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Towards a Safety Culture in Workplaces: Intelligent Rest Breaks and Social Support

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***Abstract*—Musculoskeletal disorders (MSDs) are pervasive in the workforce and constitute the single largest category of work-related illness. The root cause for MSDs is complex. However, there is little dispute that MSD morbidity is primarily due to physical and psychosocial risk factors, and these two domains of risk factors share a common upstream determinant. A work organization influences both the physical load patterns and psychosocial features. In this paper, we propose a technology-facilitated intervention program that could lead to an improved safety culture in workplaces. The program is aimed at addressing one of the physical risk factors, *i.e.,* rest breaks, and a psychosocial risk factor, *i.e.,* social support. First, a wearable soft orthosis is used to detect the types of physical activities and load patterns, and to derive an intelligent rest break schedule for each type of activity and load patterns. The orthosis would also remind the participant to take a rest break at appropriate times. Second, a mobile app is developed to cultivate a learning community where the participants could seek and provide social support and increase their awareness of occupational safety. We collected some preliminary app usage data and developed a methodology of identifying app usage patterns using both supervised and unsupervised learning. The feasibility of the method is validated using synthesized data derived from the collected data.**

***Index Terms*—Musculoskeletal disorders, occupational safety, load pattern, orthosis, learning community, KNN, Gaussian naive Bayes, decision tree, k-means clustering, the elbow method.**

I. Introduction

The total cost of workplace musculoskeletal disorders (MSDs) in the US is over $1 billion US dollars per year. The reported cost varies significantly, from a very conservative estimate of $2 billion direct medical cost per year [1] to over $100 billion per year for lower back injuries alone [2]. MSDs constitute the single largest category of work-related illness [3]. In 2004, MSDs represented a third or more of all registered occupational diseases in the United States [3]. According to the US Bureau of Labor Statistics (https://www.bls.gov/iif/oshwc/case/msds.htm), the fraction of MSDs has been slightly decreasing in recent years and in 2015, the fraction has been dropped to below 30% of cases. This reduction is presumably a positive outcome of the investment in the research and development for the promotion of the understanding of the risk factors of MSDs and the intervention methods/programs to reduce MSDs. Nevertheless, the MSDs still comprise the largest category of work-related illness and there is still a lot that could be done to further reduce their occurrences.

The root cause for MSDs is complex as reported by numerous studies [4]–[6]. The study by Punnett and Wegman [3] appears to give the most holistic view on the root cause for workplace MSDs, and the major risk factors were identified. As shown in Fig. 1, the risk factors for workplace MSDs can be categorized into two groups: (1) physical load patterns, and (2) psychosocial features. Both groups of factors can be heavily influenced by the work organization, and some of the factors are strongly correlated, for example, a high job demand typically would lead to a fast work pace, and low decision latitude and low skill utilization would typically mean repetitive physical load.

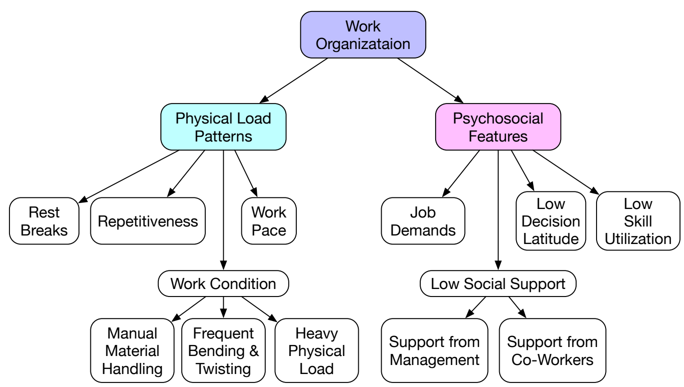

Fig. 1. Major risk factors for workplace MSDs.

