Automatic Improper Loading Posture Detection and Correction Utilizing Electrical Muscle Stimulation

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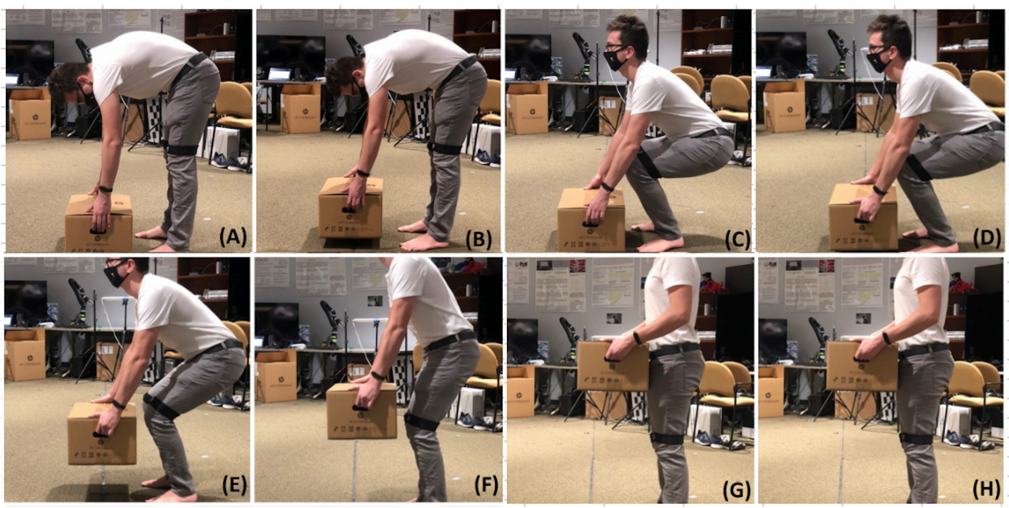

Figure 1: Improper loading posture can lead to lower back injuries and pain. Presented here are images of improper loading posture (A) & (B), corrected posture using Electrical Muscle Stimulation (C), and completion of the lifting activity (D-H).

ABSTRACT

Chronic lower back pain due to improper lifting techniques poses a major workplace safety hazard. The major risk factors for improper loading posture (ILP) include overloading, and improper loading of the lumbar muscles, ligaments, and vertebrae due to repetitive mechanical stresses exerted upon them. The current intervention technology relies on the users' intent and willingness to self-correct ILP through alert-based feedback or involves wearing bulky lift assist devices to prevent ILP. We address these issues with a physiological feedback system that utilizes IMU sensors for ILP detection and Electrical Muscle Stimulation (EMS) for automatic dynamic ILP correction for restoring ideal lifting angles for torso inclination and knee bend. In a user study involving 36 participants, our automatic approach delivered significantly faster correction and outperformed alternative feedback mechanisms (Audio and Vibro-tactile) and was perceived to be interesting, comfortable and a potential commercial product.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; *Wearable computing*; User studies.

KEYWORDS

Posture correction, Lifting, Wearable, Biological feedback, Electrical Muscle Stimulation, Preventive Healthcare

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1 INTRODUCTION

Nearly $90 billion is spent annually in the USA, for treating repetitive strain injuries (RSI) and lower body injuries arising out of poor workplace postures [13, 17]. Chronic lower back pain caused by improper loading posture while lifting objects has been known to affect nearly 80% of the population at some point in their lifetime and is one of the noted root causes of disability in the world [19, 32, 63]. ILP is characterized by high torso inclination and low knee bend which places a significant stress on the upper and lower regions of the spine (illustrated in Figure 2(A)). Whereas, correct lifting posture is characterized mainly by maintaining the natural erect curvature of the spine and using the legs to complete the lift in a safe manner. This translates to a torso inclination as allowed by the naturally erect spine without excessive curvature, and a knee bend as required to allow the legs to support the lift while minimizing the stress placed on the lower back (illustrated in Figure 2(B)). Additionally, the Occupational Safety and Health (OSH) academy estimated compressive forces exerted on the lower back in different lifting activities and compared the risk of injury for different lifting conditions. They utilized the Michigan 2-D static strength model to estimate the compressive forces and illustrate that the bent over lifting posture presents the highest risk of lower back injury. The repetitive mechanical stresses on the lower back can occur in occupational and non-occupational environments during common everyday activities such as leaning and lifting [7, 54, 66]. The major risk factors for lower back pain include overloading, improper loading, bending, twisting, and prolonged static leaning workplace postures [6, 38]. Even lifting moderate loads repetitively can increase the risk of lower back pain [10, 11, 25], weaken or damage the lumbar muscles [4], and could cause intervertebral disc degeneration or herniation [21]. The repetitive stresses exerted on the ligaments and muscle tissues can also result in fatigue, strain, and discomfort [18, 64]. This widespread characteristic of lower back pain due to improper loading has led researchers to evaluate different lifting strategies, develop ILP detection techniques, and lift assistive devices to support proper loading posture. As existing intervention technology offers only ILP detection and requires the users' willingness and effort to correct ILP, there is a fundamental need for the development of an autonomous ILP detection and correction system capable of automatically detecting ILP early in the lift phase and subsequently correcting it to mitigate risk of injury to the lower back.

As Electrical Muscle Stimulation (EMS) has been known to generate involuntary muscular contractions and induce physiological responses [15, 30, 61, 67], we developed a physiological feedback loop with an ILP detection system and EMS feedback to automatically detect and subsequently correct ILP through involuntary muscular contractions of the torso or legs. The primary aim of our work was to investigate and develop an understanding of the effectiveness of our automatic correction approach against self-correction in traditional feedback techniques. We conducted a novel between-subjects study to evaluate the performance of our automatic ILP detection and correction system across two correction strategies (torso inclination and knee bend). The performance of our automatic approach was measured by the correction response times to the EMS feedback. Qualitative data in the form of user perception rankings for

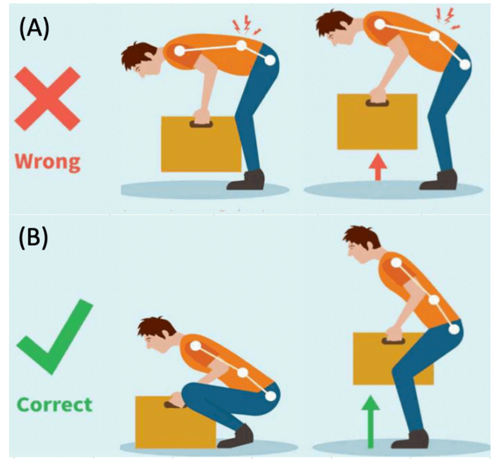

Figure 2: Improper lifting posture vs Proper lifting posture. (A) Improper lifting posture with high torso inclination and low knee bend, (B) Proper lifting posture with upright torso and ideal knee bend.

different usability parameters were recorded and analyzed. In comparison to the previous research, the main contributions of this work include:

(1) Design, development and implementation of a novel intervention prototype that autonomously detects and corrects ILP through a physiological feedback loop utilizing EMS.
(2) A validation study illustrating lifting patterns of young adults in comparison to ideal lifting patterns demonstrated by training experts.
(3) A user study for quantitative and qualitative evaluation of performance and usability of our automatic ILP detection and correction utilizing EMS feedback against two traditional feedback techniques (audio and vibro-tactile), and under two different correction strategies (torso inclination and knee bend) in breaking the habit of ILP, and for training and developing good lifting habits.

2 RELATED WORK

Previous research on ILP can be classified into two main categories: ILP monitoring and detection without feedback, and ILP detection with real-time feedback solutions.

2.1 ILP Monitoring and Detection Without Feedback

Improper loading posture detection and analysis has primarily been a domain of research in occupational therapy for investigating ergonomics of worker safety and health. Researchers have utilized computer vision, and IMU-based monitoring systems to track workers posture to obtain important information about the workers torso, knees, and ankles during different lifting activities. Researchers developed ergonomic monitoring systems using computer vision-based tracking algorithms for estimating trunk angles during lifting [23], for deep pose estimation to predict stress on the lower back during lifting activities [51], and to determine lift characteristics and classifying ILP [72]. Computer vision-based tracking systems have also utilized Microsoft Kinect for measuring strain on torso, analyzing current lifting methods, and customizing training protocols that recommend safe lifting weight limits to industrial workers [50]. Additionally, Microsoft Kinect has also been utilized to develop adaptive training systems for factory workers to lift weights in a safe manner [16], and to enable tracking of users' activity for detecting poor postures that could lead to back injuries and encourage healthy posture at home [76]. However, all the above-mentioned visual tracking systems do not provide any correctional feedback to the user and are expensive to setup, time consuming, sensitive to occlusions, field of views, surrounding environments, and only deliver post-hoc safety recommendations for further lifting.

Alternatively, IMU-based wearables have been utilized for investigating work-related musculoskeletal disorders surrounding the lower back, for assessing high risk postures and warning workers while performing hazardous operations [75], for automatically classifying ILP using supervised machine learning algorithms [22], and for assessing body weight squat techniques to deliver exercise performance feedback to the users [59]. Further, researchers developed a hybrid ILP detection technique using surface electromyography, and accelerometer measurements on the trunk for classifying lifting techniques into low and high-risk categories [9]. Finally, reducing risk of improper lifting through wearable IMUs and machine learning have been evaluated by different researchers for postural pattern recognition and ILP classification [12], for identifying potential work-related risks using smartphone sensors [56], and for understanding the effect of bio-mechanical demands of various construction related tasks on lower back disorders [70]. Although IMU-based systems solve the issues of occlusion, and are relatively less expensive compared to visual-based technologies, the above-mentioned studies focus primarily on obtaining diagnostic information on ILP and improper gait for developing preventive awareness, and rehabilitating protocols for occupational hazards.

