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A Novel Diagnostic Approach for Smartphone-Induced Finger Disorders: An Exploratory Study

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Abstract

Smartphone-related finger injuries are repetitive strain injuries caused by prolonged smartphone use. Despite the increasing prevalence of such conditions, few studies have focused on developing effective and accessible diagnostic methods. This study proposes the use of biomedical signals from the hand and fingers as diagnostic indices. Soft tissue stiffness and vibration frequency features under load are presented and tested as potential diagnostic indices. Testing revealed that the soft tissue stiffness parameter lacks reliability and suitable sensors, while the vibration frequency feature demonstrates excellent performance. After addressing several existing limitations, the vibration frequency under load emerges as the optimal diagnostic method for smartphone-related finger injuries.

Keywords: repetitive strain injury, smartphone-related finger injuries, soft tissue stiffness, vibration frequency features

1. Introduction

Smartphone-related finger injuries, historically referred to as ‘smartphone finger’, ‘cell phone thumb’, or ‘texting thumb’, represent a type of repetitive strain injury (RSI) induced by prolonged smartphone usage. This condition compromises the dexterity of the fingers and hands due to soft tissue damage from repetitive motions, leading to discomfort. In more severe cases, such RSIs can significantly impair hand function and contribute to long-term disability [1]. There has been a consistent rise in the number of patients presenting with RSI, which were traditionally associated with individuals engaged in physically demanding occupations or professional athletes subjected to high-intensity repetitive tasks. While RSI has occasionally been observed in the entertainment industry, particularly among professional performers, this marks the first instance of such a widespread prevalence of RSI attributable to smartphone usage across the general population [2]. The exponential rise in cases of finger-related RSI due to smartphone use poses a growing challenge for clinicians.

This surge is attributed not only to the increasing size and weight of smartphones but also to the significant rise in usage duration. Recent data reveals that the average individual spends approximately 3 hours and 15 minutes daily on their phone, with 1 in 5 users exceeding 4.5 hours of usage per day. This extended screen time has led to a significant and sustained increase in the incidence of RSI, highlighting a pressing public health concern [3]. Furthermore, with smartphones now averaging 6 inches in size and weighing approximately 200 grams, finger-related RSI is understandably becoming increasingly common in clinical settings. The combination of prolonged usage and the physical demands of handling larger, heavier devices places significant strain on the hands, contributing to the rising prevalence of this condition [4].

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Clinicians find finger-related RSI particularly troubling due to the high number of affected patients and the variety of associated musculoskeletal disorders. These conditions often involve tendons, muscles, and joints, as well as peripheral nerve entrapment and vascular syndromes, further complicating diagnosis and treatment [2]. The complexity is exacerbated when pain is localized to a small area of the hand or finger, making accurate diagnosis especially challenging. Moreover, the rising number of older adults using smartphones heightens the concern, as finger-related RSI could become a significant risk factor contributing to frailty and the need for intermediary care in this population [5]. The physical strain associated with repetitive smartphone use may aggravate age-related musculoskeletal decline, posing serious implications for long-term health and mobility.

Statistics indicate a direct correlation between the frequency of smartphone use and the development of rigidity, soft tissue pain, and even conditions such as De Quervain's tenosynovitis [6-7]. As a result, the diagnosis of rigid and painful soft tissues in the hand has become increasingly common in clinical settings. Diagnostic confirmation for these conditions typically involves advanced imaging techniques such as X-rays, computed tomography (CT) scans, magnetic resonance imaging (MRI), nerve conduction studies, heat and cold sensitivity tests, and capillary refill time assessments [8]. However, the high cost and time-consuming nature of these diagnostic tools often discourage patients with early symptoms of smartphone-related injuries from seeking prompt evaluation, leading to missed opportunities for early intervention. Thus, the development of affordable and efficient diagnostic methods is urgently needed.