The negative impact of MSDs among workers far exceeds the cost of workers' compensation. Studies have shown that persistent pain from the injury reduces job satisfaction and the quality of services/productivity of the worker, which degrades the staff morale and could lead to poisonous workplace culture. Ultimately, this could lead to high turn-over rate, which requires a business owner to constantly look for and train new hires. Hence, there is an urgent need to systematically address the issue of MSDs in workplaces.

This paper makes the following research contributions:

- We provide a concise overview of the risk factors for workplace MSDs and the interventions programs reported in the literature.
- We propose to focus on two specific risk factors that are not well studied: (1) lack of rest breaks; and (2) lack of social support.
- We outline a method to derive an intelligent rest break schedule based on the data collected by wrist and waist

soft orthosis.

- We developed a mobile app that can be used to facilitate the formation of a learning community for prompting occupational safety and minimizing the occurrences of MSDs, and for strengthening social support for workers. Furthermore, we present a methodology based on supervised and unsupervised learning to identify app-use patterns.

II. Related Work

Over the past several decades, we have seen great efforts in addressing the MSD problem in workplaces [7]–[20]. The US Department of Labor Occupational Safety and Health Administration (OSHA) and many state-level administrations have established guidelines and best practices for protecting workers. The recommended process from OHSA (https://www.osha.gov/ergonomics) includes: (1) provide management support, (2) involve workers, (3) provide training, (4) identify problems, (5) encourage early reporting of MSD symptoms, (6) implement solutions to control hazards, and (7) evaluate progress. For recent interventions aimed at reducing workplace MSDs, Sundstrup et al. provided an excellent comprehensive review [21]. Major types of interventions include: (1) physical exercises; (2) ergonomics; (3) multifaceted; (4) stress management; (5) rest breaks and reduced work hours; (6) cognitive behavior training; (7) technology-facilitated compliance program [22], [23]. Current studies show that only physical exercises [24] and adding rest breaks [25] are effective interventions.

III. Proposed Intervention for Reducing Workplace MSDs

Not all factors contributing to MSDs can be easily changed, such as the work condition factors. However, there are opportunities to adjust work pace and provide rest breaks at the right time and to improve social support. That is why we propose to target two important but lesser studied risk factors: (1) lack of rest breaks and (2) low social support. Providing adequate rest breaks has been proven to be effective for farm workers [25]. We aim to automatically determine rest breaks at the appropriate frequency towards reducing MSDs among workers. Even though low social support has been identified as a risk factor, we are not aware of any existing intervention program that targets this risk factor. The mobile app will be used as a vehicle to mitigate this risk factor by facilitating peer social support and the formation of a learning community among the participating workers.

A. Intelligent Rest Breaks via Soft Orthosis

In order to understand the workers' actual workload patterns, and to identify the intervention points for a break rest, a novel wearable soft orthosis is developed. Orthosis, as a type of wearable mechanical device, has a long history in the application of monitoring MSD patient pathologies and providing rehabilitation for patients with impaired mobility [26]. However, as discussed previously, besides monitoring actual workload and repetitiveness, the orthosis device for occupational safety and health has some unique requirements that it should be able to avoid altering the routine of the workers and/or intruding on workers' privacy. Conventional orthosis that has bulky size, heavy actuation and lower portability should be excluded for this application. Skin-attaching monitoring systems, though light and in small size, should be avoided as well since they are not convenient for the workers to attach and detach, and usually create discomfort for the workers [27]. The system based on camera and image processing has a risk to intrude workers' privacy and lack ability to measure the workload [18].

The novel orthosis system has unique features of high adaptability, easy don-doff design, light weight and compact size [28]. More specifically, wrist orthosis and waist orthosis have been developed to monitor work pace in the wrist and waist joints for preventing the two common MSDs including back pain and epicondylitis (injury of tendons that bend the wrist toward palm) [29].

B. Social Support via Learning Community

Participating in a learning community has been proven to be an effective way to improve learner engagement levels in the context of both formal and informal education [30]. The learning community emphasizes collaborative learning and peer support [31], and it could happen both online and offline (*i.e.,* in-person). Learning community increases the participants' social capital [32] and enhances their self-efficacy [33] in several aspects [34]. The social capital of an individual refers to the resources one has access to in his or her social structure [35], which is instrumental to one's social support.