2.2 ILP Detection with Feedback

Although several studies have examined the trunk, hip, and knee stability during occupational lifting, and classified improper loading postures, relatively few studies have dealt directly with providing correction feedback to the user. Researchers have developed an IMU-based smart garment with real-time audio feedback to facilitate rehabilitation therapy in patients with spinal disorders when poor loading postures were detected [74]. Similarly, "Lift Alert" was developed by Safety Alert Systems to provide an auditory biofeedback alerts to the user [20]. Although the study concluded that Lift Alert was reliable in detecting trunk flexion angles, their system addressed only a single component of safe lifting i.e., only trunk flexion while the knee position which also plays a crucial role in safe lifting, was not considered. Further, researchers have developed "CareJack", an IMU-based vibro-tactile feedback system designed for analysis of ergonomic human lifting behaviors, detecting poor loading posture, and presenting correction feedback to the user [37]. Even though the above-mentioned feedback techniques using audio and vibro-tactile modalities have been known to improve posture by mitigating the incidence of improper loading posture, and reduce the time spent in poor posture, they still relied on the speed of correction feedback presented to the user, the users' readiness, and desire to correct their position when feedback was presented.

Alternatively, researchers have developed passive, and active lift assist wearable exoskeletons for preventing ILP, and effecting controlled lifting strategies, respectively. Passive exoskeletons have been designed using spring-based mechanisms to store energy during the lowering phase of a lift, and leverage the stored energy to support the lifting phase of the lifting activity. These systems have proven to be effective in reducing stress and strain on the spine and lower back while performing lifting activities [1–3, 49, 71]. Building upon this, researchers designed and developed active exoskeletons to mitigate the risk of spinal, and lower back injuries. Active exoskeleton systems developed for lift assistance and increasing the versatility, employed control systems, actuators, and external power sources for mitigating risk of injury by preventing improper loading posture [5, 26, 33, 55, 69]. These systems were able to demonstrate reduced effort, stress, and strain on the back muscles [39, 53]. Additionally, these control systems are not autonomous, and incapable of detecting users' intent prior or during the lifting activity to allow activation of actuators for power assistance. Power assistance through these exoskeletons is usually triggered manually using extra buttons [34] or switches [53]. However, these exoskeleton systems are known to be bulky, and place an increased physical load on the users' body which hinder movement during normal daily activities and could cause increased leg muscle activity, discomfort, and deconditioning [14]. Further, these devices require manual control of the actuators which places an additional cognitive load on the user, make lifting tasks intermittent, and reduces the work efficiency and acceptability in work environments. Finally, most active exoskeleton systems require triggering the actuators manually, and may cause operational errors while lifting heavy loads. For all these reasons, the development of an autonomous ILP detection and correction system capable of automatically detecting ILP as soon as it starts and subsequently correcting this posture can turn out to be crucial. This presents a gap in the research for developing an autonomous system for detection and correction of ILP during lifting activities to mitigate the risk of injury to the lower back, knees, and ankles.

Our proposed automatic ILP detection and correction system addresses the above issues by automatically restoring good lifting posture through involuntary muscular contractions using EMS, thereby reducing the additional cognitive load required for self-correcting posture.

2.3 Electrical Muscle Stimulation (EMS)

EMS has traditionally been a non-invasive technique for pain management therapy through application of electrical impulses to the muscles and nerves. Alternatively, EMS has also been utilized for rebuilding strength post-surgery [67] and recovery rehabilitation protocols [8, 15]. Further, clinical research studies have also evaluated the use of EMS for restoring function and extending hand grasping mobility in hemiplegic patients [15], enabling muscle contractions to support swallowing [62], and development of neuro-prosthetic control systems [61].

Recently, EMS has found increasing interest in the human-computer interaction (HCI) domain due to its ability in producing discrete vibro-tactile and somatosensory feedback for increasing immersion in virtual reality (VR), augmented reality (AR), and extended reality (XR) applications [35, 40, 43, 65]. Owing to its adaptability, EMS has been employed for developing novel interaction techniques, for enabling activity training, for developing spatial interfaces, and providing enhanced immersive experiences. EMS has been utilized to demonstrate learning new motor skills such as playing a musical instrument [68], extend affordances to objects [46], and accelerating preemptive reflex actions [28, 29, 57]. Additionally, EMS has allowed researchers to enhance immersion through shared kinesthetic experiences for experiencing tremors in Parkinson's disease patients [58] and, stimulating experiences of fear and pain [36], and enabling discrete communication of emotions between people [24]. Further, EMS has been integrated with input/output technologies to develop biological feedback loops for proprioception [45], smart navigation(Cruise Control) [60], automatic posture correction to correct slouching [30], and balance asymmetry [31]. This has paved the way for using EMS to develop a correction feedback system to correct ILP.

The current literature has suggested that traditional alert feedback systems rely completely on the users' desire and intent to correct improper posture, and automatic ILP correction through EMS has not been fully explored. Additionally, even though, the validation of adaptability and capability of EMS feedback for delivering distinct and focussed feedback, our work investigates the feasibility of EMS-based automatic ILP correction for restoring safe lifting posture and mitigating risk of injury.

3 AUTOMATIC ILP DETECTION AND CORRECTION

To address the issue of detecting and automatically correcting ILP, we developed a physiological feedback loop-based wearable intervention prototype relying on IMU sensors and EMS (illustrated in Figure 3). Our prototype employed three Metawear MMR wireless sensors for measuring angular changes in human posture, and the openEMSstim package [42] for presenting the EMS correction feedback for restoring healthy posture during lifting activities. To complete the physiological feedback loop, a C#-based user interface using the Metawear C# SDK was developed for monitoring the posture information from the IMUs and integrated with the EMS hardware for presenting correction feedback when poor lifting postures are detected. Improper loading posture is mainly characterized by excessive inclination of the torso, and insufficient knee bending [27] (illustrated in Figure 1 (A)). To monitor the torso inclination, IMU 1 is placed at the center of the collar bone above the chest (illustrated in Figure 4 (A)), and to monitor the knee bend angles, the other IMU's 2 and 3 were placed on each knee (illustrated in Figure 4 (B) & (C)).

3.1 Torso Inclination and Knee Bend Angle Thresholds

Improper loading posture can be detected from measuring the offset between actual, and ideal torso inclination and knee bend angles. Our proposed system detects ILP when the user's torso inclination is greater and knee bend angles is lower than the ideal torso inclination and knee bend angles. The change in posture is

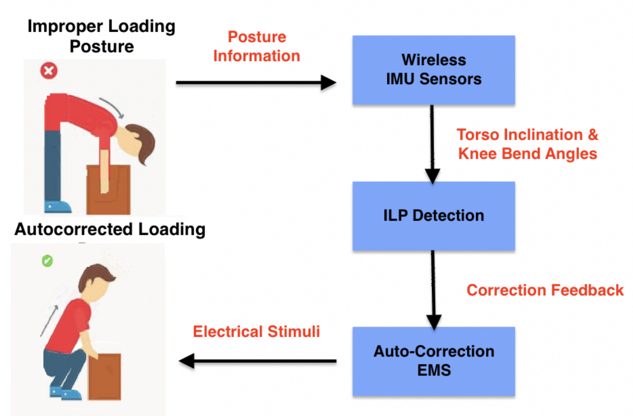

Figure 3: Physiological Feedback Loop: Automatic Improper Loading Posture Detection and Correction System. Improper loading posture (top) illustrates excessive torso inclination and insufficient knee bending that can lead to long term low back pain and the auto-corrected posture (bottom) illustrates the restored proper lifting posture achieved through using EMS.

calculated from the angular information obtained from the IMU sensors. The user's torso inclination angle is calculated from the pitch of IMU_1, and the knee bend angles are calculated from the average yaw of IMU_2 and IMU_3. The orientation of the IMU_1 is such that the measured angle is the pitch rotation around the X-axis, and for IMU_2, and IMU_3, the measured angle is the yaw rotation around the Z-axis. The orientation of the IMUs for the torso and knee are illustrated in the Figure 4(D) and (E) respectively. The torso inclination is calculated from the corrected pitch of IMU_1 as follows:

$$\tau_t^1 = \tau_t - \tau_o, \tag{1}$$

where τ_o is the initial torso pitch on IMU_1 (rotation around X-axis) at the initial position as illustrated in 4(C), τ_t is the torso pitch at timestamp t on IMU_1 (rotation around X-axis), and τ_t^1 is the corrected pitch at timestamp t on IMU_1.

The knee bend angles are calculated from the corrected yaw of the IMU_2 and IMU_3 as follows:

$$k_t^1 = \frac{(l_t - l_o) + (r_t - r_o)}{2}, \tag{2}$$

where l_o is initial left knee yaw on IMU_2(rotation around Z-axis), l_t is the left knee yaw at timestamp t on IMU_2(rotation around Z-axis), r_o is initial left knee yaw on IMU_3, r_t is the left knee yaw at timestamp t on IMU_3, and k_t^1 is the average knee bend angle at timestamp t.

