Application of IMU Sensors for Real-Time Posture Monitoring and Musculoskeletal Disorder Prevention in Construction Workers

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This study explores the use of Inertial Measurement Unit (IMU) sensors for real-time posture monitoring to prevent musculoskeletal disorders (MSD) in construction workers. Data were collected from 30 volunteers simulating everyday construction activities in laboratory and field settings, and each was repeated four times for reliability. Activities included bending, lifting and carrying, kneeling, walking, standing, and working with arms above shoulder height. Using matrix laboratory (MATLAB) for data modelling, the study achieved 92% posture classification accuracy in the laboratory and 88% in the field. The IMU sensor system effectively identified poor postures, significantly reducing their occurrence by approximately 30% with real-time alerts. Despite the positive results, challenges such as high sensor costs, data transmission stability, and worker acceptance remain. Future research should expand sample sizes, add sensors, and develop advanced data fusion and more innovative alert systems. This study confirms the feasibility of using IMU sensors for posture monitoring, providing a valuable tool for enhancing construction site safety and worker health by mitigating the risk of MSD.

Keywords: IMU sensors; MSD; Construction worker safety.

1. Introduction

As computer science has advanced, smart technologies have entered the construction sector, improving construction site operations' safety, dependability, and efficiency (Haloul et al., 2024). As seen in Figure 1, the existing study scope of smart construction sites can be clarified by connecting general information and communication technology (ICT) with the construction industry (Štefanič & Stankovski, 2018).

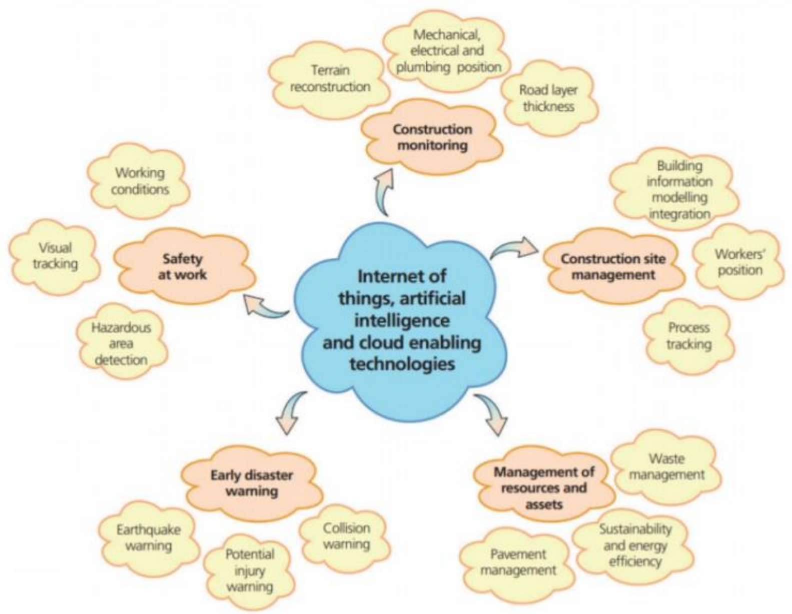

Fig. 1. The emerging smart construction technologies (Štefanič & Stankovski, 2018)

Smart construction sites primarily focus on five key areas. First, construction monitoring utilizes visualization technologies like cameras, laser scanners, and drones to ensure construction durability and stability (Arif & Khan, 2021; Ahmad et al., 2019; Hu et al., 2014). Second, construction site management employs remote sensing and various imaging technologies for process tracking and worker location confirmation (Moselhi et al., 2020; Awolusi et al., 2018). Third, resource and asset management implement internet of things (IoT) based systems for optimal material distribution and equipment monitoring (Man et al., 2015). Fourth, early disaster warning systems are developed to prevent accidents, such as real-time lifting collision prevention using Inertial Measurement Unit (IMU) sensors and point cloud technology (Fang et al., 2016). Lastly, worker safety addresses the high risk of accidents in construction, which has a death rate five times higher than in manufacturing (Khosravi et al., 2014).