The formation of a learning community connects people who otherwise barely have any opportunity to communicate with each other, which could become each other's social capital. The learning community also promotes two key cornerstones in self-efficacy: (1) participants would get together sharing their knowledge, experiences, and opinions in the community, which promotes closeness and sense of belonging; (2) unlike in the workplace where there is a formal hierarchy among the workers, participants of a learning community are basically equal and everyone has a chance to voice his or her opinion, which helps develop a strong sense of autonomy.

Another important benefit of learning community is that it helps enhance awareness of occupational safety among both workers and managers because it has a convenient platform for the participants to share their experiences, observations, and insight regarding potential issues and solutions on occupational safety at their workplaces. While doing so, valuable new knowledge could also be created regarding how to reduce MSDs by those who are working on the frontline.

IV. Implementation of the Soft Orthosis

As shown in Fig. 2 (a) and (b), the wrist orthosis is made of a regular cloth wrist wrap embedded with two types of sensors, including one Force Sensitive Resistor (FSR) sensor

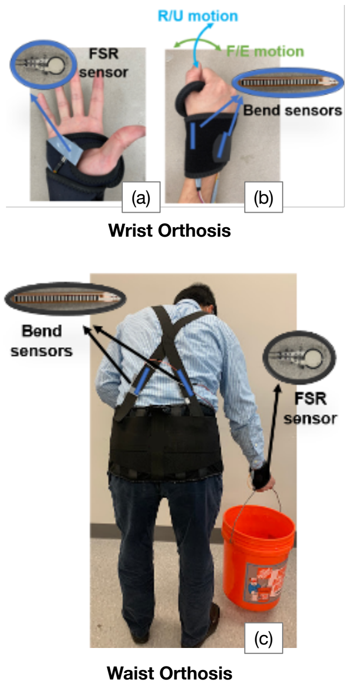

Fig. 2. Wrist and waist orthosis.

for gripping force measurement at the edge of the palm thenar and two flex bend sensors at the hand back for wrist motion tracking. After wrapped around the human hand, the Velcro tape will fix the sensors to the right places for measurement. As the human hand mostly interacts with the palm thenar in gripping, choosing it for gripping force measurement will largely reflect actual interaction force f. The two bending sensors fit align with axes for the Flexion/Extension (F/E) and Radial/Ulnar deviations (R/U) motion of the wrist; thus, they also accurately measure the rotation of the two movement of F/E and R/U as θ and β respectively. With this information, we can get the instant power P of the wrist, and the energy E consumed during a period of δt. The biomechanics and body physical parameters are denoted as α, which mainly includes the lengths and locations of the detected parts, and the user's weight and estimated weight distributions. The power and accumulated energy will be used as important parameters for the worker's work pace tracking.

The waist orthosis, as shown in Fig. 2 (c), is also made with a regular cloth back belt embedded with sensors. For the waist joint tracking, two flexible bend sensors are fixed across the lower back to track the waist bent angle γ. Directly measuring the torque/force is impossible; thus, the orthosis system still uses the gripping force f measured by the wrist orthosis and merge the worker's biomechanics and body physical parameters to calculate the torque/force in the waist. With this information, we can also derive the instant power and energy consumed in the waist joint.

Some preliminary results are shown in Fig. 3. For the wrist orthosis testing, a person was fastening a screw where the F/E motion is tracked. For the waist orthosis testing, the motion of waist bend motion of lifting and lowering box was measured. These preliminary results demonstrate the functionality and the feasibility of the proposed orthosis method.

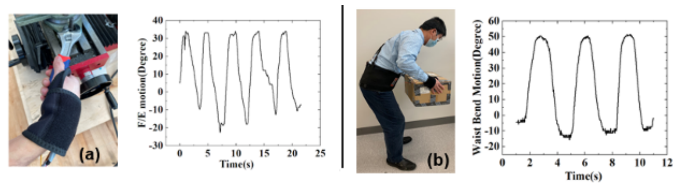

Fig. 3. Preliminary result for using the wrist and waist orthosis to measure (a) the F/E motion of the hand and (b) the waist bend motion.