To determine the extent of ILP in young adults, we collected data from 10 participants (Male=7, Female=3) with mean age of 21.8 years (S.D= 3.9 years) while performing a task involving lifting 4 different boxes of different sizes and weights illustrated in Table 1. To determine the ideal torso and knee bend angles for each box, we also collected torso inclination and knee bend angles from five certified fitness trainers (Male=3, Female=2) performing the same

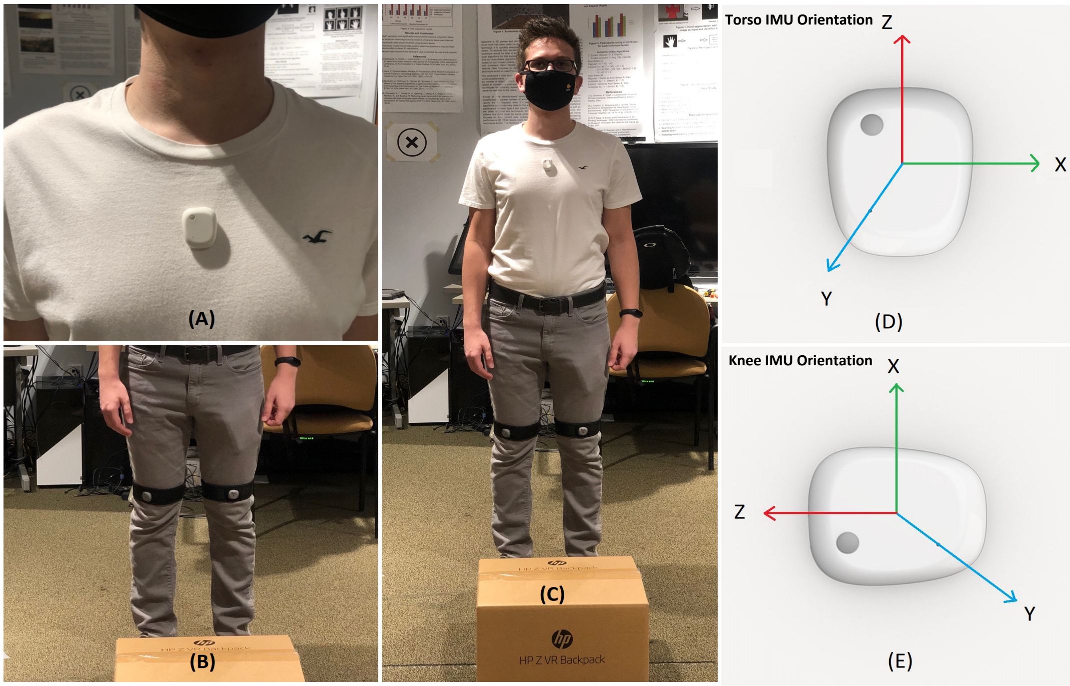

Figure 4: Wireless IMU sensor placement for improper loading posture detection: (A) Front view showing sensor placement below center of collar bone above the chest, (B) Front view showing sensor placement above each knee, (C) Front view showing sensor, box placement and experiment set up, (D) Orientation of the IMU_1 for measuring Torso Inclination, (E) Orientation of IMU_2 & IMU_3 for measuring Knee Bend.

Table 1: Size and Weight of Boxes.

Box	Weight	Size (LxWxH) cm
Box 1	5 lbs (2.7 Kg)	25.4 x 25.4 x 16.5
Box 2	10 lbs (4.54 Kg)	38.1 x 30.48 x 25.4
Box 3	15 lbs (6.8 Kg)	43.18 x 27.94 x 27.94
Box 4	20 lbs (9.07 Kg)	53.34 x 38.1 x 40.64

lifting task at the University's Recreation and Wellness Center with a mean age of 21.4 years (S.D=1.9 years). All trainers were certified by the following organizations: AFAA [1], NASM [2], NSCA [3], and ACSM [4]. All participants were required to lift the four boxes three times in a random order. The young adults from the general population were allowed to lift each of the boxes in their own natural technique while the trainers were required to demonstrate good lifting posture during their lifting tasks. The torso inclination and knee bend angles for each participant were recorded for each box.

The torso inclination and knee bend angular patterns of young adults/trainers while lifting each of the four boxes are illustrated in Figure 5. The average maximum torso inclination angles and maximum knee bend angles among young adults from a general population and the trainers were calculated and illustrated in Figure 6. The ideal angles demonstrated by the trainers using good lifting posture showed lower torso inclination ranging between 38° to 48° and the higher knee bend angles ranging between 63° to 88°. The lower torso inclination angles are representative of a straight and upright torso position and the higher knee bend angles indicate greater knee bending which allows the user to leverage the weight of the load using the stronger leg muscles. On the contrary, the young adults exhibited high torso inclination angles ranging between 76° to 88° and low knee bend angles 38° to 57°. The higher torso inclination angles are representative of a bent over improper loading posture, and the lower knee bend angles place higher stresses on the relatively less stronger lower back muscles and vertebrae, to complete the lift and hence present a higher risk of injury to the lower back. The difference in the measured torso inclination and knee bend between the trainers and young adults indicated that young adults normally exhibited bent over poor lifting techniques with greater torso inclination and insufficient knee bend. The average maximum torso inclination and knee bend angles exhibited by the certified trainers for the different boxes were recorded and utilized to preset thresholds as ideal torso inclination and knee bend angles in our ILP detection system to improve the detection of poor lifting posture or ILP. These thresholds were chosen to overcome measurement errors and ensure random movements do not lead to false positive improper loading posture detection.

[1]https://www.afaa.com
[2]https://www.nasm.org
[3]https://www.nsca.com
[4]https://www.acsm.org

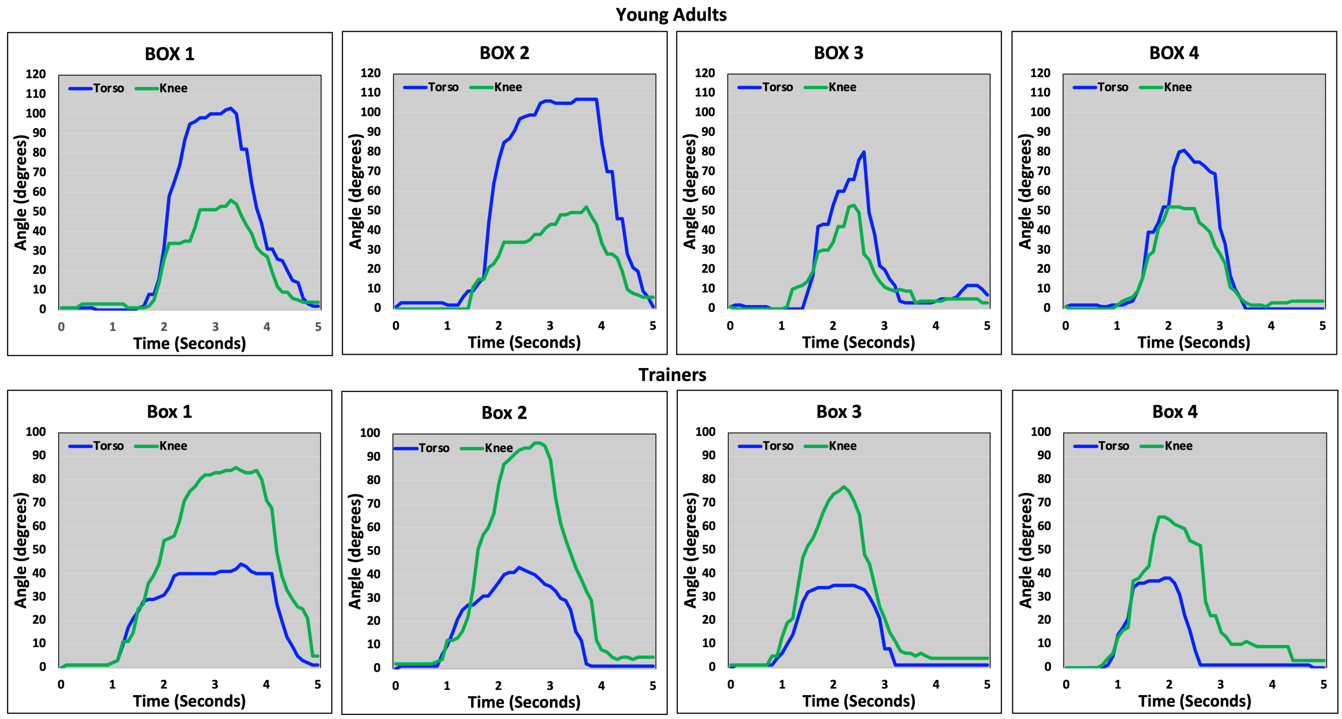

Figure 5: Torso inclination and knee bend angular change patterns exhibited by one randomly chosen young adult and one trainer (as an example) while lifting each of the four boxes. While lifting each of the same boxes, the young adult shows high torso inclination and low knee bend, while in contrast, the trainer demonstrating ideal lifting techniques shows low torso inclination and high knee bend.

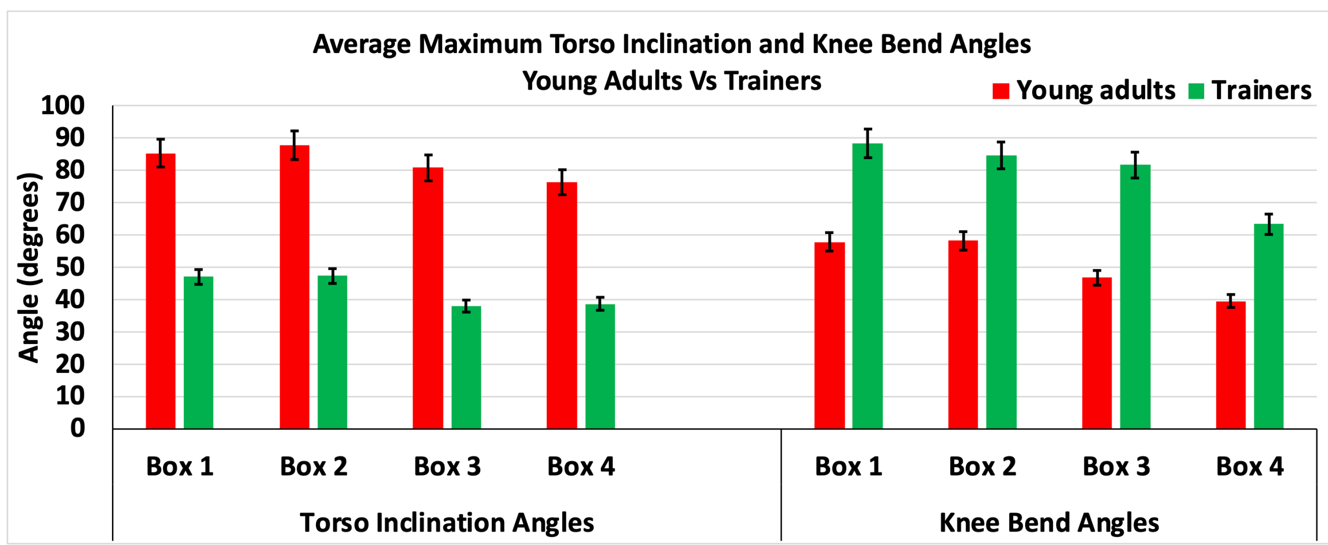

Figure 6: Average maximum torso inclination and knee bend angles exhibited by young adults and trainers while lifting different boxes of different weights and sizes. Error bars:95% CI.