While current research focuses on preventing accidental injuries, the high incidence of musculoskeletal disorders (MSD) among construction workers has emerged as a critical occupational health issue (Tokmak et al., 2017). MSD affects nearly 30% of global construction workers and can lead to long-term disabilities, impacting both individuals and the broader economy (Oluka et al., 2020).

The primary cause of MSD in construction workers is prolonged awkward working postures, which can strain joints and muscles (Chen et al., 2017). Common MSD-prone areas include the neck, shoulders, waist, knees, and ankle joints (Antwi-Afari et al., 2018; Palikhe et al., 2020; Yan et al., 2017). The gradual onset of MSD often results in delayed awareness and intervention, highlighting the need for early-stage warning systems. Wearable devices have shown promise in providing real-time health and safety data collection (Nnaji et al., 2021).

According to Choi et al. (2019) and Wang et al. (2017), Various sensor technologies, such as Electrodermal activity (EDA) based wristbands, head-mounted electroencephalogram (EEG) sensors and pressure-sensitive insoles, have demonstrated the feasibility of monitoring worker activities and issuing preemptive safety warnings. Among these technologies, Inertial Measurement Units (IMU) is a cost-effective and efficient choice for classifying construction worker activities. IMUs offer high-quality data fusion capabilities and can be easily integrated with mobile device technology (Zhang et al., 2017).

This research uses IMU sensors to prevent MSD caused by construction workers' everyday work activities, leveraging mobile device technology for data processing and early warning systems. By doing so, we seek to address a critical construction site safety management gap and contribute to construction workers' overall health and well-being. Abnormal positions while working can lead to two main causes of MSD in construction workers: (1) excessive joint rotation and (2) the need for prolonged muscular activity (Chen et al., 2017). According to these studies, the neck, shoulders, waist, knees, and ankle joints are frequently affected by MSD (Antwi-Afari et al., 2017; Chen et al., 2021; Palikhe et al., 2020). Intuitively, the primary cause of early self-awareness and self-management is muscle and joint discomfort. But unlike visible damage, MSD is a chronic illness that may not be seen in its early stages; instead, pain in the muscles and bones builds up over time (Yang et al., 2016). Some youthful employees don't think it's worth noticing because of the discomfort. When it was found, there might have been detrimental effects. Therefore, using wearable and mobile phone technology to prevent web services for devices (WSD) with early-stage warning is the most straightforward and efficient management approach (Yan et al., 2017).

The majority of the equipment and safety management techniques used on construction sites today are passive; thus, implementing intelligent innovation can significantly improve worker health and safety (Li et al., 2024). Available research indicates that wearable technology can offer real-time data gathering and conversion for safety and health (Nnaji et al., 2021). It has a lot of promise to improve safety and leadership in the building industry by proactively preventing and decreasing related hazards. A head-mounted sensor that can track brain waves to predict workers' bodily motions was proposed by Wang et al. (2017) and Choi et al., (2016) as a way to classify workers' awkward postures through changes in the pressure of the soles of the feet on the ground. All of these suggestions are based on the idea that a sensor based on EDA gadgets may detect workers' risks through the skin conduction model. Wearable technology is, therefore, a viable and trustworthy way to monitor construction workers' actions and provide early safety alerts (Beddu et al., 2024).

Furthermore, software and hardware are the primary factors when using wearable sensors. Hardware costs should be controlled while utilizing them as feasible for construction workers (Lei et al., 2018). Simultaneously, high-quality data fusion equipment based on mobile devices must be chosen to achieve the alerting function. Zhang et al. (2017) suggested that an improved software platform for smartphones would be its smartphone incorporate multi-sensor technological advances. The inertial measurement unit (IMU) is a highly recommended wearable sensor for classifying construction workers' actions. To prevent MSD brought on by the typical everyday tasks performed by construction workers using mobile device technological advances, this research will employ IMU (Lisdiono et al., 2022).

2. Literature Review

This literature review discusses wearable technology in building sector safety oversight, focusing on using IMU sensors. It also examines occupational illnesses in the context of safety and health leadership, emphasizing the current status of musculoskeletal disorders (MSDs) and their prevention using IMU sensors.