The implementation model of the two orthoses follows the same pattern and control flow as shown in Fig. 4. The model mainly includes two sections: offline modeling and real-time intervention. For the offline modeling, the orthosis is used to measure the force/torque and motion data, and the data are transformed into instant power and energy. Then, surveys from the workers and the physical therapist's input will be merged into the data collected from the orthosis to identify the risk points that appear in the power spectrum. The offline model is embedded into a real-time control system. The orthosis is used to track the force/torque and motion information to identify break moment and rest duration for the rest intervention and generate vibration/buzz to remind the worker for a break.

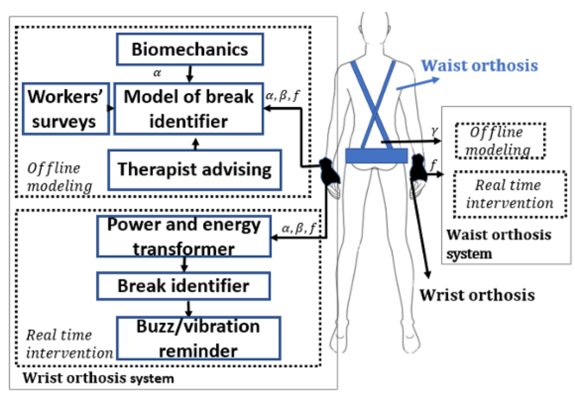

Fig. 4. Key components in the orthosis.

V. Implementation of the Mobile App

The learning community mobile app has two primary components: (1) content related to occupational safety and how to minimize MSDs; and (2) social networking. The content component is for increasing awareness of occupational safety related to MSDs. The social networking component is for providing social support to workers. The mobile app is developed using the Expo framework (https://docs.expo.dev/) using the JavaScript programming language. The big advantage of using the Expo framework is that the application developed can be deployed on both the Web and the mobile interfaces (including both iOS and Android devices). The Google Firebase cloud service is used as the backend to provide user authentication and data storage. Firebase offers very straightforward application programming interfaces (APIs) for its services. Furthermore, for low network traffic, Firebase incurs no charges.

The mobile app consists of a set of screens, with each screen having a clearly defined functionality. Fig. 5 shows some of the screens, including the login screen, the dashboard a user would see after login, a few screens designed for users to learn about MSDs.