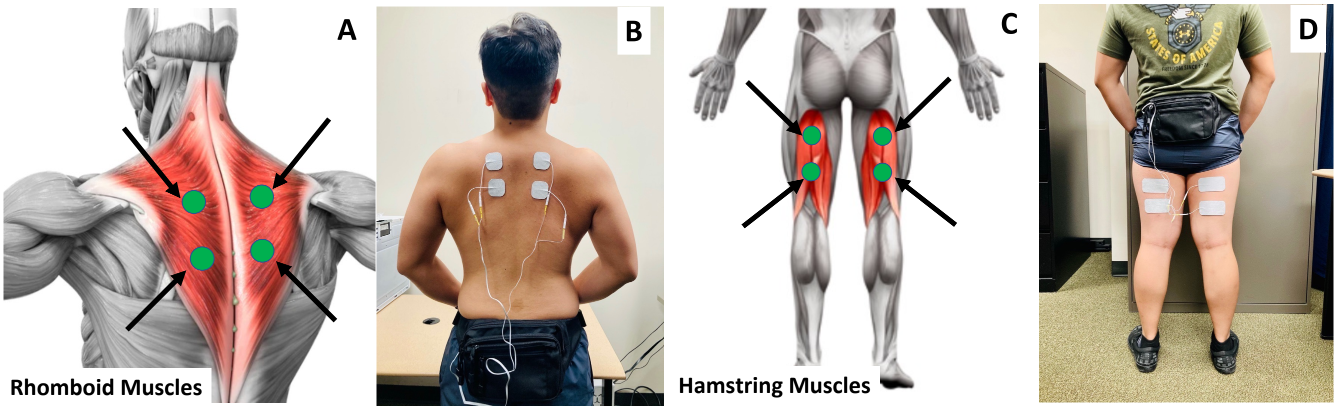

Figure 7: (A) Anatomical landmarks of the Rhomboid muscles (B) EMS electrode placement on Rhomboid muscles for torso inclination correction, (C) Anatomical landmarks of the Hamstring muscles, & (D) EMS electrode placement on Hamstring muscles for Knee bend correction.

The threshold torso inclination and knee bend angles were used to initiate the feedback loop and present the correction feedback.

3.2 ILP Detection and Correction Feedback

Our proposed system detects ILP with respect to each of the four boxes when both of the following conditions are met:

(a) Users' torso inclination is greater than the ideal torso inclination angle obtained from the validation study in Section 3.1, and
(b) Users' knee bend is lower than the ideal knee bend angle obtained from the validation study in Section 3.1.

Subsequently, when improper loading posture was detected, we employed two separate posture correction strategies to automatically restore proper loading posture by applying EMS to the two different affected locations separately as follows:

- Torso Inclination Correction
- Knee Bend Correction

To correct torso inclination, EMS is applied to the rhomboid muscles through two pairs of electrodes (illustrated in Figure 7 (B)). Knee bend correction is achieved by applying EMS to the hamstring muscles through two pairs of electrodes (illustrated in Figure 7 (D)). Correct lifting posture requires both sets of muscles to work together, as the inclination of the torso affects the bend of the knee, and vice versa to complete the lifting task. For example, correcting the torso affects knee bending, and correcting the knee bend affects the torso inclination. This is due to the nature of the human anatomy and the biomechanics involved with a lifting task. It is not possible to have a high torso inclination with ideal knee bend angles, or low knee bend with ideal torso inclination angles for a safe lift with correct posture.

3.2.1 Torso Inclination Correction Strategy. In the torso inclination correction strategy, ILP was detected when the users' current torso inclination and knee bend angles were below ideal torso inclination and knee bend angles recorded from the trainers, and automatic correction through EMS was applied to the rhomboid muscles to restore ideal torso inclination angles. An involuntary rhomboid muscle contraction generates a pulling force in the opposite direction from the improper torso inclination posture and thereby generates a physiological response to stabilize the torso inclination. As a result of this torso inclination correction, ideal knee bend are affected by the user in order to reach the box and perform the lifting task. Two pairs of electrodes are utilized for contraction of the rhomboid muscles which causes the shoulder blades to be pulled back and to restore an upright torso to the ideal torso inclination angles.

3.2.2 Knee Bend Correction strategy. Alternatively, in the knee bend correction strategy, ILP was detected when the users' current torso inclination and knee bend angles were below ideal torso inclination and knee bend angles, and automatic correction through EMS was applied to the hamstring muscles to cause an involuntary contraction to produce necessary bend angles at the knees. As a consequence of achieving the ideal knee bend angles, the users' torso inclination is also restored back to ideal torso inclination angles. Two pairs of electrodes are utilized for contraction of the hamstring muscles (one pair for each hamstring) to cause the knees to bend toward the ideal bend angles. The preset torso inclination and knee bend angle thresholds were determined from the validation study described above in Section 3.1.

Additionally, IMU and EMS calibration play a crucial role in the effectiveness of the system. The calibration process includes correcting all three IMUs' offset values in the standing upright position of the user and monitoring the angular change in the proper and improper loading posture with respect to the standing upright position. The EMS intensity calibration is manually incremented to deliver an intensity that is optimal for generating involuntary muscular contraction and avoid any pain. This EMS intensity provided to the user for generating the necessary involuntary contraction for correcting the improper loading posture and restoring the proper loading posture is recorded and utilized during the experiment. The TENS device can deliver intensities between (0-100mA) based on requirement and user comfort. A continuous 75 Hz square wave pulse at the recorded EMS intensity and a pulse width of 100 μs is supplied as the electrical stimulus to the users [30, 31, 41].

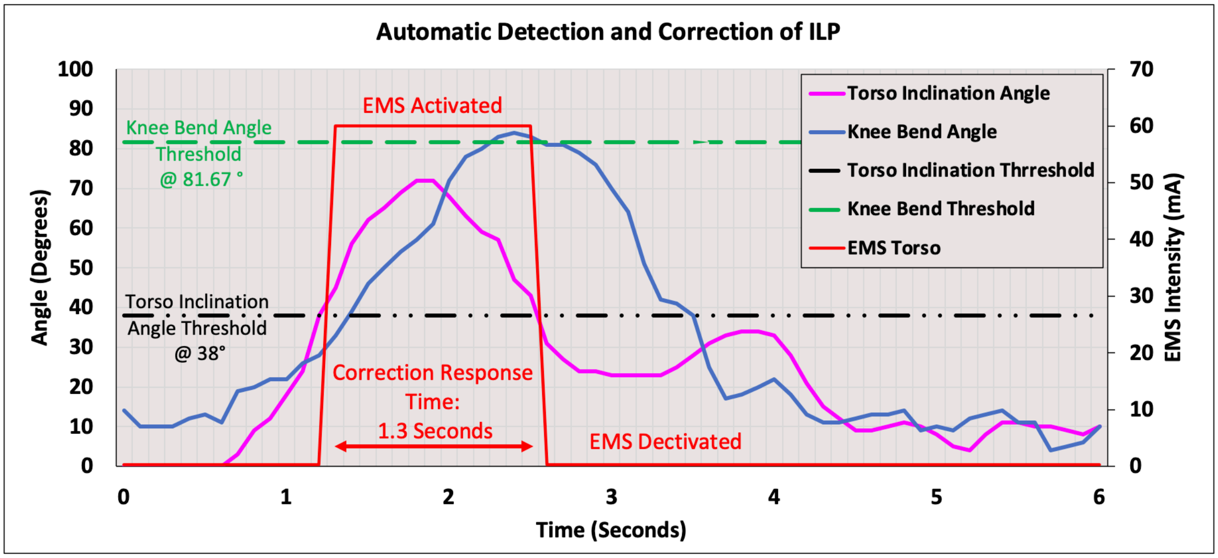

Figure 8: Automatic ILP Detection and Correction: Graph showing EMS activation and deactivation. When ILP was detected from the user's high torso inclination and low knee bend angle, EMS was activated on the torso/knees for ILP correction. EMS was deactivated when ideal torso inclination and knee bend angles are achieved.

3.3 Operation

Our physiological feedback loop for detecting and correcting ILP relied on the angular changes from the sensors placed on the torso and knees to measure torso inclination and knee bend angles respectively. ILP occurs when a user attempts to perform the lifting task with a high torso inclination and low knee bend angles. This would be representative of a bent over lifting posture which places an unnecessary stress on the lower back and increases the risk of injury. To detect these improper loading postures, our system utilized the torso inclination and knee bends angles obtained from the trainers as ideal threshold angles for each box. As an example, Figure 8 illustrates a scenario where one participant experiences activation and deactivation of EMS correction feedback when ILP was detected and corrected for that participant during the torso correction strategy part of the study. The participant exhibited ILP (as in Figure 1(A)) while lifting Box 3. For Box 3, the ideal torso inclination and knee bend angles were 38° and 81.67°, respectively (determined in Section 3.1). When the participant's torso inclination exceeded the ideal torso inclination threshold, and the knee bend was sufficiently lower than the ideal knee bend angle for Box 3, ILP was detected. The ILP detection automatically activates the EMS correction feedback by applying the participant's recorded optimal stimulus of 60 mA for invoking an involuntary contraction of the participant's rhomboid muscles and for generating a physiological response of stabilizing the torso in an upright position towards the ideal torso inclination angles. This in turn causes the user to bend knees to the ideal knee bend angles in order reach and lift the box with good lifting posture. The EMS remained active until the ideal torso inclination and knee bend angles were reached, and EMS was automatically deactivated upon reaching the ideal thresholds. A correction response time of 1.3 *seconds* was recorded between activation and deactivation of the EMS for torso stabilization.