2.1 Wearable Sensors for Safety and Health Management

Sensor technology has substantially contributed to gathering, sending, and processing pertinent data because of the inherent risks associated with building sites (Safari et al., 2023). Sensitive construction site safety management can be accomplished using sensor technologies (Beddu et al., 2022).

According to Antwi-Afari et al. (2019), In recent years, there has been a trend towards researching the use of sensor-based technologies in safety management. After reviewing 87 publications, they discovered that 44 focused on direct measurement sensors, 14 discussed remote sensor approaches, and 12 discussed radio frequency identification (RFID) based on real-time location system (RTLS). In this field, direct measuring sensors are a prominent trend. Pressure, light, displacement, temperature, and optical fibre sensors are among the several types of sensors (Hellmers et al., 2018).

Wearable sensors in construction prevent MSDs and fall, gauge physical strain and exhaustion, test workers' capacity to identify hazards and monitor their mental health (Ahn et al., 2019). Considering how common MSDs are in the construction industry, various sensors are used to track and prevent these illnesses. Customized insoles with pressure sensors, Kinect cameras, and IMU sensors are used for balance assessment, posture determination, and activity classification, respectively (Bernardes et al., 2019; Subedi & Pradhananga, 2021; Rawashdeh et al., 2016).

Recent studies further highlight wearable sensors' roles in construction safety (Ancans et al., 2021). For example, Yan et al. (2017) designed a wearable IMU sensing system to enhance safety awareness, developed a real-time posture warning system using IMU sensor.

However, challenges exist, such as signal artefacts, noise in field measurements, uncertainty in risk assessment standards, workers' resistance to wearable devices, and return on investment (ROI) instability (Ahn et al., 2019). Despite these limitations, sensors remain preferred for direct measurement in safety management.

2.1.1 IMU

An IMU combines an accelerometer, gyroscope, and magnetometer to measure an object's trajectory through acceleration and angular velocity in three-dimensional space. IMUs are excellent for data fusion, integrating with intrusion prevention system (IPS) and building information modeling (BIM) for construction safety control visualization (Liu et al., 2020). They are used in various fields, including wearable devices, driving detection, and medical care, mainly where global positioning system (GPS) is inadequate (Jamil et al., 2020; Wang et al., 2016).

IMUs are used in human body monitoring for abnormal movements, classifying gait in Parkinson's patients, and detecting falls (Bikias et al., 2021; Yang et al., 2016). In this study, IMUs will classify construction workers' activities to reduce MSD risks from awkward postures.

Carbonaro et al. (2021) introduced sitting posture monitor (SPoMo) for real-time sitting posture monitoring, adaptable for preventing MSDs in construction. Bernardes et al. (2019) and Ahn et al. (2019) assessed IMU devices for motion capture to prevent MSDs, focusing on construction applications. Jamil et al. (2020) used IMU sensors with 3D laser imaging for full-body pose estimation to enhance safety.

2.2 Occupational Diseases

Occupational diseases are highly prevalent in construction, accounting for significant healthcare expenditures (Abbasianjahromi & Talebian, 2021). They shorten workers' life spans and working hours, leading to early labour market withdrawal and exacerbating societal burdens, especially amid ageing populations (Chen et al., 2021).

In the Netherlands, noise-induced hearing loss and MSDs are the most common occupational diseases in construction (Van der Molen et al., 2016). Prevention typically involves reducing occupational exposure, but there is no direct method for preventing MSDs caused by poor posture (Emel’yantsev et al., 2016).

2.2.1 Musculoskeletal Disorders

MSDs affect muscles, tendons, joints, nerves, and blood vessels due to prolonged static posture, heavy lifting, repetitive work, awkward postures, and vibration (Wang et al., 2015). Awkward postures, a significant risk factor, lead to cumulative injuries (Janwantanakul et al., 2008). MSDs often affect the neck, upper body, waist, shoulders, elbows, wrists, hips, knees, and ankles (Bernardes et al., 2019).