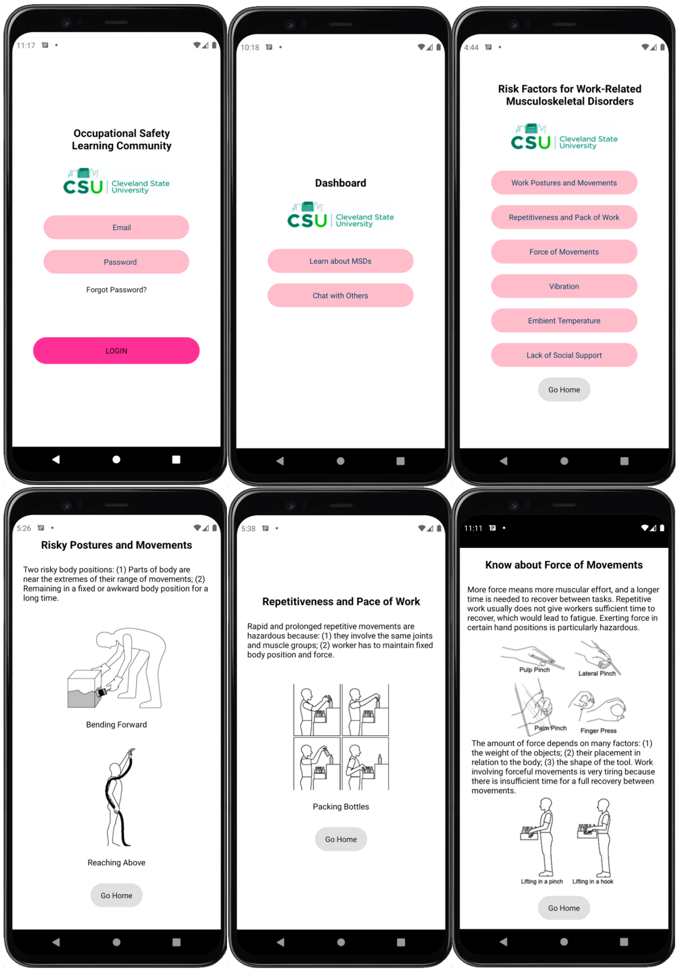

Fig. 5. Selected screens in the mobile app for social support and MSD education.

To establish the feasibility and acceptability of long-term use of the online portal for increased awareness of occupational safety and for seeking social support in a learning community, a user-specific log is collected by the app. Each log is identified by a pseudonymous user identifier to protect the user's privacy. The log contains the timestamps of each event, such as logging in, logging out, loading a particular screen, submitting a practice game, connecting to a peer, the amount of text exchanged and the time spent communicating with another peer or a group (the content is not analyzed to protect the privacy of the participants). The data logging and processing methodology follows our previous work reported in [36]. All data were recorded by the first author using his smartphone (Huawei P30) running the learning community app. During the analysis, we choose to use only the logged time for the app. Each entry has the form of (year-month-day-time, duration), referring to each time the user used the app continuously for a period of time.

The daily-usage statistics of the learning community app is shown in Fig. 6. We can make the following observations

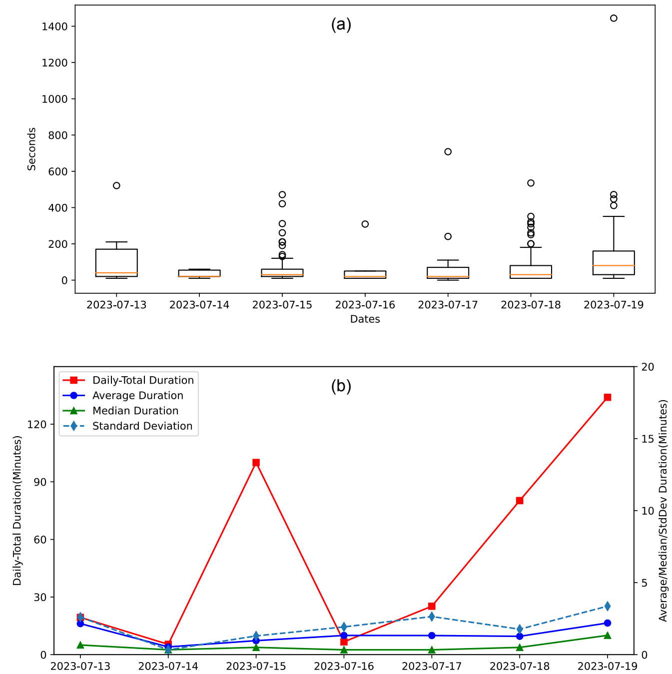

Fig. 6. The daily usage statistics of the app in a 7-day window. (a) The box-and-whisker plot; (b) The daily mean, median, standard deviation, and daily total duration of the app usage.

from the app daily-usage statistics: (1) the total app usage duration varies significantly from day to day; (2) the daily mean, median, and standard deviation of the per-use duration are relatively stable from day to day; (3) as evidenced by the fact that the median is lower than the mean, short-duration app-use is the dominating pattern.

It would be interesting to establish patterns of the app-use among different users. To explore the feasibility and develop a methodology in recognizing different patterns, we created a set of synthetic data based on the collected data. Ideally, we should be using the actual data collected in a formal human subject trials. Unfortunately, this is not yet possible with very limited funding and the very early stage of the development.