Biomedical signals offer a cost-effective and efficient approach to diagnostics and are frequently employed in non-invasive procedures, such as electrocardiography (ECG) and vibroarthrography (VAG) [9-10]. In a study by Hochman [11], vibration signals, also known as joint acoustic emissions, were utilized as biomedical indicators for diagnosing wrist disorders. Acoustic emissions are elastic or acoustic waves generated when deformation, damage, or destruction occurs in a material or organism[12]. As a biosignal, acoustic emissions are the acquisition of signals when damage occurs to tissues in the body. On this basis, this study hypothesizes that early-stage motor deficits in the fingers, resulting from smartphone overuse, can be effectively diagnosed using vibration signals, specifically the vibrations of soft tissues.

To validate this hypothesis, this study draws on diagnostic methodologies employed in the detection of Parkinson's disease [13]. However, unlike Parkinson's disease, where finger tremors caused by the nervous system are monitored during muscle relaxation, this study focuses on tremors induced by the motor system under conditions of muscle tension. In this state, biomedical signals related to motor function, including vibration signals, are collected and analyzed to establish diagnostic criteria. As an initial investigation, this study seeks to achieve two primary objectives while testing the aforementioned hypothesis. First, it introduces the concept of soft tissue acoustic emissions to establish a theoretical foundation for the future development of biomedical signal monitoring devices. The second objective is to offer a cost-effective and efficient diagnostic solution for smartphone-related finger disorders, to mitigate the growing incidence of disability among affected individuals.

2. Methodology

This section explores the biomechanics of one-handed smartphone use, focusing on RSI-prone areas such as the thumb and little finger. By analyzing vibration signals and soft tissue stiffness in these regions, it seeks to reveal the physiological effects of prolonged device usage and enhance understanding of its impact on hand function related to RSI.

2.1. The RSI area under observation

Before the introduction of experimental methodology, it is essential to first examine the biomechanics of finger movements during smartphone use. As illustrated in Fig. 1, the little finger and thumb play crucial roles in one-handed smartphone operation. The little finger bears the phone's entire weight from below, while the thumb interacts with the touch

screen. These actions involve repeated flexion and extension, placing prolonged or high-frequency stress on the tendons located in regions prone to RSI, as indicated by the 'Thumb' and 'Little finger' in Fig. 1. This repetitive strain primarily affects the tendons, nerve fibers, and blood vessels, all situated just beneath a thin layer of skin in the palm and forearm muscles. Consequently, this study focuses on observing the RSI-prone areas in the hand [14].

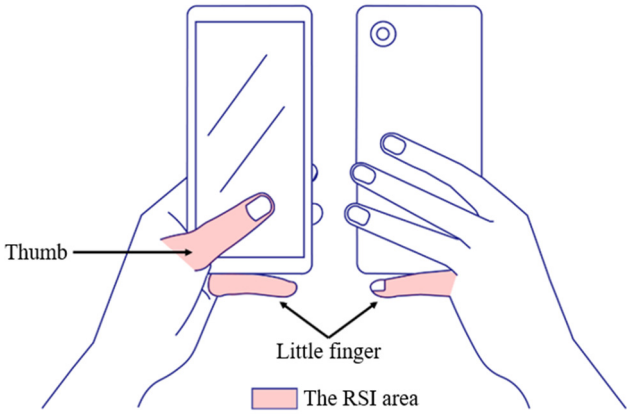


Fig. 1 The RSI area when operating a smartphone with one hand

2.2. Measurement of vibrations

After identifying the target observation areas, the next step is to measure the tremors, i.e., the vibration signals within the RSI-affected regions. As noted in the previous section, the identification of these areas suggests that the soft tissue has weakened, reducing its ability to bear stress. Therefore, this study focuses on observing changes in finger vibration before and after loading. Given that the most straightforward method for loading the fingers involves gripping, the fingers must remain in a state of grip while measuring the vibration signals. For this purpose, an isotropic rubber ring was selected as the device for measuring finger grip strength. As shown in Fig. 2, when the fingers exert pressure on the rubber ring, it undergoes linear deformation, and the load from the hand can be quantified using a custom-made deformation measurement apparatus [15].

In this study, an LED light inside the pre-processor serves as a trigger indicator to signal the level of deformation. Notably, the applied load varies for the same level of deformation depending on the Young's modulus of the rubber ring used. The device is used in the following way: a bending sensor within the deformation measurement device was affixed inside each ring using double-sided tape, enabling the sensor to deform in sync with the rubber ring. The inner circle of the ring compressed into an elliptical shape, and the trigger indicator was activated only when the short semi-axis of the ellipse reached half the radius of the initial circle.