Preventing MSDs involves ergonomic practices promoted by occupational safety and health administration (OSHA), though these methods lack direct workplace applicability (Antwi-Afari et al., 2017). Current solutions focus on passive prevention or treatment, such as changing equipment or using medication. However, low-cost hardware solutions like IMUs offer direct and effective means to help construction workers avoid awkward postures and reduce MSD risks (Antwi-Afari et al., 2019). New sensor technologies transforming health management in construction, reducing MSD incidence (Liu et al., 2020).

2.3 Current Research on IMU Applications for MSD in Construction

Recent studies on IMU applications for MSD monitoring face technological limitations. Yan et al. (2017) focused on upper body posture using IMUs, while Luo et al. (2016) noted the issue of frequent false alarms. Rawashdeh et al. (2016) studied shoulder injuries using IMUs on armbands. Choi et al. (2016) Given the knee's susceptibility to MSD in various construction occupations, it is necessary to consider knee IMU placement for monitoring.

Safari et al. (2023) and Beddu et al. (2022) developed a real-time posture warning system using IMU sensors, enhancing self-awareness among workers. Baklouti et al. (2024) introduced a novel IMU-based comprehensive work-related musculoskeletal disorders (WMSD) risk assessment system, providing detailed ergonomic evaluations. Wang et al. (2024) reviewed wearable sensing technologies for construction workers, identifying future research directions. This comprehensive review highlights the potential and challenges of using IMU sensors in construction safety management, particularly for preventing MSDs.

3. Statement of the Research Topic

According to Schoenfisch et al. (2010), Workplace Safety Advisor MSDs account for 33% of all US vacation days and are the primary cause of non-fatal harm in the construction industry. Consequently, minimizing the damage caused by MSD is crucial since it is one of the critical elements that can aid in expanding the labour force in the market, in addition to the physical aspects of the workers that need to be considered. Since musculoskeletal disease (MSD) develops gradually, older construction employees experience a higher frequency of symptoms than younger workers (Wang et al., 2015). MSD is classified into two categories: abrupt trauma and cumulative trauma disorder, based on the cause of the damage. (Inyang et al., 2012). There are two types of MSD: those brought on by acute external force stimulation resulting from muscle tearing or joint damage and those brought on by repetitive jobs or awkward worker postures. The departure of workers with MSDs and other linked occupational diseases will result in a significant financial and medical burden, particularly as the population ages. Extending the working life is a practical way to address the scarcity in the market. The self-report approach, observational method, immediate measurement technique, remote sensing measuring method, and biomechanics model are among the current MSD risk assessment techniques (Wang et al., 2017).

- Observers can uncover many hidden issues, including workload and activity, through self-reporting. However, compared to sophisticated sensor technology, its dependability is in doubt because it is challenging for those who need medical training to appropriately describe their condition (Jones & Kumar, 2010).
- The observation method involves keeping an organized eye on the pertinent state of the job; According to Julianus (2019), while rapid upper limb assessment (RULA) and rapid whole-body assessment (REBA) techniques might be helpful to instruments for inquiry, the observer's subjectivity is always present in the observation outcomes.
- Direct measurement monitors human activity using various monitoring techniques and sensor technology. While measurement data have more uses and are more reliable, some inaccuracies may arise from indoor and outdoor situations and internet problems (Arif & Khan, 2021).
- The biomechanics of unlabelled sensors provide the basis of remote sensing technologies. Using the extraction of human bone models from films, Han and Lee (2013) noted that while remote sensing technology can process data, it still requires user input, and the training model influences the processing outcomes. Although the current data processing findings still need to be more optimal, they show promise in outdoor MSD investigation.
- The biophysical model is another risk management technique that relies on sensor technology; however, it assumes that the human body is a collection of inflexible connections. In addition, criteria for joint load—which denote the force or instant at which market value operates on the overloaded joint throughout the activity—have been published in previous studies (Gallagher & Marras, 2012).