The knee bend correction strategy works similarly to achieve the ideal knee bend angles, which in turn cause the torso to stabilize towards ideal torso inclination angles to establish good lifting posture. The EMS intensity is calibrated for each individual based on achieving the desired muscle contractions for generating corrective physiological responses and their level of comfort, and differs from one individual to another. The EMS calibration procedure is described in detail in Section 4.4 below.

4 USER EVALUATION

We conducted a user study to evaluate the effectiveness of our automatic ILP detection and correction based on EMS feedback, and also the effect of the two correction strategies on user perception. Participants performed the lifting tasks and were free to lift in their own natural way. We compared our automatic approach against two alternative feedback systems (audio and vibro-tactile) requiring self-correction, and across both correction strategies. We also evaluated the user perception of correction feedback, comfort, disruption, posture awareness, and preferences.

4.1 Subjects and Apparatus

We recruited 36 participants (Male=22 , Female=14). All participants were aged 18 years and above with a mean age of 22.6 years ($S.D$ = 3.6), mean weight of 70.4 Kg ($S.D$ = 11.8Kg), and mean height of 170.4cm ($S.D$ = 11.2cm). All participants were able bodied and had no upper and lower body injuries. For monitoring the torso inclination and the knee bend angles, three Metawear MMR IMU sensors were utilized. The Metawear MMR IMU sensors contain an inbuilt vibration motor for delivering vibro-tactile feedback notifications. The EMS is generated with an off-the-shelf Tens unit and controlled by the openEMSstim package for activating and modulating the intensity of the electrical stimuli supplied to the

Figure 9: Experimental setup showing the four different sized boxes with different weights that need to be moved from zone A to B, and vice versa based on instructions presented to them via a Microsoft Surface 50-inch display placed in front of them.

Table 2: User ranking on Lifting task, ILP, alert devices, and EMS. User ranking on a 7-point Likert scale. T:Torso inclination correction strategy, K: Knee bend correction strategy.

User Experience	Strategy	Mean	S.D
Lifting Tasks/Deadlift/Squats	T	3.22	2.41
	K	3.44	1.69
Experienced ILP	T	3.78	1.21
	K	3.83	1.29
Exposure to ILP alert devices	T	2.33	1.28
	K	1.94	0.94
Exposure to EMS	T	1.83	1.09
	K	1.89	0.90

muscles. The hardware used for the study user interface was a 14" Intel i7 Laptop, and a Microsoft Surface 50 inch display screen. Four boxes of different sizes and weights were utilized for the study. The size and weight of the boxes are illustrated in the Table 1. The Microsoft Surface display screen was utilized during (a)Calibration: for presenting participants with information on Torso inclination and Knee bend angles, and assisting them to get in to the initial upright torso and no knee bend position, and (b)Main study: for display commands about which box to lift and where to place it. Torso inclination and knee bend angles were not presented to the participants during the main study.

From the pre-questionnaires, participants ranking of their prior exposure to posture alert devices and EMS, experience with posture problems, and improper loading posture were noted and illustrated in Table 2. Participants ranked their exposure and experience on a 7-point scale with 1 meaning never/no experience and 7 meaning frequently/very experienced.

4.2 Experimental Design

A 2 (correction strategies) by 3 (feedback modalities) mixed subjects experiment involving 36 participants with 18 participants for each correction strategy was conducted to investigate the performance and feasibility of our approach. The within subject factor was the feedback type (audio, vibro-tactile, and EMS) and the between subject factor was the correction strategy (Torso inclination correction, and Knee bend correction). We compared the performance of our automatic ILP correction using the EMS feedback against the self-correction in the audio and vibro-tactile feedback techniques. Average correction response times and user perception of the system across the two correction strategies and the three feedback types were evaluated. The experimental set up is illustrated in Figure 9.

4.2.1 Task. To determine the effectiveness of our approach, all participants had to perform the following task to experience the different correction feedback and correction strategies:

- Lift each box from zone A, move to zone B, and place box in zone B.
- Lift each box from zone B, move to zone A, and place box in zone A.

The order in which the participants moved the boxes from Zone A to Zone B or vice versa were randomized. The participants were required to lift each of the four boxes separately and complete all three feedback modalities in one of the two correction strategies allotted to them as follows:

- **Modality 1:** Audio feedback and self-correction
- **Modality 2:** Vibro-tactile feedback and self-correction
- **Modality 3:** EMS feedback and automatic correction

In each modality, participants were required to pick up all four different boxes in a counterbalanced order to minimize learning effects. The independent variables in the study were the three different modalities and the dependent variables were the average correction response times, and user perception parameters such as overall experience, accuracy of correction feedback, task disruption, comfort, and posture awareness. Each study session lasted approximately 20-30 minutes and the participants were compensated $10 for their participation.

4.3 Research Hypotheses

The study was designed to determine the effectiveness of automatic or self-posture correction on user experience across the two correction strategies and the three modalities. As such, we expect significant differences between the three modalities and the two correction strategies which could influence user experience. For investigating the system performance and user perception, we have four research hypotheses:

- **H1:** Automatic EMS-based correction feedback will deliver a faster correction to ILP in comparison to the self-correction based audio, and the vibro-tactile feedback across the two correction strategies.
- **H2:** User perception of correction feedback accuracy in the automatic EMS-based correction feedback will be greater than audio, and vibro-tactile feedback across the two correction strategies.
- **H3:** Automatic EMS-based correction feedback will deliver an equally comfortable user experience in comparison to audio, and vibro-tactile feedback across the two correction strategies.
- **H4:** No evidence will be found for a difference in task disruption across the audio, vibro-tactile, and EMS correction feedbacks across the two correction strategies.

4.4 Experimental Procedures

Prior to starting the experiment, participants were required to review the consent form that details the experiment, safety, risks, compensation, compliance, and provide consent for the study session to start. Participants then completed a survey on their knowledge and experience on workplace related posture issues, intervention technology, and EMS as illustrated in Table 2. Next, IMU sensors were placed on the participants knees and center of the collar bone above the chest (as shown in Figure 4 (A) & (B)), for detecting improper loading posture and data collection. Adhesive EMS electrodes were placed on the rhomboid or hamstring muscles prior to the EMS feedback session for torso inclination correction strategy or knee bend correction strategy respectively. Subsequently, IMU sensors were calibrated for each participant and corrected for offset errors. Correct IMU sensor functioning and operation were verified during the calibration by monitoring the angular changes when participants were in upright, proper, and improper loading positions.

Before the EMS feedback session in both torso inclination and knee bend correction strategies, an EMS intensity calibration process was done manually for each participant on the respective locations. After electrode placement on the rhomboid or hamstring muscles, moderators would increment the intensity until an involuntary muscular contraction causing posture correction occurs. The participants would be calibrated manually only once for EMS intensity to generate a physiological response of correcting the torso inclination and knee bending for restoring proper loading posture while picking up the box.

In the case of the torso inclination correction strategy, EMS was applied to the rhombus muscles to invoke an involuntary contraction which generates a physiological response of stabilizing the torso in an upright position. Alternatively, in the case of the knee bend correction strategy, EMS was applied to the hamstring muscles to invoke an involuntary muscular contraction that generates a physiological response of bending the knees. During EMS calibration, participants were asked to emulate an improper loading posture, and moderators manually incremented the EMS intensity applied to the torso and knee independently to cause torso inclination correction, or knee bend correction. As EMS also produced a tactile or haptic effect even at low intensities, participants were asked to not respond to the tactile or haptic effect to ensure the haptic/tactile component of EMS does not contribute to the automatic correction process in any way. Moderators additionally asked participants to verbally respond specifically to the following questions during calibration to ensure rhomboid or hamstring muscular contractions and participant comfort: 1) when they initially felt the stimulation (haptic sensation), 2) when the intensity was generating an involuntary muscular contraction and/or when they experienced a pulling force on their torso in the opposite direction in case of torso inclination correction, and when a downward pulling force causing their knees to bend is experienced due to contraction of their hamstrings in case of knee bend correction, and 3) when any pain was experienced. For each participant, when involuntary muscular contractions were confirmed verbally by the participant and visually verified by the moderators, the optimal EMS intensity that was generating the involuntary muscular contraction to correct the improper loading posture was recorded and selected for the EMS part of the study.

The study comprises three parts: audio, vibro-tactile, and EMS feedback for torso inclination correction strategy or knee bend correction strategy. Each part of the study is 5 minutes in duration and all participants were required to finish all parts to complete the study. The participants were given a 5-minute break after each part of the study. Participants then completed a survey about their experience after each part and a comparative survey on their overall experience at the end of the study. Participants completed all three parts of the study in a counterbalanced order. In all three parts, participants were required to pick up each of the four boxes separately in their own natural lifting technique. The order of the boxes that the participants were required to lift was randomized and command prompts were presented to the participants from a C# user interface displayed on a Microsoft Surface 50 inch display placed in front of them (illustrated in Figures 9 a & b). Participants were required to follow the commands presented to them and perform the task described in 4.2.1. Their posture was monitored for

ILP detection and application of correction feedback with respect to the modality and correction strategy.