Previous tests revealed that traditional accelerometers face significant challenges in securing attachment to the hand and accurately capturing hand tremors. Despite the high precision of these sensors, their application to soft tissue remains difficult, and monitoring the entire hand would require an array of multiple accelerometers, making data acquisition and multi-channel analysis both expensive and complex. To enhance practicality, a piezoelectric sensor was utilized for vibration measurement. The sensor, a 50-cm long wire (RBS-DM-STD, RoboSensor), was wrapped around the palm to measure vibrations across the whole hand, as illustrated in Fig. 2. Both deformation and vibration signals were collected using a data acquisition system (DAQ) (4262, Picoscope) with 16-bit sampling accuracy and a 5-kHz sampling rate.

In addition to the biomedical signals previously discussed, a commonly observed symptom among smartphone users is a reduction in finger dexterity, often manifesting as increased rigidity. Specifically, heightened soft tissue stiffness in RSI-affected areas significantly impairs finger mobility. This phenomenon is, in principle, analogous to the diagnostic approach for shoulder pain [16]. In this study, soft tissue stiffness in the region near the thumb's RSI is assessed with a stiffness meter (TDM-NA1, TRY-ALL) while the rubber ring is gripped in the hand [17].

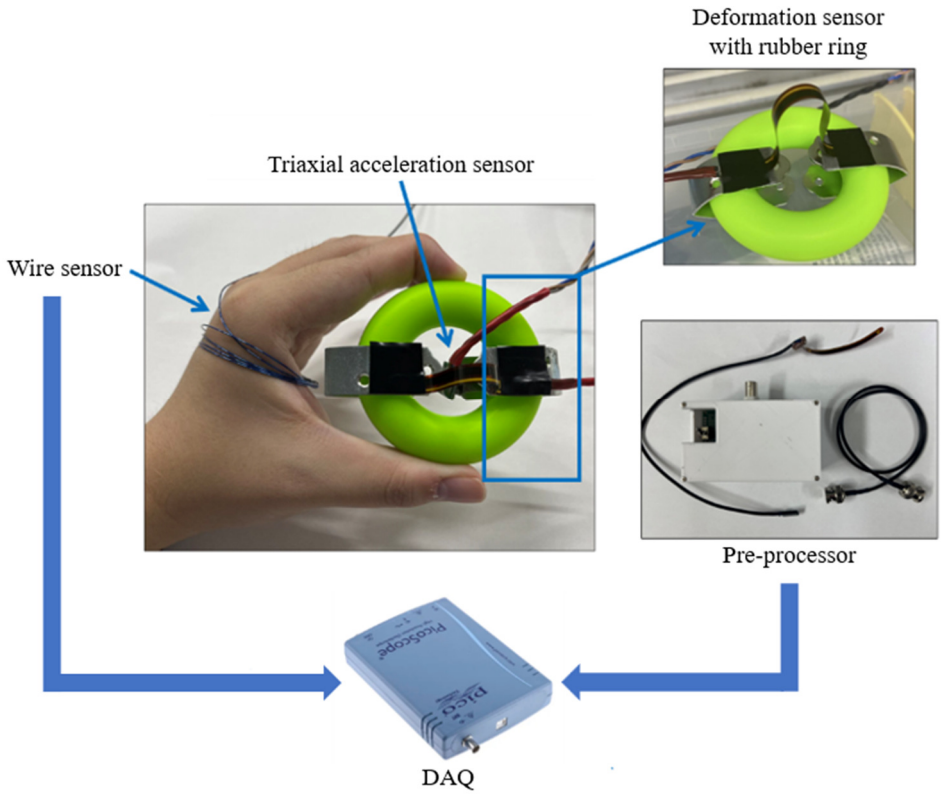


Fig. 2 Measuring device consisting of a rubber ring deformation sensor and wire sensor

As a preliminary study, this research prioritizes feasibility. Hence, only one subject was included: a healthy, right-handed male in his 30s. According to data from his iPhone 13 (iOS 17) with dimensions of 71.5 mm in width, 146.7 mm in height, 7.65 mm in thickness, and a weight of 173 g, the participant averaged 3 hours and 17 minutes of daily smartphone use over the past three months with his dominant hand, indicating a high risk for RSI. This method involved administering the same test item multiple times to verify the consistency of the participant's responses. Further details on this experimental methodology are provided in the following subsection. Before commencing the research, the study underwent ethical review to ensure compliance with research ethics principles, as approved by the Tokyo Metropolitan University Ethics Committee under approval number H4-164.