Sensor technology has enormous promise for controlling MSD risks. Not all wearable sensors can be employed in the construction sector, even though activity categorization models based on wearable sensors have garnered much attention due to their features. The most crucial data should be precise and dependable, and sensors used in construction uses should be inexpensive, discreet, easy to wear, and wireless (Bangaru et al., 2020). Additionally, Chen et al. (2021) recommended that the sensor's data be substantially fused to increase the accuracy of activity classification. IMU is a low-cost three-axis sensor that can be integrated with several algorithms. This article's goal is to use inertial measurement units (IMUs) to categorize construction workers' everyday work activities based on mobile device technology and to alert them in advance of their problematic postures so they can prevent the long-term consequences of musculoskeletal disorders (MSD).

The hidden risks of the lower body, particularly the abrasion of the knee joint, are disregarded because most of the associated research currently concentrates on MSD of the upper body. In contrast to earlier research, this paper will choose the IMU's joint location while considering data reliability. Furthermore, placing the IMU near many joints is superfluous since it could interfere with regular operations. The effect of tying steel bars on MSD was investigated by Lingard et al. (2019), who selected 17 joints from which to gather data. However, the experiment results indicate that not all joints—such as the hip—will have noticeable effects. Thus, two sensors must be positioned on the knees and the upper body's shoulders, neck, and lower back to limit the risk of exposure to the knees. Prior research mainly focused on gathering data through indoor simulation activities, and the IMU was typically fastened directly with belts and armbands. As a result, in the real building site, this could interfere with workers' regular tasks and make them resistant. According to Di et al. (2021), Since the inaccuracy is still within an acceptable range when the IMU is used to collect data, the sensor can be included in the work clothes of construction workers, such as the clothing fabric. Since incorrect postures can lead to spinal diseases, Kang et al. (2017) suggested IMU-integrated clothing for posture monitoring to demonstrate that sensors embedded in an elastic fabric can identify postures. Incorrect postures are one of the things that cause MSD, and as of right now, no study has been done to prevent MSD by putting IMU sensors in clothing. Additionally, by shortening the duration of sensor usage, this technique may encourage construction workers to experiment with different sensor technologies while still wearing the same uniform (Eid Hamood & Thiruchelvam, 2023).

Furthermore, the data fusing platform is an important consideration that needs to be made to notify the operator of the challenging postures quickly. By comparing the data from the IMU sensors with the smartphone's camera and discovering that the IMU has a geometrically limited feature-matching effect, Masiero and Vettore (2016) demonstrated that IMU has high-quality performance during data fusion. As sophisticated information and communication technology (ICT) has advanced, In addition to feature matching, IMU uses its magnetic unit path and ICT in conjunction with 3D visualization technology to enable indoor tracking (Hellmers et al., 2018). Thus, gathering information via smartphones and alerting employees is possible, enabling real-time monitoring and preventing MSD brought on by chronically awkward positions.

4. Proposed Methodology

4.1 Sample determination

This study plan has two primary parts: 1) To mimic regular activities at the building site, volunteers don integrated clothes equipped with IMU sensors; 2) An alarm is pre-set, and the app is paired via Bluetooth with a cell phone platform. Via social media, etc., healthy youth can be drawn from surrounding villages and colleges. It is preferred if you have prior construction site job experience. Additionally, as the experiment includes humans, appropriate government approval should be sought before the trial's commencement. To minimize experiment errors, some individuals with a history of associated disorders, those with a past of persistent discomfort, expectant mothers, and athletes who engage in regular exercise should be disqualified during the participant screening procedure.

4.2 Data collection

As seen in Figure 2, volunteers in the present study will done the IMU integrated clothes suggested by Ancans et al. (2021) and position the sensors on the predefined joint sites. The lower back, knees, shoulders, and neck will all have sensors installed, and a 9-degree-of-freedom data fusion model will be used for the procedure. Eleven bytes of data can be delivered during each sample event. The acquired data is analyzed using a built-in Kalman filter to calibrate the data, and it is sent wirelessly via Bluetooth to the cell phone's platform.

