (both linear and nonlinear) was assessed using the Shapiro–Wilk test.

Linear measures included the total CoP path length and CoP path length in the AP and ML directions for each of the EO, EP, and SMS trials. Additionally, data on the FRTi were collected from the same EO, EP, and SMS trials under dynamic conditions. Nonlinear parameters included SampEn, FD, and LyE in the AP and ML directions for each EO, EP, and SMS trial under static conditions.

A Friedman ANOVA with Dunn–Bonferroni post hoc analysis was then performed to determine whether significant differences existed in the values of linear and nonlinear measures, as well as in FRTi scores, across the three trials (EO, EP, and SMS). Additionally, the percentage of participants who held the phone with one or both hands, depending on the task, was analyzed under static and dynamic conditions.

Friedman ANOVA was first conducted separately for linear measures: (1) total CoP path length, (2) FRTi (each with three variables corresponding to EO, EP, and SMS conditions), and (3) CoP path length in the AP and ML directions combined (six variables). The p-values obtained in this step determined whether post hoc analysis was performed, provided that $p < 0.05$. The same procedure was applied to nonlinear measures.

3. Results

After the Shapiro-Wilk test was performed, the results showed that nine out of twelve linear variables deviated from a normal distribution. These included the CoP path length and CoP path length in the AP and ML directions for both the EO and SMS trials, as well as CoP path length and CoP path length in the ML direction for the EP trial. Additionally, the values of FRTi in the EO trial also differed from a normal distribution. For nonlinear measures, LyE values in both the AP and ML directions deviated from normality in the EO trial. In the EP trial, SampEn values in the AP direction, as well as FD and LyE values in the ML direction, were non-normally distributed. Similarly, in the SMS trial, FD values in the ML direction and LyE values in the AP direction also differed from a normal distribution.

3.1. Linear Measures and Fall Risk Test Index (FRTi)

Friedman's ANOVA analysis revealed no statistically significant differences in the overall CoP path length recorded during the three trials under static conditions: $F(N = 33, df = 2) = 4.71$, $p = 0.0947$. However, there were significant differences in the CoP path lengths in the AP and ML directions: $F(N = 33, df = 5) = 68.25$, $p = 0.0001$.

Post hoc tests revealed that the CoP path length in the AP direction was significantly ($p < 0.05$) longer than in the ML direction for all trials (EO, EP, and SMS). Additionally, the CoP path length in the AP direction for the EP trial was significantly ($p < 0.05$) longer than that noted in the ML direction in the EO trial, and the same was true for the SMS trial compared to the ML direction of the EO trial (Table 2).

Table 2. Median (lower; upper quartile) for linear measures and fall risk index (FRTi) values.

Parameters	EO Trial	EP Trial	SMS Trial
Total CoP path length [mm]	159 (136; 190)	165 (150; 181)	166 (150; 180)
CoP path length ML [mm]	80 (66; 101)	84 (64; 95)	82 (65; 103)
CoP path length AP [mm]	109 (96; 141)	129 (104; 142)	120 (108; 140)
FRTi [-]	1.2 (0.8; 1.4)	2.3 (1.7; 3.6)	3.4 (4.4; 2.7)

CoP—center of pressure, ML—mediolateral direction, AP—anterior–posterior direction, EO—both-leg standing with eyes open, EP—both-leg standing while holding a phone with the screen off, SMS—both-leg standing while typing a text message on a phone.

The CoP path length in the AP direction in the EO trial was also significantly ($p < 0.05$) longer than that noted in the ML direction in the EP and SMS trials. Furthermore, in both the EP and SMS trials, the CoP path lengths in the ML direction were significantly ($p < 0.05$) shorter than the corresponding path lengths in the AP direction. Lastly, the CoP path length in the AP direction in the EP trial was significantly ($p < 0.05$) longer than that observed in the SMS trial in the ML direction (Table 2).

Moreover, Friedman's ANOVA revealed statistically significant differences in the FRTi across the trials: F(N = 33, df = 2) = 48.01, $p = 0.0001$. The highest FRTi values were observed during the texting trial, which were significantly ($p < 0.05$) greater than those recorded during both the EO and EP trials (Table 2).

3.2. Nonlinear Measures

Friedman's ANOVA revealed no statistically significant differences between trials for FD: F(N = 33, df = 5) = 7.46, $p = 0.1886$. However, statistically significant differences were observed for both SampEn: F(N = 33, df = 5) = 18.88, $p = 0.0020$, and LyE: F(N = 33, df = 5) = 104.82, $p = 0.0001$.

A post hoc analysis of SampEn values revealed that the values noted in the ML direction for the EO trial were significantly higher than values observed in the AP direction for the EP trial (Table 3).