3. Experiments and Data Processing

This part details the experiments and data processing methods. The experiments are conducted in two rounds: one for soft tissue stiffness and the other for soft tissue vibration. These experiments aim to further test the functional and biomechanical effects of RSI on the hand and fingers.

3.1. Experiments

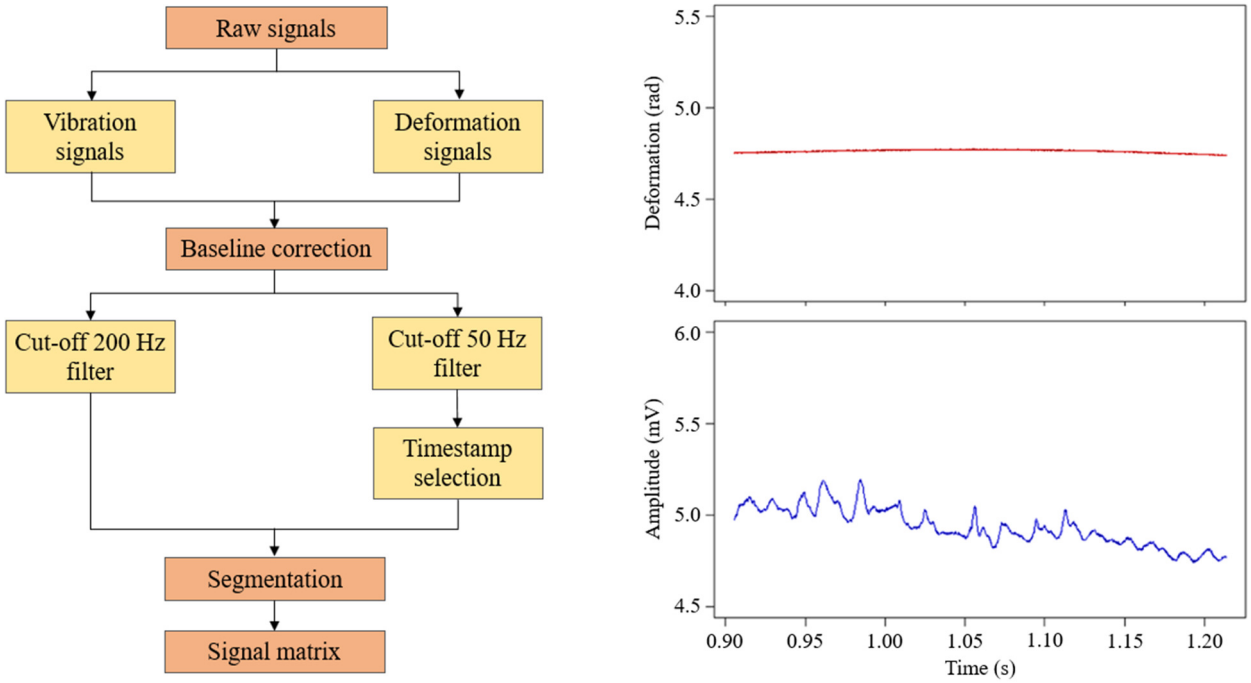
First, the three rubber rings used in this study, A, B, and C, have mean Young's moduli of 0.0702 GPa (soft), 0.0755 GPa (medium-hard), and 0.0791 GPa (hard), respectively. Aside from differences in Young's modulus, these rings are identical, with negligible variation in shape and size. Before the experiment, the subject underwent sufficient training and practice to ensure accurate task execution. During the experiment, the subject applied pressure to each rubber ring, as depicted in Fig. 2, over two rounds. In Round 1, no vibration sensor was enabled, and soft tissue stiffness in the RSI area near the thumb, as marked in Fig. 1, was measured using the same measurement device by the same staff when enough pressure was applied to activate the trigger indicator. This procedure was repeated for each rubber ring, with both the left and right hands, over three cycles. As a calibration step, stiffness measurements of the RSI area were also taken without the rubber ring (sensor deformation only).