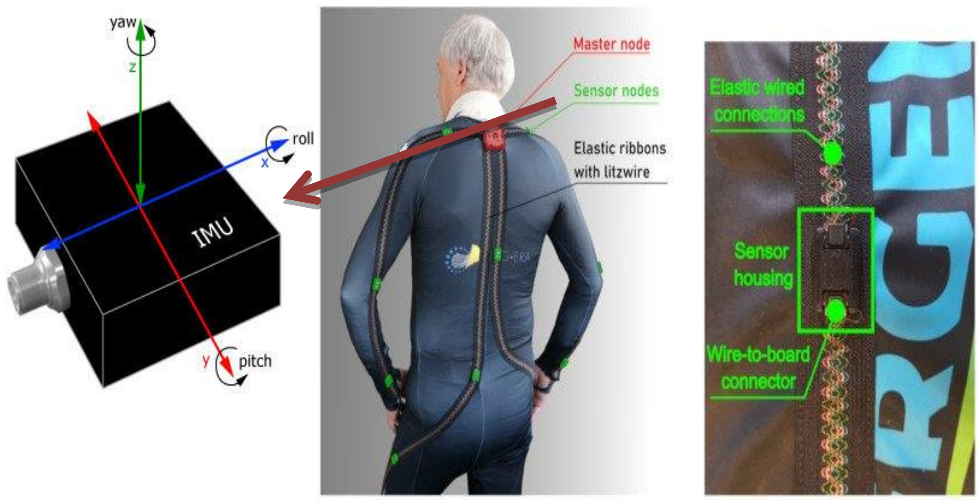

Fig. 2. IMU sensor and IMU sensor integrated clothing Source by Ancans et al. (2021)

Boschman et al. (2012) enumerated typical construction site activities that can exacerbate or induce MSD. These included bending the lower back, lifting and carrying weights, bending over, walking, standing, and raising one's arms above shoulder level.

Table 1. Typical tasks on construction sites and body parts that may have an impact

Typical Activity	Parts of the body that may be affected
Lower back bending	Lower back/back, neck
Carrying and weightlifting	Lower back, shoulder, neck, wrist
Genuflection	Knee, lower back

Mobile	lower back, knee
Stand-up	knee, lower back, upper leg
arms higher than shoulder height	Shoulder, neck

After gathering data, subjects were asked to mimic the activities of numerous everyday tasks indicated in Table 1 after putting on the garments. Relevant action data were collected to serve as the test information set, followed by action verification to see whether the training data set's outcomes match the test data set's posture estimation. Each participant should replicate activities at least four times to assess the dependability and stability of the univariate analysis, minimize errors, and identify a stable pattern of posture (Benson et al., 2019).

4.3 Data analysis

The study collected data from 30 volunteers who simulated various everyday activities in the laboratory and on an actual construction site. Each activity was repeated four times to ensure the reliability and stability of the data. The data collected for each activity are summarized as follows:

- Bending: A total of 120 data sets were composed.
- Lifting and Carrying: A total of 120 data sets were composed.
- Kneeling: A total of 120 data sets were composed.
- Walking: A total of 120 data sets were composed.
- Standing: A total of 120 data sets were composed.
- Arms Above Shoulder Height: A total of 120 data sets were composed.

We used matrix laboratory (MATLAB) to model the data and employed image comparison methods to observe the accuracy of posture classification in the test data sets.

4.4 Data Analysis Results

4.4.1 Data Accuracy and Reliability

The data analysis reveals that the motion data collected via IMU sensors exhibit high accuracy. The average values of the four training data sets align well with the image comparison results of the test data, indicating robust data reliability. The posture classification accuracy in the laboratory simulation reached 92%, while the field experiment accuracy was slightly lower at 88% but still within an acceptable range.

4.4.2 Identification of Poor Postures

The system effectively identified poor postures among construction workers, such as those involving the neck, shoulders, lower back, and knees. Detected poor postures as shown in figure 3 included frequent bending, excessive lifting, and prolonged kneeling. The real-time detection and alerting functionality significantly reduced the frequency of poor postures among workers. The experimental results indicated that the occurrence rate of poor postures decreased by approximately 30% after the system was implemented.