From the collected data (which we refer to as the first class C1), three additional classes (C2, C3, and C4) of app-use behavior are derived. The four classes are based on the observation that the behavior of most people is cyclic for each week. C1 reflects the pattern of heavy users throughout the entire week. C2 reflects the pattern of light use during the week days (*e.g.,* due to the job) and heavy use of the app during the weekend. C3 reflects the pattern of heavy app use during the week days and light use during the weekends (*e.g.,* due to family duty). C4 reflects the pattern of light app use throughput the week. Data for C2, C3, and C3 are generated by following a normal distribution of each app use (using the Python Numpy library) with the mean standard deviation of the collected data and a reduced mean for the weekdays and/or weekend days. We used three levels of mean reduction: at 25%, 50%, and 75%. We generated 10,000 samples for each class. The feature vector consists of the per-use duration for each day of the 7-day week, *i.e.,* the feature vector has the form $< f1, f2, f3, f4, f5, f6, f7 >$.

Three models, the k-nearest neighbor (KNN), Gaussian Naive Bayes (GNB), and Decision Tree (DT) (part of the scikit-learn python library) were used to classify the four types of patterns with 10-fold cross-validation. The classification results are shown in Fig. 7. Fig. 7(a) shows the the classification accuracy for the three levels of reductions for the three models. The performance of KNN and GNB differ very little and are significantly better than that of DT. Fig. 7(b), (c), and (d) show the confusion matrices corresponding to the three levels of reduction. It is obvious why the classification accuracy is better when the reduction level is increased. The confusion matrices reveal very similar trends regarding the prediction mistakes. C1 is most often confused with C3, and second most often confused with C2, due to the similarity between C1 and C3 during the weekdays, and the similarly between C1 and C2 during the weekends. C2 confuses with C4 the most due to the similarity during the weekdays, and C2 confuses with C1 the second most due to the similarity during the weekends. C3 confuses with C1 the most due to similarity during the weekdays, and confuses with C4 the second most due to the similarity during the weekends. C4 confuses with C2 the most due to the similarity during the weekdays, and confuses with C3 the second most due to the similarity during the weekends.

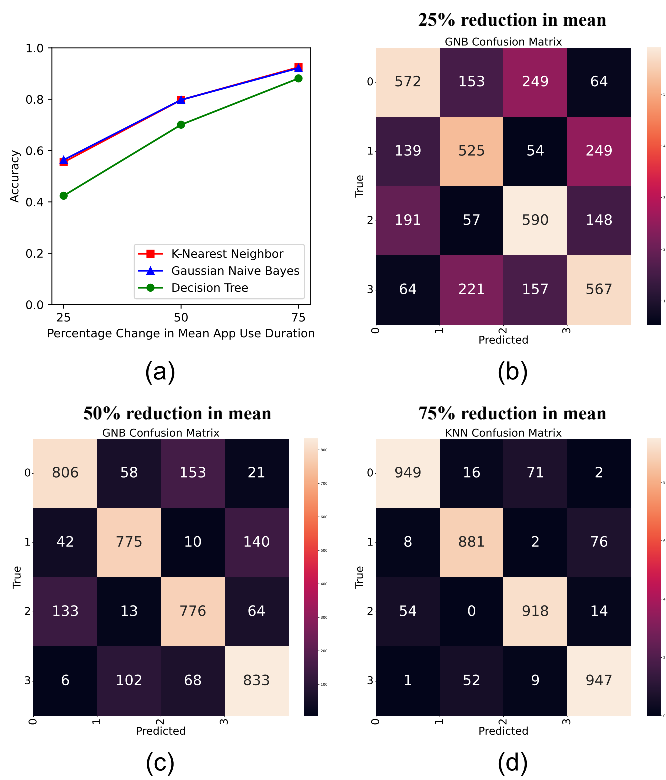

Fig. 7. The classification accuracy for KNN, GNB, and DT for three different levels of mean reduction and the confusion matrices at the three levels using the classifier that has the best accuracy.