4.4.1 Audio feedback and self-correction. When ILP was detected by the system based on the IMU sensor feedback, an audio notification in the form of a distinct auditory tone was presented to the users, and the users were required to self-correct their ILP. Both momentary, and continuous auditory tones have been utilized as feedback in numerous posture correction studies. However, for the purposes of this study we selected momentary auditory notifications as in other previous studies [30, 31, 52]. During our initial pilot study, we observed that participants were distracted and expressed concerns about feeling over-conscious due to the continuous auditory sound drawing unnecessary attention from people in the vicinity. Lifting activities are fast-paced and dynamic in nature, and we found in our pre-study trials that the typical duration for completion of a lift ranged between 1 and 2 Seconds. As a result, we presented the users with a momentary auditory tone with a 1 Second duration when ILP was first detected and another 1 Second auditory tone after the ILP correction is achieved.

In the case of the torso inclination correction strategy, participants were required to correct their ILP by stabilizing their torso towards the ideal torso inclination angle until a second auditory tone indicating corrected posture (with ideal torso inclination and knee bend angles) was presented to the user. In the case of the knee bend correction strategy, participants were required to correct their ILP by bending their knees towards the ideal knee bend angles until a second auditory tone indicating corrected posture (with ideal torso inclination and knee bend angles) was presented to the user.

4.4.2 Vibro-tactile feedback and self-correction. When ILP was detected by the system based on the IMU sensor feedback, a haptic notification in the form of continuous vibration was activated on IMU_1 placed on the torso (for torso inclination correction strategy), or IMU_2 and IMU_3 placed on the knees (for knee bend correction strategy), and the users were required to self-correct their ILP. In the case of the torso inclination correction strategy, participants were required to correct their ILP by stabilizing their torso towards the ideal torso inclination angle until the continuous haptic vibration notification on IMU_1 stops, indicating restoration of proper loading posture (with ideal torso inclination and knee bend angles). In the case of the knee bend correction strategy, participants were required to correct their ILP by bending their knees towards the ideal knee bend angles until the continuous haptic vibration notification on IMU_2 and IMU_3 stops, indicating restoration of proper loading posture (with ideal torso inclination and knee bend angles) was presented to the user. The time between the activation and deactivation of the continuous haptic notifications was recorded as response times for self-correcting ILP.

4.4.3 EMS feedback and automatic correction. When ILP was detected by the system, the EMS feedback was activated to apply the recorded EMS intensity to the rhomboid/hamstring muscles to invoke an involuntary muscle contraction in the torso inclination/knee bend correction strategy respectively. In the case of the torso inclination correction strategy, the rhomboid muscle contraction produces a pulling force in the opposite direction to torso inclination. This generates the physiological response of stabilizing the torso to an upright position towards the ideal torso inclination angle for restoring proper loading posture. Figure 1 (A) & (B) illustrate the improper loading posture and Figure 1 (C) illustrates the corrected loading posture. The EMS was deactivated immediately when proper loading posture with the ideal torso inclination and knee bend angles have been achieved or restored. In the case of the knee bend correction strategy, the hamstring muscle contraction produces a downward pulling force. This generates a physiological response of bending the knees towards the ideal knee bend angles restoring proper loading posture. The EMS was deactivated immediately when proper loading posture with the ideal torso inclination and knee bend angles have been achieved or restored. The response times for correcting the improper loading posture were recorded.

5 RESULTS

For the torso inclination correction strategy, the mean EMS intensity required for stabilizing the torso and correcting ILP was 43.3 mA ($S.D = 7.3\ mA$). For the knee bend correction strategy, the mean EMS intensity required for bending knees and correcting ILP was 35.8 mA ($S.D = 6.5\ mA$). To analyze the performance of our approach and to test the hypotheses in 4.3, we used repeated-measures 2-Factor $ANOVA$ to determine the influence of feedback modality and correction strategy types on each dependent variable. For the non-parametric user perception Likert scale data, we utilized the Aligned Rank Transform (ART) tool [73] and performed repeated measures 2-Factor $ANOVA$ tests on the aligned ranks for the user perception Likert scale data.

5.1 Average Correction Response Times

Average correction response times are calculated as a mean of the correction response times across all the four boxes for each modality for each participant. For H1, the main effect for feedback modality type yielded $F(2, 60) = 24.69$, $p < 0.001$, indicating a significant difference between Audio ($M = 1.43$, $S.D = 0.52$), Vibro-tactile ($M = 1.17$, $S.D = 0.38$), and EMS feedback modalities ($M = 0.71$, $S.D = 0.27$). A pairwise comparison between the three modalities indicated that EMS feedback modality delivered faster correction response times than both the audio and vibro-tactile feedback modalities illustrated in Figure 10(A). The main effect for correction strategy type yielded $F(1, 30) = 0.20$, $p > 0.05$, indicating that the effect of correction strategy type was not significant between torso inclination ($M = 1.08$, $S.D = 0.57$), and knee bend correction strategies ($M = 1.12$, $S.D = 0.48$) as illustrated in Figure 10(B). The interaction effect was not significant $F(2, 60) = 5.80$, $p > 0.05$. Significant differences were found in the system performance with regards to average correction response times between the different feedback modalities with the EMS feedback delivering the fastest correction.

5.2 User Perception of Correction Feedback Accuracy

For H2, the main effect for feedback modality type yielded $F(2, 68) = 11.32$, $p < 0.01$, indicating a significant difference between Audio ($M = 5.14$, $S.D = 1.36$), Vibro-tactile ($M = 5.92$, $S.D = 0.81$), and EMS feedback modalities ($M = 6.08$, $S.D = 0.84$) as illustrated in

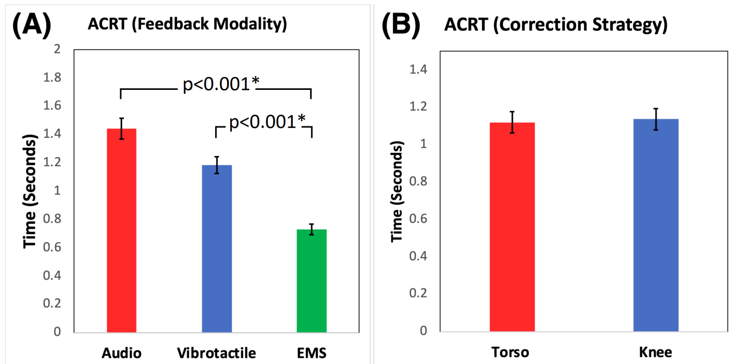

Figure 10: Average correction response times (ACRT) across (A) Feedback Modality, & (B) Correction Strategy. Error bars: 95% CI. Note: $*$ indicates statistically significant results.

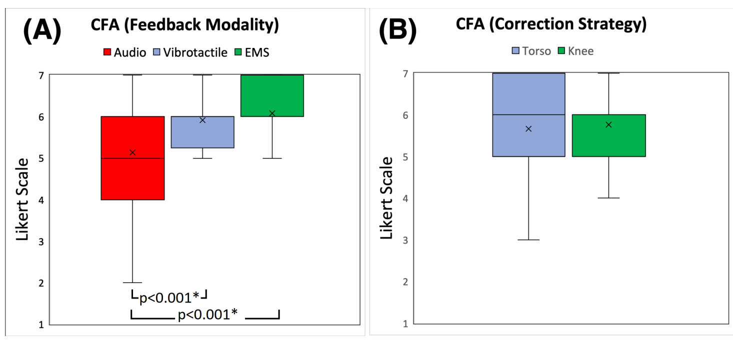

Figure 11: User perception of Correction Feedback Accuracy (CFA) across (A) Feedback Modality, & (B) Correction Strategy. Note: $*$ indicates statistically significant results.

Figure 11(A). A pairwise comparison of the means showed significant differences between the audio and vibro-tactile, and audio and EMS feedback types but no evidence of significant differences between the vibro-tactile and EMS feedback. The participants perceived EMS feedback to be more accurate than the audio, but not vibro-tactile feedback. The main effect for correction strategy type yielded $F(1, 34) = 0.15$, $p > 0.05$, indicating that the effect of correction strategy type was not significant between torso inclination ($M = 5.67, S.D = 1.18$), and knee bend correction strategies ($M = 5.76, S.D = 1.03$) as illustrated in Figure 11(B). The interaction effect was not significant $F(2, 68) = 1.7$, $p > 0.05$.

5.3 User Perception of Comfort

For H3, the main effect for feedback modality type yielded $F(2, 68) = 0.67$, $p > 0.05$, indicating no significant difference between Audio ($M = 5.81$, $S.D = 1.35$), Vibro-tactile ($M = 6.03$, $S.D = 0.99$), and EMS feedback modalities ($M = 5.75$, $S.D = 1.05$) as illustrated in Figure 12(A). The main effect for correction strategy type yielded $F(1, 34) = 0.14$, $p > 0.05$, indicating that the effect of correction strategy type was not significant between torso inclination ($M = 5.91, S.D = 1.2$), and knee bend correction strategies ($M = 5.81$ $S.D = 1.08$) as illustrated in Figure 12(B). The interaction effect was also not significant $F(2, 68) = 0.5$, $p > 0.05$. As no significant differences were found in the main effects for modality or the correction strategy type, neither modality nor correction strategy had any influence on the user comfort. All three feedback modalities across both correction strategies delivered an equally comfortable user experience.

5.4 User Perception of Task Disruption

For H4, the main effect for feedback modality type yielded $F(2, 68) = 0.68$, $p > 0.05$, indicating no significant difference between Audio ($M = 2.58$, $S.D = 2$), Vibro-tactile ($M = 2.25$, $S.D = 1.40$), and EMS modalities ($M = 2.44$, $S.D = 1.18$) as illustrated in Figure 13(A). The main effect for correction strategy type yielded $F(1, 34) = 0.07$, $p > 0.05$, indicating that the effect of correction strategy type was not significant between torso inclination ($M = 2.37$, $S.D = 1.63$), and knee bend correction strategies ($M = 2.48$, $S.D = 1.50$) as illustrated in Figure 13(B). The interaction effect was also not significant $F(2, 68) = 0.39$, $p > 0.05$. As no significant differences were found in the main effects for feedback modality or the correction strategy type, neither feedback modality nor correction strategy had any influence on task disruption. All three feedback modalities across the two correction strategies disrupted the participants task equally.