Subsequently, in Round 2, the wire-shaped piezoelectric vibration sensor was wrapped around the subject's palm, and simultaneously, all sensors were turned on while pressure was gradually applied to each rubber ring. The key difference in this round was that, after the trigger indicator light was illuminated, the subject was required to maintain the applied load for at least 0.2 seconds (capturing over 1,000 samples) before slowly releasing the pressure until the rubber ring returned to its original shape. The next action would then commence. A minimum of ten valid cycles was required from both the dominant hand (target group) and the non-dominant hand (control group).

3.2. Data preprocessing and analysis

When biomedical signals are collected by the digital oscilloscope, they are stored on a computer as digital signal data. In this study, R Studio and the 'signal' package were employed for signal preprocessing and analysis [18]. Statistical analyses were performed using JASP version 0.18.3 [19]. Given that the biomedical signals in this study involve vibrations, noise reduction is essential. Since the frequency of soft tissue tremors in the RSI-affected area is below 200 Hz, a low-pass filter was applied to reduce noise. Specifically, a 3rd-order Butterworth low-pass filter was utilized.

Additionally, the deformation signal requires smoothing to accurately identify the loading timestamp. To achieve this, the same 3rd-order Butterworth low-pass filter and robust scatter plot smoothing were applied, with the cutoff frequency set to 50 Hz. All collected signals were free from missing values and outliers, so the preprocessing did not involve signal interpolation. The biomedical signals were clipped based on the deformation timestamps, and the signals were stored as matrices aligned with the same number of samples. Fig. 3 illustrates a signal processing flow and the typically processed signal waveforms.



(a) A signal preprocessing flowchart in this study (b) Deformation and vibration signals under load (ring A)

Fig. 3 A Signal processing flow and typical processed signal waveforms

In this study, the focus of signal analysis is on extracting and comparing frequency domain features of the biomedical signals. This is achieved through the application of the Fourier transform with a Hamming window, while feature extraction is based on descriptive statistical features. A representative extracted variable is shown in Fig. 4, which illustrates the frequency at which spectral energy is highest—namely, the soft-tissue tremor of the hand, which is altered by RSI-induced soft-tissue damage. This method has been employed in multiple instances of vibration signal analysis within the field of clinical medicine [10, 20].

Due to the small sample size (fewer than ten groups in both rounds), the data did not pass the Shapiro-Wilk test for normality. As a result, nonparametric tests were used for statistical analysis. The Kruskal-Wallis test with Dunn's post hoc test was employed to assess statistical significance in Round 1, while the Wilcoxon-Mann-Whitney test was applied in Round 2, both serving as nonparametric alternatives to test the null hypothesis. The Spearman's test was used to calculate the correlation coefficient (r).

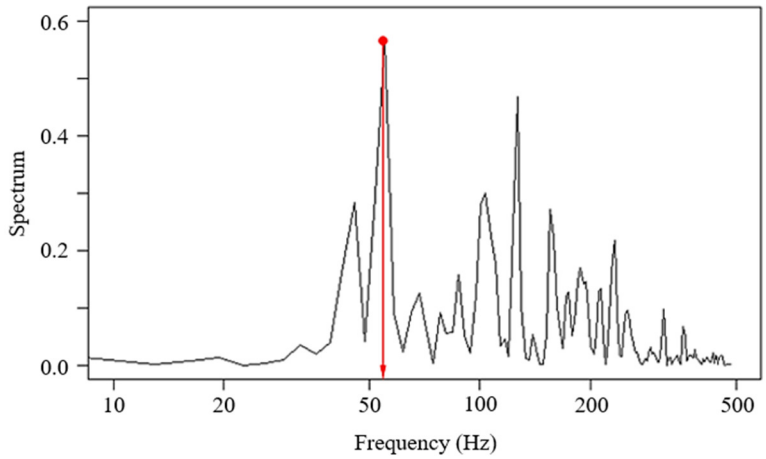


Fig. 4 Vibration spectrum of rubber ring A under load (peak frequency indicated)