Table 3. Median (lower and upper quartiles) for nonlinear measures.

Parameters	EO Trial	EP Trial	SMS Trial
SampEn_ML [-]	0.09 (0.06; 0.12)	0.08 (0.05; 0.09)	0.07 (0.06; 0.10)
SampEn_AP [-]	0.07 (0.06; 0.09)	0.06 (0.05; 0.08)	0.07 (0.06; 0.09)
FD_ML [-]	1.29 (1.24; 1.36)	1.27 (1.23; 1.33)	1.27 (1.26; 1.33)
FD_AP [-]	1.27 (1.23; 1.32)	1.28 (1.25; 1.33)	1.26 (1.24; 1.32)
LyE_ML [-]	0.97 (0.90; 1.08)	1.01 (0.96; 1.07)	0.98 (0.93; 1.13)
LyE_AP [-]	1.32 (1.26; 1.37)	1.33 (1.29; 1.45)	1.36 (1.33; 1.41)

SampEn—sample entropy, FD—fractal dimension, LyE—Lyapunov exponent, ML—mediolateral direction, AP—anterior–posterior direction, EO—both-leg standing with eyes open, EP—both-leg standing while holding a phone with the screen off, SMS—both-leg standing while typing a text message on a phone.

Post hoc analysis for LyE revealed significantly more differences, with ML direction values for the EO trail being significantly lower than AP direction values for the EO, EP, and SMS trials. In addition, LyE values for the AP direction in the EO trial were significantly higher than those recorded in the ML direction for the EP and SMS trials. The LyE values in the ML direction for the EP trial were significantly lower than those observed in the AP direction for the EP and SMS trials. The LyE values for the AP direction and EP trial were significantly higher than those for the SMS trial in the ML direction. LyE values for the SMS trial in the ML direction were significantly lower than those recorded for the AP direction in the same trial (Table 3).

3.3. Limb Involvement in Holding the Phone

The analysis of phone usage in different conditions and activities revealed distinct participant preferences, with variations in limb involvement that may influence postural control and balance.

In static conditions, when using the phone passively, most participants (78.79%) held the device with one hand, while only 21.21% opted for a two-handed grip. However, when texting, this trend reversed: 90.91% of participants used both hands, and only 9.09% typed with one hand, consistently using the upper right limb.

In dynamic conditions, a similar pattern emerged. During passive phone use, 72.73% of participants held the phone with one hand (typically the right hand), while 27.27% used both hands. When texting, 93.94% of participants used two hands, with only 6.06% relying on one-handed typing.

It is important to note that all participants identified their right hand as dominant, which likely explains the preference for the right hand in one-handed use. This finding is particularly relevant to postural control, as asymmetric phone-holding habits may contribute to lateral weight shifts, altering balance stability. The restriction of free arm movement, especially during bimanual phone use, can further impact postural adjustments, limiting the body's ability to counterbalance shifts in the center of gravity.

4. Discussion

This study examined the impact of smartphone use, including passive phone holding and active texting, on postural control and fall risk in healthy young adults. Notably, the experiments were conducted on both a dynamic balance platform, simulating less controlled environments like bus riding, and a static platform, representing a stable and safe environment. The hypothesis, which suggested that mobile phone usage would impair postural control and increase the risk of falls, was supported by the findings.

The linear measures, including CoP path length, revealed a significant increase in the AP direction under both passive phone holding and texting conditions. Specifically, the CoP path length was significantly longer in the AP direction for the EP and SMS trials compared to the baseline EO trial. This suggests that holding a phone, especially while texting, leads to a more pronounced shift in the body's center of pressure, potentially indicating compromised postural stability. The dynamic nature of texting, which requires additional motor and cognitive processing, may explain these alterations in postural control [32,33]. Interestingly, while the total CoP path length did not differ significantly across the three trials, differences in the CoP path length in the ML and AP directions were notable. This implies that the directionality of balance control is more affected by phone usage during standing. The increase in CoP path length in the AP direction aligns with the requirement for more forward and backward postural adjustments when the user is distracted by a mobile device [20]. The FRTi also showed significant differences between trials, with the highest values recorded during the texting trial. These findings are in agreement with the notion that multitasking, especially cognitive–motor tasks such as texting, is linked to increased fall risk. The substantial increase in FRTi during the SMS trial indicates that the dual-tasking required in this condition may significantly impair postural control. These results underscore the risks of performing tasks that demand cognitive attention while standing, as it compromises the individual's ability to maintain postural stability. This aligns with the findings of Cho et al. [34].