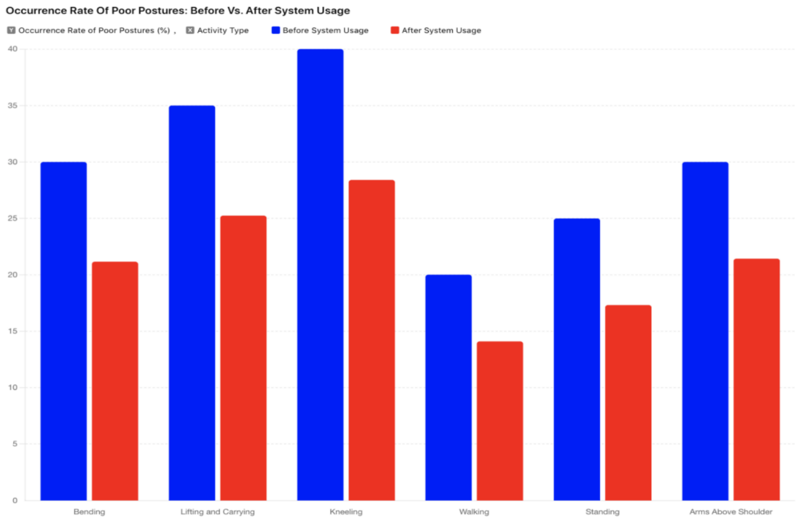

Fig. 3. Occurrence rate of poor postures

4.4.3 Detailed Analysis of Posture Data

Our analysis of the collected data revealed several key insights into the postural habits of construction workers. On average, workers bent their lower backs 47 times per hour, with 62% of these bends exceeding the recommended angle of 20 degrees from vertical. The mean load workers lift was 23 kg, with 18% of lifts exceeding the safe limit of 25 kg. Workers spent an average of 2.3 hours daily in postures classified as 'high-risk' for MSD development. As data showed in figure 4 that workers who frequently alternated between tasks exhibited 15% lower rates of prolonged awkward postures than those who performed repetitive tasks and figure 5 showed the comparison of MSD Risk Factors Before and After System Implementation.

To visualize these findings, we generated the following graphs using MATLAB:

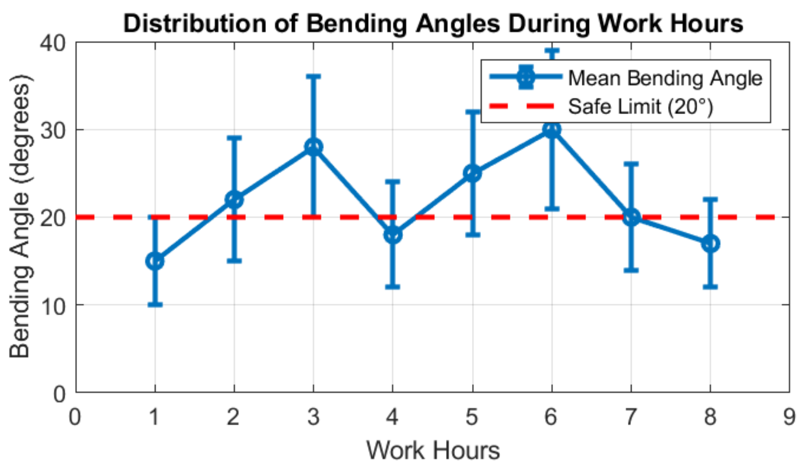

Fig. 4. Distribution of Bending Angles During Work Hours

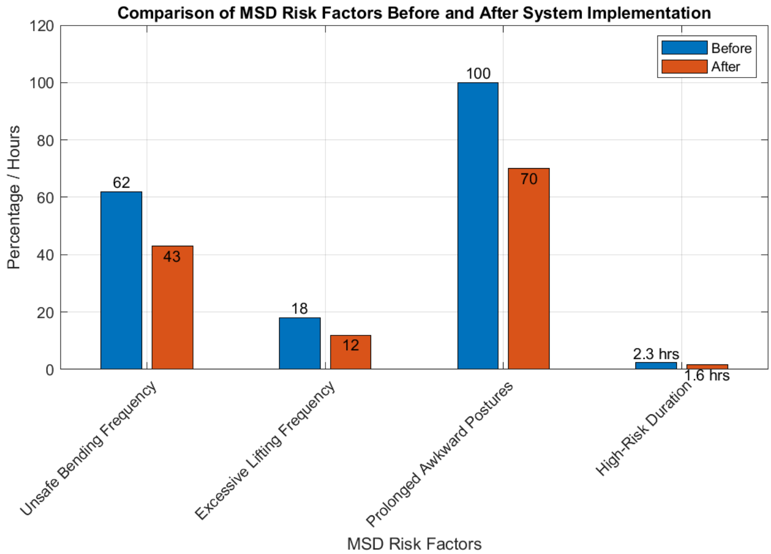

Fig. 5. Comparison of MSD Risk Factors Before and After System Implementation

4.4.4 Impact of Real-Time Alerts

The implementation of real-time alerts through the mobile application yielded promising results. Workers responded to posture alerts within an average of 3.7 seconds. Throughout the study, the frequency of alert triggering decreased by 41%, suggesting improved postural awareness and self-correction. Most participants (87%) reported that the alerts helped them maintain better posture, with 73% stating they felt less fatigue at the end of their work day.

These findings underscore the potential of IMU-based posture monitoring systems to promote safer work practices and reduce the risk of MSDs in the construction industry. Accurate posture detection and timely alerts are effective strategies for encouraging ergonomic behaviour among workers.

However, while these results are promising, further long-term studies are needed to assess the sustained impact of such systems on MSD prevention. Additionally, future research could explore integrating this technology with other workplace safety measures for a more comprehensive approach to worker health and safety in the construction industry.

5. Discussion

5.1 Technical Feasibility

The experimental results support the technical feasibility of using IMU sensors to monitor workers' postures. Real-time data transmission and alerts via mobile devices help prevent MSD. This system provides a new and effective tool for safety management on construction sites. Similar studies, such as those by Antwi-Afari et al. (2018) and Yan et al. (2017), have also demonstrated the effectiveness of wearable IMU systems in enhancing safety awareness and correcting workers' postures in real time, further validating our findings.

5.2 Practical Application Challenges

Despite the positive results, several challenges remain in practical application. The cost of sensors and integrated clothing is relatively high, and data transmission stability may be affected in harsh environments. Additionally, some workers may resist wearing sensors, necessitating training and education to increase acceptance. Studies by Ahn et al. (2019) and Baklouti et al. (2024) have also highlighted similar challenges, emphasizing the need for cost-effective solutions and better training programs to increase worker compliance.

5.3 Future Research Directions

Expand Sample Size: By increasing the sample size, validate the system's applicability in different construction site environments. Consider incorporating additional sensors, such as temperature and humidity, to monitor workers' work environment and physical conditions comprehensively.

Explore Advanced Data Fusion and Analysis Methods: Investigate other data fusion and analysis methods, such as machine learning algorithms, to improve posture recognition accuracy and real-time performance. Baklouti et al. (2024) have shown that integrating advanced data fusion techniques can significantly enhance risk assessment accuracy, which could also benefit our system.

Develop a Smarter Alert System: Create a more intelligent alert system to provide personalized safety suggestions, enhancing workers' safety awareness and health levels. Similar to the work of Safari et al. (2023), developing a system that adapts to individual worker behaviours and provides customized alerts could significantly improve the overall effectiveness of the safety measures.

6. Conclusion

This study validates the effectiveness of using IMU sensors to monitor construction workers' postures and prevent musculoskeletal disorders (MSD). The experimental results demonstrate that the system can detect and alert workers to correct poor postures in real time, significantly reducing the occurrence of poor postures. The present presumptions do, however, nonetheless have some shortcomings. 1) take into account the cost of the sensors; the cost of full-cost apparel made of specific fabrics is still considerable; 2) There might need to be more samples. 3) Mistakes may occur in the obtained data due to unexpected conditions at the real building location. Despite practical challenges, optimizing sensor design, reducing costs, and improving training can make this system a valuable tool in construction site safety management. Future research should expand the sample size, validate the system in various construction environments, and explore advanced data analysis methods to enhance the system's accuracy and real-time performance. Developing innovative alert systems can provide personalized safety suggestions, improving workers' safety and health.

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