4. Results

The results from Round 1 of the data analysis are presented below. Fig. 5 illustrates the soft tissue stiffness in the RSI areas under each rubber ring at the same level of deformation. When deformation was applied solely to the sensor, minimal differences in soft tissue stiffness were observed between the left and right hands. In the non-dominant left hand, applying deformation through the rubber ring did not increase soft tissue stiffness in the RSI area, as Young's modulus of the rubber rings increased. In contrast, in the dominant right hand, under the same deformation conditions, the soft tissue stiffness in the RSI area increased as Young's modulus increased. Statistical analysis revealed no significant differences in the left-hand data, whereas the right-hand data exhibited significant differences ($p < 0.05$).

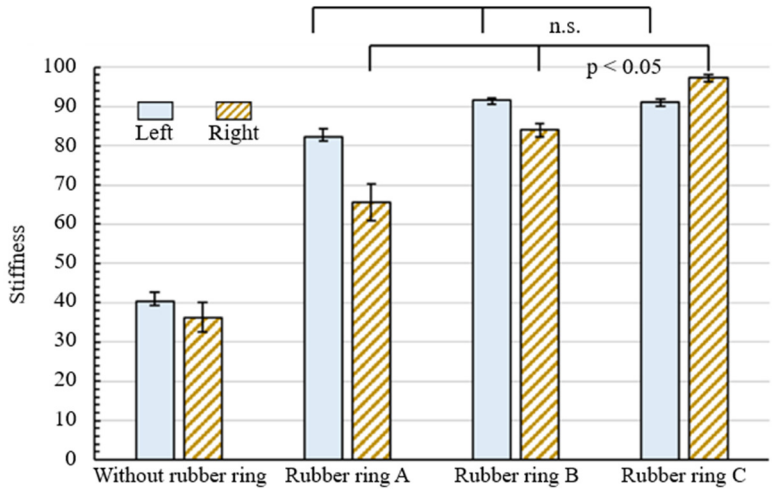
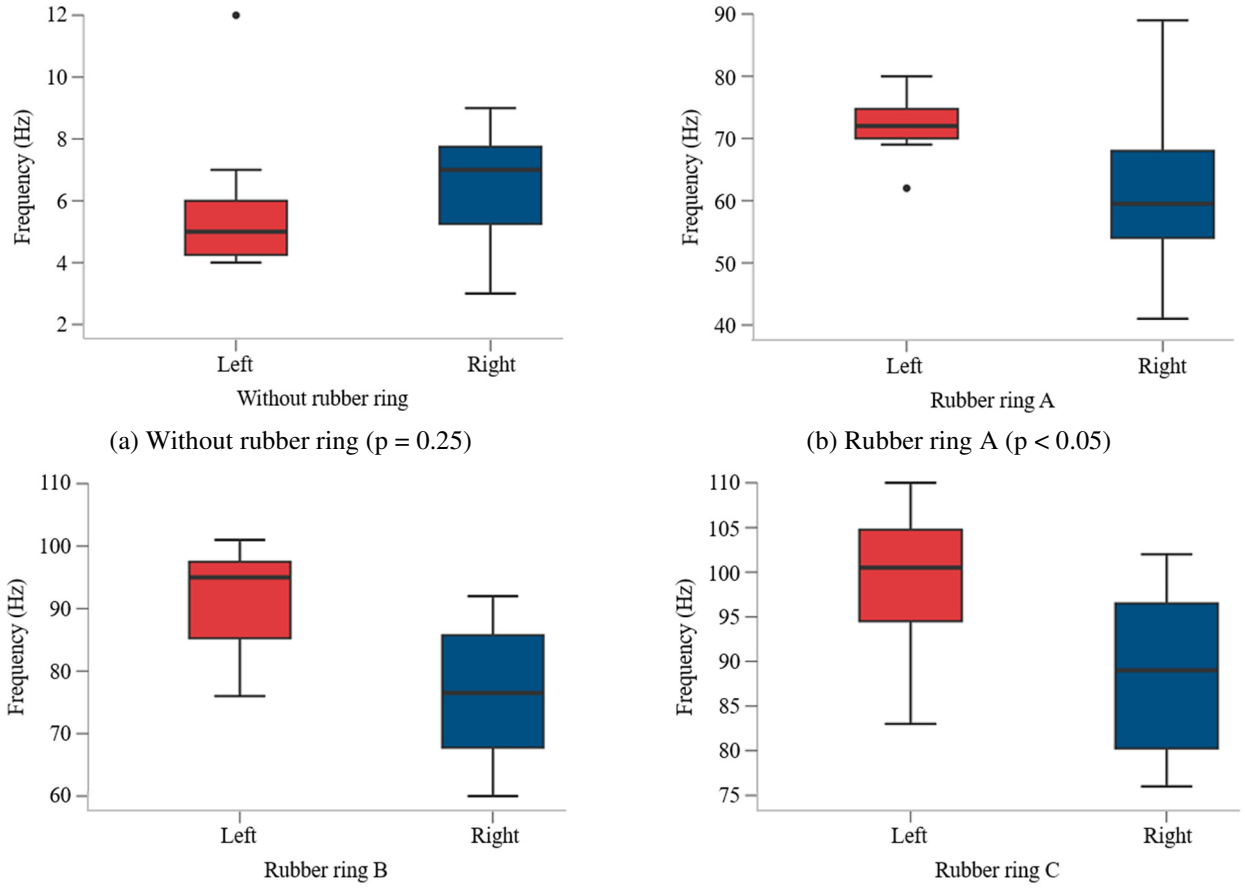