This study reinforces previous research indicating that smartphone use negatively impacts postural control, particularly during dual-task activities. Specifically, the observed increase in CoP variability, especially in the AP direction during phone use, aligns with Kedziorek and Blazkiewicz's [4] assertion that nonlinear measures are critical in evaluating balance. Increased CoP variability indicates decreased efficiency in the adaptive mechanisms required to maintain stability. The cognitive–motor dual task of texting significantly reduced SampEn values, signaling diminished adaptive control. Potvin-Desrochers [5] obtained similar results, showing that cognitive distractions, such as texting, interfere with the automatization of postural control. Additionally, the reduced LyE values during texting suggest limited adaptability to environmental changes. This supports Omid Khayat's [7] findings on how task complexity and age can influence CoP signals. Although there were no significant changes in FD, indicating that postural complexity was not entirely compromised, the reduced SampEn and LyE values suggest an increase in postural rigidity. This rigidity was further reflected in the high FRTi observed during texting trials, which parallels Nasar and Troyer's [16] findings linking mobile phone use to an increased incidence of falls. Nonlinear measures of postural control, such as SampEn and LyE, also revealed substantial differences between the trials. SampEn, a measure of postural complexity, showed reduced values during the EP and SMS trials, particularly in the AP direction. This reduction suggests that mobile phone use, especially while texting, diminishes postural control complexity, making it more predictable and less adaptable. The lower SampEn values during phone use indicate a loss of adaptability in postural control, heightening the risk of falls under dynamic conditions. Similarly, LyE, which quantifies the divergence of nearby trajectories in a dynamic system, reflected the variability in postural adjustments during static conditions, exhibiting significantly higher values in the AP direction for the EO trial compared to both EP and SMS trials. This suggests that, even under static conditions, the postural control system involves dynamic processes that can be assessed using LyE to capture the stability and adaptability of balance. This finding suggests that postural control in the AP direction becomes more chaotic and less stable during phone use, particularly when texting. The decrease in LyE during the SMS trial in the ML direction may reflect a reduced sensitivity to small postural disturbances, signaling a diminished ability to respond to shifts in balance. Finally, the fact that nonlinear parameters consistently revealed significant differences, whereas linear measures showed less sensitivity, supports the hypothesis that mobile phone use interferes with more subtle aspects of postural control—issues that might not be captured by simpler linear measures like CoP path length.

The analysis of limb involvement during phone use revealed clear patterns based on the task at hand. During static conditions, most participants used one hand to hold the phone, while texting necessitated the use of both hands. This shift was even more pronounced under dynamic conditions, with nearly all participants using two hands to text. The connection between limb involvement and postural stability is particularly relevant, as asymmetric weight distribution and restricted arm movement can influence balance and postural control [35,36]. The preference for right-hand dominance, especially in one-handed phone use, aligns with the participants' self-reported hand dominance, indicating that this factor may influence how phone use impacts postural control.

This connection to postural control is especially important in dynamic conditions, where the ability to make balance adjustments is crucial. The reliance on both hands for texting limits compensatory arm movements, potentially increasing instability. Moreover, holding the phone with two hands restricts the natural sway of the upper limbs, which normally assists in maintaining balance.

Interestingly, the increased reliance on both hands for texting may have contributed to greater postural instability in the SMS trial. Holding the phone with two hands, as opposed to one, likely shifts the body's center of mass and requires additional motor coordination, which may have compromised balance during the texting task.

5. Limitations and Future Research Directions

While this study provides valuable insights, several limitations must be considered. The sample size was relatively small, and all participants were young, healthy adults, which limits the generalizability of the findings to other age groups or individuals with balance impairments. Future research could examine the effects of smartphone use on postural control in older adults or individuals with known balance disorders to better understand the broader implications of phone use on fall risk.

Additionally, the study focused on a specific type of cognitive–motor dual task (texting), and future studies could explore other common smartphone-related tasks, such as browsing or watching videos, to determine how these activities affect postural control. The influence of environmental factors, such as different types of surfaces or levels of instability, should also be considered in future investigations to better replicate real-world conditions.

Furthermore, while we acknowledge the potential impact of factors such as hand dominance on phone use and balance control, we were unable to incorporate additional experiments within the scope of this study. However, we have included these aspects as potential directions for future research. Investigating whether using the dominant versus the non-dominant hand influences postural stability could provide further insights. Similarly, future studies could explore ergonomic interventions aimed at reducing the fall risk associated with smartphone use, offering practical recommendations based on experimental validation.

6. Conclusions

In conclusion, this study has provided strong evidence that smartphone usage, particularly when engaging in texting, significantly impairs postural control and increases fall risk for young, healthy adults. The findings suggest that both linear and nonlinear measures of postural control are affected by mobile phone use, with texting showing the most pronounced effects. Given the widespread use of smartphones, these results highlight the importance of understanding the potential risks associated with phone use in situations requiring balance and stability.

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