It is also interesting to see if unsupervised clustering could be used to identify app-use patterns. We choose to use the k-means clustering algorithm as part of the scikit-learn python library. The first step is to find the optimal number of clusters using the elbow method. According to the elbow method, we calculate the within-cluster sum of square (WCSS) for different number of clusters from 1 to 10. The WCSS is the highest when the number of cluster is one. When the number of clusters increases, the WCSS would decrease. However, at some point, the rate of reduction in WCSS will flat off. This point is referred to as the elbow (because the shape of the WCSS curve looks like an elbow). The WCSS vs. number of clusters curve for our data is shown in Figure 8(a). As can be seen, the elbow point happens at cluster number four, which corresponds to the four classes that we created. The elbow curve has similar shape and identical elbow point for all three levels of reduction.

To illustrate the clusters in app-use patterns, we will have to reduce the dimension of the feature vector from 7 to 2. We perform the dimensional reduction by exploiting the fact that the daily patterns for weekdays are similar, and daily patterns for weekends are also similar. To respect the 5-day weekdays and 2-day weekends, the new 2-dimension feature vectors are weighted accordingly (*i.e.,* the weekday component carries a weight of 5/7, and the weekend component carries a weight of 2/7). The clusters with the 2-dimensional feature vectors are illustrated in Figure 8(b), (c), and (d). As can be seen, the clusters are more separated with greater degrees of reduction in the mean per-use duration.

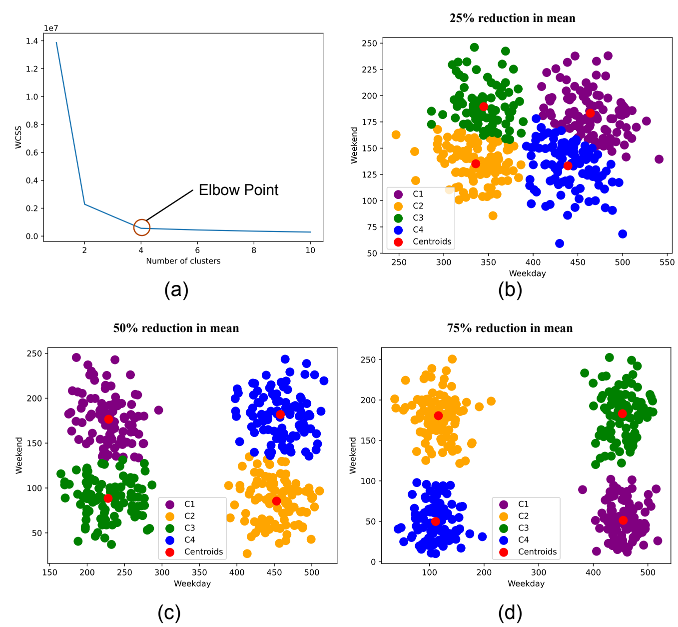

Fig. 8. The elbow curve (a), and clusters for the four app use patterns with mean reduction of 25% (b), 50% (c), and 75% (d).

VI. Conclusion

In this paper, we provided a concise overview of the risk factors for workplace MSDs and the interventions programs reported in the literature. We then described a technology-facilitated intervention program that could lead to an improved safety culture at workplaces. The proposed intervention program focuses on two specific risk factors that are not well studied: (1) lack of rest breaks; and (2) lack of social support. First, we argued that an intelligent rest break schedule could be determined based on the data collected by wrist and waist soft orthosis. The data collected could be used to detect the types of physical activities and load patterns, and subsequently to derive an intelligent rest break schedule for each type of activity and load patterns. Second, a mobile app has been developed to facilitate workers to gain the knowledge regarding MSDs, the risk factors, and how to minimize MSDs, and to make it easy for the workers to communicate with each other for social support. We collected some pilot app usage data and developed a methodology for identifying app usage patterns using both supervised and unsupervised learning. The feasibility of the method is validated using synthesized data derived from the pilot data.

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