Fig. 5 Average soft tissue stiffness under ring compression

The results of the second round of data analysis are presented below. As shown in Fig. 6, the frequency for both hands was analyzed when the sensors and rubber rings A, B, and C reached the same level of deformation, with box plots depicting the frequencies at the peak of the spectrum. In Round 2, when deformation was applied without the rubber ring, the median peak amplitude of the spectrum was below 10 Hz for both hands, with no significant difference observed. However, when

deformation was applied with the rubber ring, the frequency increased to several tens of Hz, rising in correlation with Young's modulus of the rings. Notably, the median frequency of the left hand was consistently higher than that of the right hand, with significant differences.

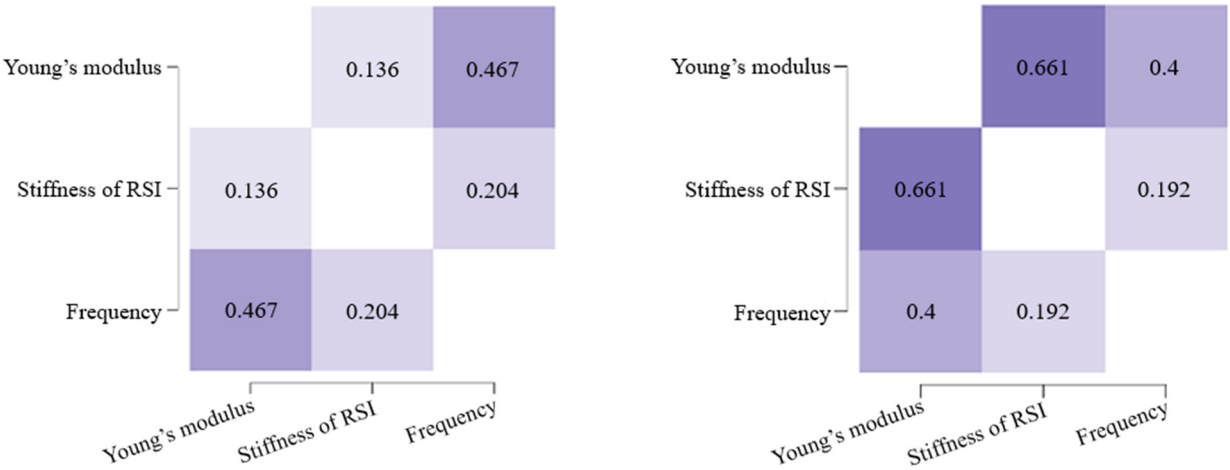


(a) Without rubber ring ($p = 0.25$) (b) Rubber ring A ($p < 0.05$)

(c) Rubber ring B ($p < 0.05$) (d) Rubber ring C ($p < 0.05$)

Fig. 6 Vibration frequency peaks across rubber ring conditions

From A, B, and C, three rubber rings, each randomly selected three of Young's modulus measurements, stiffness, and frequency to do the correlation test, the results are shown in Fig. 7. Left-handed Young's modulus and frequency were moderately positively correlated, whereas the rest were not. Right-handed Young's modulus, stiffness, and frequency were moderately positively correlated, while the rest were not. However, the p-values showed that none of them were significantly correlated.