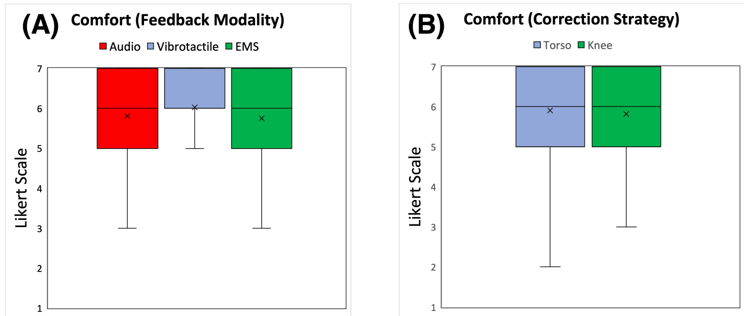

Figure 12: User perception of Comfort across (A) Feedback Modality, & (B) Correction Strategy.

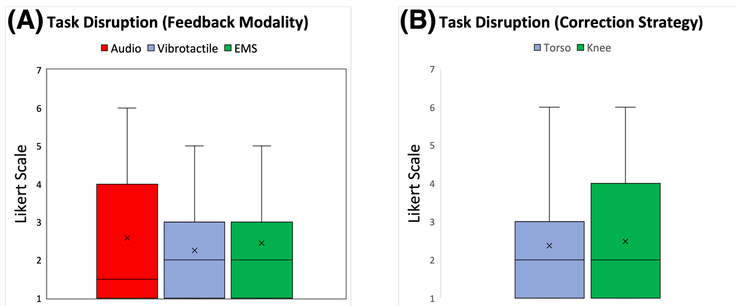

Figure 13: User perception of Task Disruption across (A) Feedback Modality, & (B) Correction Strategy.

5.5 User Perception and Preference

Mean rankings for user perception of correction feedback accuracy, ILP correction assistance, comfort, and task disruption are shown in Figure 14. Participants ranked their ILP correction assistance on a 7-point scale where 1 means not at all, and 7 means completely assisted to restore proper lifting posture. Participants' ranking indicated that EMS feedback modality delivered the best ILP correction assistance ($M = 6.17$, $S.D = 0.97$), followed by the vibro-tactile feedback ($M = 5.86$, $S.D = 1.09$), and audio feedback delivered the lowest ($M = 4.67$, $S.D = 1.41$). Additionally, the participants' ranking of ILP correction assistance across the two correction strategies indicated that both torso inclination ($M = 5.89$, $S.D = 1.28$), and knee bend correction strategies ($M = 5.54$, $S.D = 1.32$) delivered equally good assistance in correcting ILP.

Further, participants reported their preferred modality for correcting ILP across both correction strategies. In torso inclination correction, 56% of the study population preferred EMS feedback, while 39% preferred the vibro-tactile feedback, and 5% preferred the audio feedback. In knee bend correction, 28% of the study population preferred EMS feedback, while 55% preferred the vibro-tactile feedback, and 17% preferred the audio feedback. However, 14 participants in the torso inclination, and 12 participants in the knee bend correction strategies reported that they would be willing to purchase an EMS feedback device with torso inclination correction for ILP posture correction if it were a commercially available product. Participants also ranked their shared responsibility with auto-correction utilizing EMS on a 7-point scale where 1 means not at all and 7 means completely. The mean shared responsibility exhibited by the participants was 2.25 ($S.D = 1.36$). Participants ranked EMS feedback modality to be a highly interesting concept for automatic ILP correction with a mean ranking of 6.71 ($S.D = 0.46$) on a 7-point Likert scale.

6 DISCUSSION

With the recent advancements and interest in EMS for interactive HCI applications, and development of EMS feedback-based automatic detection and correction systems for sedentary poor posture (slouching) [30], semi-static asymmetric weight distribution (AWD) poor posture [31], dynamic navigation [60] and accelerating preemptive reflexes [28, 29, 57], we were interested in understanding the capabilities of EMS feedback in automatic poor posture correction of a dynamic activity such as ILP. In comparison to the alternative traditional feedback systems, we found several benefits to automatic posture correction using EMS feedback. Our automatic approach utilizing EMS feedback was able to achieve significantly faster correction at a high accuracy while delivering an equally comfortable user experience. Even though research has been conducted on detecting poor posture and alerting users through traditional feedback systems, the system's correction responsiveness and user perception parameters have not been measured or reported. Therefore, our research primarily focused on evaluation of the system performance and user perception of our EMS feedback based automatic poor posture detection and correction technique against traditional audio, and vibro-tactile feedback mechanisms requiring self correction by the user.

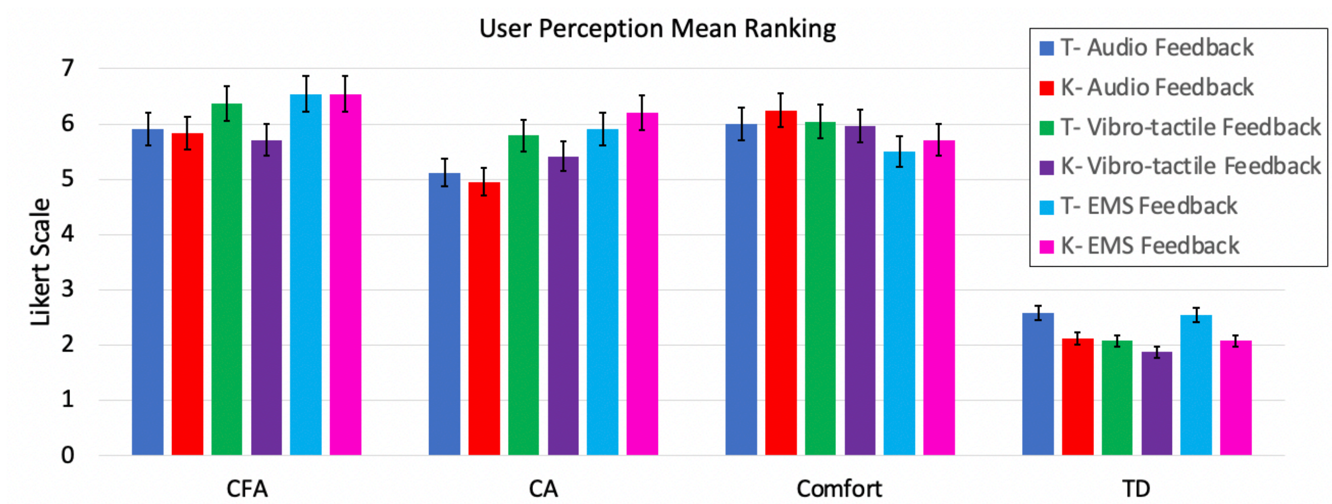

Figure 14: User perception mean rankings for correction feedback accuracy (CFA), ILP correction assistance (CA), comfort, and task disruption (TD) across all feedback modalities and correction strategy types. Likert Scale: 1-meaning not at all, 7-meaning completely. T: Torso inclination correction strategy, K: Knee bend correction strategy. Error bars: 95% CI.

Table 3: Average EMS Intensity utilized for stimulating different muscle groups for different tasks, applications, & activity levels

Application	**Activity Level**	**Stimulated Muscle**	**Task**	**EMS Intensity (mA)**
Slouching [30]	Sedentary	Rhomboid	Text Entry	39.72
			Mobile Game	47.22
AWD [31]	Semi-Static	Tibialis	Quiet Standing	50.55
			Mobile Game	51.94
VR/AR Haptics [47]	Dynamic (Upper Body)	Palm Extensor	Wall repulsion	16
		Shoulder/Triceps	Picking up objects	20/15
		Palm Extensor/Bicep	Pushing box	15/15
Cruise Control [60]	Dynamic (Lower Body)	Sartorius	Navigation	52.68
ILP*	Dynamic (Upper/Lower Body)	Rhomboid	Lifting boxes	40.34
		Hamstring		36.7

Note: ∗ indicates current work presented in this paper.

6.1 EMS Intensity

Previous research on EMS-based correction feedback through involuntary muscular contractions relied primarily on the intensity of the EMS being applied to the different muscles for generating physiological responses to increase immersion in VR/AR applications, navigation, and to effect posture correction and restoring/maintaining good posture. Table 3 illustrates the different muscles stimulated for VR/AR Haptics, Cruise control, and correcting slouching, AWD and ILP, and the corresponding mean EMS intensity applied to the muscles to generate an involuntary muscular contraction. Torso stabilization for correcting slouching, and ILP (torso inclination correction strategy) through the stimulation of the rhomboid muscle required approximately 39 *mA* to 47 *mA*. ILP knee bending correction through hamstring muscle stimulation required approximately 36 *mA*, navigation (Cruise Control) through Sartorius muscle stimulation required 52.68 *mA* and counter-weight shifting for AWD correction through the tibialis muscle stimulation required approximately 50 *mA* to 52 *mA*.

The different intensities required for the different applications may be primarily due to the difference in activity levels, muscle physiology, muscle location, and their accessibility. The rhomboid, and the hamstring muscles are more accessible physiologically in comparison to the tibialis muscles which are regarded as a more deeper muscle group requiring higher EMS intensities for achieving muscular contractions. The sartorius muscles in Cruise Control required higher EMS intensities due to the nature of the application and the size of the muscle group. Additional factors may be the level of engagement during tasks, and the constraints to the range of movement while performing the tasks. It was interesting to note that EMS feedback was able to correct poor postures across activity levels ranging from sedentary activity in slouching correction, to moderate activity in AWD correction, and dynamic high activity in navigation and ILP correction. It was also interesting to note that the slouching correction in the text entry task and ILP torso inclination correction strategy required lesser EMS intensity to stabilize the torso in comparison to the slouching correction in the mobile game task. This may be due to the level of engagement in the mobile game task, and the constraints it places on the users' torso while being tethered to a smart phone device, and a highly engaging game.