(a) Heatmap of left-handed r values (b) Heatmap of right-handed r values

Fig. 7 The r values heatmap of Young's modulus, stiffness, and frequency

5. Discussion

The results of this study reveal several key insights and challenges. Besides, distinct differences were observed between the dominant and non-dominant hands. The dominant right hand exhibited increased soft tissue stiffness and frequency changes under higher loads, suggesting greater susceptibility to RSI-related damage. Conversely, the non-dominant left hand reached its upper stiffness limit at a lower load, potentially reflecting structural or functional disparities between the hands. These findings align with existing literature highlighting variations in muscle tension and structural adaptation between dominant and non-dominant hands [21].

Vibration frequency emerged as a reliable metric for evaluating RSI-related damage compared to soft tissue stiffness. Unlike stiffness, vibration frequency remained consistent within a reasonable load range and was less influenced by variations in hand size or strength. The higher variance in frequencies observed in the right hand, particularly under conditions of RSI damage, underscores its potential as a diagnostic indicator.

This study, however, has several limitations. First, the sample size consisted of only one participant, limiting the generalizability of the findings. While repeated experiments ensured internal consistency, future studies should involve larger and more diverse cohorts. Second, the methodology was constrained by the homogeneous nature of the rubber rings, which allowed only a single scalar measurement of force. Typically, real-world smartphone use involves complex, multi-directional loads distributed across all fingers. Therefore, incorporating individual pressure sensors for each finger and employing advanced analytical methods, such as uncontrolled manifold analysis, could provide more comprehensive insights [22].

Friction between the wire-shaped piezoelectric sensor and the skin introduced noise into the data, highlighting the need for improved sensor design and attachment methods. While the circular device used in this study effectively applied a single load, its design may require modification to account for multiple loads. Thus, future iterations could adopt a form factor resembling a smartphone to better simulate real-world conditions and enhance diagnostic accuracy.

The findings of this study have significant clinical implications. By integrating indicators such as RSI, finger pain, soft tissue stiffness, and vibration frequency, this study provides a preliminary framework for understanding and diagnosing RSI-related conditions. These insights are particularly relevant for individuals engaged in repetitive hand tasks, such as smartphone use, typing, or gaming, who face an elevated risk of hand trauma.

Future research should address the study's limitations by expanding the participant pool and refining measurement techniques. In particular, the validity of the methodology proposed in this study was tested using the proximity device [23]. Developing multi-sensor systems capable of capturing individual finger loads and reducing noise in signal collection will enhance the validity and applicability of the findings. Moreover, conducting community cohort studies can further elucidate the mechanisms and preventive strategies for RSI of the hand and fingers, ultimately improving clinical management and intervention strategies.

6. Conclusions

This study proposed the use of soft tissue stiffness and vibration frequency characteristics in the RSI area under hand load as diagnostic indices for smartphone-related finger conditions. Upon evaluating both indices in the dominant (high RSI risk) and non-dominant hands of the same subject, it became evident that soft tissue stiffness was unsuitable as a reliable index, whereas vibration frequency proved to be a more viable diagnostic feature. Despite existing limitations in device design, signal acquisition, and analysis methods, the study has progressed significantly in the right direction. Building upon these findings, the study will focus on refining diagnostic methodologies through device optimization and large-scale testing, to establish a practical diagnostic solution for smartphone-induced finger disorders.

Conflicts of Interest

The authors declare no conflict of interest.

Statement of Ethical Approval

(a) Statement of human rights

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Statement of informed consent

Informed consent was obtained from all individual participants included in the study.

Acknowledgment

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