6.2 Average Correction Response Times

The correction response time was measured as the time between the activation and deactivation of the feedback after ILP was detected and corrected, respectively. The average correction response time was calculated from the mean of the correction response times to ILP across all the boxes. Our automatic correction with EMS feedback delivered the fastest ILP correction with an average response time of 0.71 seconds, while the vibro-tactile feedback delivered significantly longer corrections at 1.17 seconds, and the audio feedback was the longest at 1.43 seconds. Therefore, we accept H1. The EMS feedback was faster because the correction occurred automatically without requiring any effort from the participant. In contrast, the audio and vibro-tactile feedback placed a cognitive load on the user to assess their torso and knee bend position while performing the lifting tasks. This cognitive load may have resulted in additional correction time. Both torso inclination correction and knee bend correction across all three modalities delivered fast ILP corrections, with 1.09 seconds for torso inclination correction and 1.14 seconds for knee bend correction. Faster corrections through EMS could be crucial in preventing the onset of a long-term RSI and may reinforce healthy postural habits for better lifting techniques. Additionally, the faster correction times may be a result of the participants' ability to learn and improve their posture as they go about completing the lifting tasks. The results also indicate that EMS would be capable of delivering fast ILP corrections across different boxes of different sizes and loads, making it especially advantageous as a smart wearable intervention device for manual workers in construction, factories, and shipping who handle a range of loads every day.

6.3 User Perception of Correction Feedback Accuracy

Participants ranked their perception of the correction feedback accuracy across all modalities and correction strategies. The EMS and the vibro-tactile feedbacks were perceived to be highly accurate, while the audio feedback was perceived to be the least accurate among the three modalities. As a result, we reject H2. Additionally, participants perceived both correction strategies to be equally highly accurate with mean rankings of 5.67 and 5.76 for torso inclination and knee bend correction strategies respectively. The high rankings for the EMS and vibro-tactile feedbacks may due to the distinct somatosensory confirmation offered through the activation and deactivation of vibro-tactile and EMS feedbacks allowing the user to better respond to feedback.

6.4 User Perception of Comfort and Disruption

Previous EMS-based studies attempted to increase immersion in Virtual/Augmented reality applications for training [44, 47, 48] and were primarily interested in subjective measures of *realism* and *enjoyment* that participants felt while using their system in AR/VR related tasks. Cruise control [60], another EMS-based device was designed to help navigate and avoid obstacles during walking was more focussed on reliability and modification of direction. They also determined that participants felt that EMS-based feedback for enabling navigation and avoiding obstacles did not have a negative impact on user experience. However, their study did not compare the EMS feedback modality against other modalities. In contrast, our work involved real-time automatic correction of poor lifting posture and as such were not concerned with *realism* or *enjoyment* but were more interested in the effect of EMS corrective feedback on user perception of comfort and task disruption.

Participants ranked their comfort and disruption across the three modalities and the two correction strategies. Neither the feedback modality nor the correction strategy had any significant influence on the user comfort or task disruption. In comparison to the audio and vibro-tactile feedback types, EMS feedback produces stronger somatosensory effects through its involuntary muscular contractions. However, participants ranked all three modalities equally comfortable and equally disruptive. As a result, we accepted H3 and H4. Careful EMS calibration played an important role in achieving the desired ILP correction in both torso inclination and knee bend correction strategies with an acceptable level of comfort and disruption similar to the comfort and disruption delivered in the audio and vibro-tactile feedback mechanisms. The participants' rankings showing similar level of comfort and disruption across the feedback modalities and correction strategies indicated an acceptance of EMS feedback as a potentially equal alternative to the traditional feedback systems along with an additional benefit of automatic ILP correction. Additionally, EMS feedback being equally comfortable and equally disruptive in comparison to alternative feedbacks (audio, visual, and vibro-tactile) is also in line with previous studies on EMS based posture correction studies for correcting *slouching* [30] and *AWD* [31].

6.5 System Performance and User Preferences

Participants' ranking of their ILP correction assistance during the two correction strategies indicated that EMS feedback delivered the best correction assistance followed by the vibro-tactile feedback, and audio feedback offered the worst correction assistance. Both the torso inclination and knee bend strategies offered an equally good correction assistance. This may be due to the fact that both strategies are linked towards delivering ideal lifting angles for the torso inclination and knee bend. This finding illustrates the fact that participants perceived both EMS feedback-based correction strategies as a potential alternative intervention techniques to correcting ILP. This also presents an opportunity to develop a smart wearable ILP intervention device that delivers a fast and discrete feedback capable of correcting ILP. Also, this would make EMS-based smart intervention wearable technology accessible for use especially by manual laborers and construction workers who are involved with handling procurement and shipment of boxes of different sizes and loads. It was also interesting to note that the EMS intensity required for effecting torso correction, and knee bend were approximately 43 *mA*, and 36 *mA* respectively. The torso correction EMS intensity was similar to the torso stabilization EMS intensity (43.47 mA) in case of correcting slouching [30] by stimulating the same rhomboid muscles. The EMS intensity for knee bend correction was slightly lower than the torso correction. This may be due to the fact that the rhomboid muscles in the torso are more active and relatively less sensitive to EMS than the less active and more sensitive hamstring muscles.

6.6 User Dependency and Learning Effects

Participants reported feeling a shared responsibility in aiding the automatic ILP correction process with the EMS feedback mechanism (as discussed in Section 5.5). Although their reported level of shared responsibility was low on the 7-point Likert Scale, this indicates the learning effects of the automatic ILP detection and correction system on the participants, and their willingness to get involved in the correction process for better posture control during lifting. This also demonstrates that the somatosensory feedback from the EMS feedback made participants feel like they were involved in the correction process, even though the EMS was automatically correcting their posture in about 0.7 seconds. This indicates that the participants felt encouraged and eager to get involved in the correction process. The learning effects of using the automatic EMS-based ILP correction led to the development of correct lifting habits, which may make users less dependent on the ILP correction system.

A longitudinal study of the learning effects and habit formation produced by different levels of usage would provide more insights on user dependence on the ILP correction system and the time needed to develop correct lifting habits. This information would be useful in determining usage protocols based on the need for continued or periodic use of ILP correction feedback. Although the system may be effective in developing proper lifting habits with long-term regular use, one participant reported that "I can use this regularly when I do difficult squat workouts," and another user said "it's very useful for lifting boxes while moving" (implying during changing residences).

6.7 Validation Study Results

The validation study played a crucial role in informing our design choices for the development of an EMS-based ILP correction feedback prototype. Our findings revealed a trend of poor lifting habits among young adults, which differed significantly from the safe lifting techniques demonstrated by trainers. This finding motivated us to develop the EMS-based ILP correction system to aid, assist, or automatically correct improper lifting posture (ILP).

Overall, based on the performance of the ILP correction using EMS and feedback from participants, we envision our system to be deployed in the form of a wearable vest or clothing with IMUs and EMS electrodes positioned optimally for increased accuracy of ILP detection and effectiveness of correction. The wearable clothing will be accompanied by a smartphone application for calibrating IMUs and EMS intensity, as well as allowing for easy customization based on the user's preferences. Our proposed system has the potential to be a portable, accessible, and fully customizable posture correction device that requires minimal training or the presence of an expert for setup, calibration, or operation. This would enable our EMS-based ILP correction system to be widely adopted by a range of individuals for maintaining healthy postural habits and for use in fitness and training. Additionally, the system has potential applications in enhancing proper posture in sports athletes (for example: arm joint angles, torso inclination, and knee bend during a golf swing or a baseball swing), and aiding correct exercise form in a variety of gym exercises (for example: performing yoga exercises, weight lifting, dead-lifting, and squats)

7 LIMITATIONS AND FURTHER WORK

Identifying IMU sensor placement, and EMS electrode placement locations presented challenges as each participant was different with different physiology and muscular density. To resolve this, we plan to integrate the sensors and electrodes into wearable clothing designed to suit a majority of the population. Using standard clothing size conventions, the optimal placement position of the IMUs and the EMS electrodes can be determined and incorporated in to the design of our ILP correction wearable. Another limitation is the EMS intensity calibration which needs to be done carefully with emphasis on user comfort, and safety while achieving the desired muscle contraction to generate a physiological response necessary for correcting ILP. To address this issue with calibration, an AI-based auto-calibration system that can customize to each individual's comfort and responsiveness needs to be developed. Further, our study employed momentary auditory tones (1 Second duration) due to the fact that during the pilot studies we found participants were typically completing the lifts in under 2 Seconds. However, it would be interesting to determine the effect of encoded continuous auditory tones and the learning effects it provided to the users. Finally, as this work was primarily focussed on the capabilities of EMS feedback to correct poor posture through involuntary muscular contractions and the effectiveness of our automatic approach, the effects of EMS on muscle fatigue in long term regular usage has not been investigated and a longitudinal study needs to be conducted to determine if EMS based posture correction is able to reinforce development of good postural habits over time.

8 CONCLUSION

We have demonstrated that our physiological feedback loop based on automatic ILP detection and correction with EMS is a viable approach to supporting ILP correction while stabilizing torso and knee bending towards ideal lifting angles to prevent risk of injury. Our auto-correction system utilizing EMS feedback demonstrated significantly faster ILP correction response times compared to the self-correction in the audio and vibro-tactile feedback. Our approach also showed that participants perceived EMS feedback to be highly accurate, equally comfortable, and produced no more disruption than the alternative techniques it was tested against in both the torso inclination and knee bend correction strategies. Therefore, our autonomous ILP detection and correction system utilizing EMS shows promising results and could be a useful alternative or inclusion to existing environment, health, and safety (EHS) guidelines for mitigating risk of workplace injury, improving employee health, and preventive health care.

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