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Evaluation of an Under-Body Force Sensor for Real-Time Monitoring of Chest Compression Force during Cardiopulmonary Resuscitation: A Manikin-Based Feasibility Study

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Abstract

Background:

High-quality chest compressions are essential for effective cardiopulmonary resuscitation (CPR) to maintain adequate cardiac output and cerebral perfusion. Current accelerometer-based feedback devices estimate chest compression depth from sternal displacement; however, their accuracy decreases when CPR is performed on soft surfaces or when chest-mounted sensors interfere with rescuer technique. This study aimed to evaluate an under-body force sensor as a nonintrusive alternative for real-time monitoring of chest compression force, and to determine whether the recorded force could serve as an indirect indicator of compression depth quality.

Methods:

In this experimental study, 102 undergraduate students with prior Basic Life Support (BLS) training performed 2 minutes of continuous chest compressions on a Laerdal Resusci Anne manikin positioned on a rigid backboard integrated with a custom-designed under-body force sensor. The system recorded real-time compression forces via Bluetooth. Force output (in Newtons) was categorized based on the manikin's built-in visual feedback indicators: yellow (insufficient depth), green (optimal depth, approximately 5–6 cm), and red (excessive depth). The 2-minute session was divided into four 30-second intervals to assess stability and category distribution of the applied forces over time.

Results:

The under-body force sensor reliably distinguished between insufficient, optimal, and excessive compression categories during simulated CPR. The mean optimal force ranged between approximately 510 and 580 N, closely matching values reported in reference literature. Forces corresponding to shallow compressions averaged around 300 N, while excessive compressions exceeded 770 N. The sensor output also revealed residual force patterns between compressions, suggesting possible detection of incomplete chest recoil.

Conclusions:

An under-body force sensor demonstrated feasible and accurate performance for real-time assessment of chest compression forces in a manikin-based simulation. The force-based feedback effectively reflected compression depth categories, showing good agreement with standard CPR performance indicators. This approach offers a promising nonintrusive alternative for CPR quality monitoring, particularly in scenarios where chest-mounted sensors may interfere with rescuer performance or where compliant surfaces compromise depth accuracy.

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Introduction

Cardiac arrest remains a leading cause of sudden death worldwide, and survival outcomes still depend largely on the quality of cardiopulmonary resuscitation (CPR) provided at the scene (1, 2). According to international guidelines from the American Heart Association (AHA) and the European Resuscitation Council (ERC), high quality CPR requires an adequate compression depth of 5–6 cm, full chest recoil, and a rate of 100–120 compressions per minute (3, 4). However, maintaining these targets consistently during resuscitation is difficult due to rescuer fatigue, variation in manual technique, and the limited availability of reliable real-time feedback (5, 6).

To improve CPR quality, several feedback technologies have been developed. Most commercial systems are chest-mounted and estimate compression depth through sternal displacement measured by accelerometers (7, 8). While effective in controlled settings, their accuracy decreases on soft or compliant surfaces, such as hospital mattresses, where mattress deflection leads to overestimation of compression depth and may mislead rescuers into believing compressions are sufficient (9–11).

Under-body force measurement systems provide an alternative approach. Rather than inferring depth from displacement, they directly measure the net force transmitted through the thorax to a stable support surface (12, 13). When positioned beneath the torso—similar to a resuscitation backboard—they do not interfere with hand placement or alter chest compression mechanics, enabling more realistic simulation and uninterrupted rescuer performance (12, 14). Moreover, on soft or deformable surfaces, under-body sensors may more accurately reflect how much of the applied force is effectively delivered to the chest, a parameter that chest-mounted devices cannot capture (15, 16).

Despite these benefits, empirical data on under-body force monitoring remain limited. Few studies have assessed their capability to distinguish between insufficient, optimal, and excessive compression forces during CPR (17–19). Additional research is therefore needed to determine whether these systems can provide accurate and practical feedback suited for both simulation-based training and clinical environments (18, 19).

The present study aimed to evaluate the feasibility of a custom-designed under-body force measurement system integrated into a rigid backboard for real-time assessment of compression force during simulated CPR. Specifically, we examined whether the forces recorded by this system correspond

consistently to the manikin's real-time visual feedback zones—yellow (insufficient depth), green (optimal depth), and red (excessive depth)—and whether these force patterns remain stable during consecutive 30-second intervals. By confirming this relationship, we aimed to explore the potential role of force-based monitoring as a complementary tool for improving CPR education and quality control.

Methods

Study design and setting

This evaluation study was conducted between 2023 and 2024 in the Clinical Skills Simulation Laboratory of Shahrekord University of Medical Sciences (Shahrekord, Iran). The primary objective was to assess the feasibility of a custom under-body force measurement system and its agreement with manikin visual feedback indicators (yellow: insufficient, green: optimal, red: excessive) during chest compressions in simulated CPR. The overall study design and compression protocol were aligned with contemporary international CPR guidelines regarding compression duration and provider rotation to minimize fatigue effects (3,4,20).

Participants

Participants were undergraduate students conveniently recruited from Shahrekord University of Medical Sciences who had prior experience with CPR training. Eligible students had successfully completed both Basic Life Support (BLS) and Advanced Cardiac Life Support (ACLS) courses, consistent with recommended training standards in simulation-based CPR research (3,4,21). Inclusion criteria were: (i) current enrollment at the university, (ii) documented completion of BLS and ACLS, (iii) absence of musculoskeletal, cardiac, or respiratory conditions that could limit CPR performance, and (iv) willingness to provide informed consent. Students were excluded if they discontinued the session due to fatigue or discomfort, or withdrew consent at any stage. Both male and female students with a wide range of body weights were included to capture natural variability in compression force application and to reflect realistic differences in rescuer anthropometrics (5,19,22).

Sample size determination

Sample size calculations were performed a priori. Assuming a standard deviation of 2 kgf for chest compression forces, a margin of error of 0.5 kgf, and a two-sided α of 0.05, the minimum required sample size was estimated as 62 participants. To increase statistical power and to compensate for potential dropouts of approximately 20%, recruitment continued until 102 participants completed the protocol. Force data were initially recorded in kilograms-force (kgf) and then converted to Newtons (N) using the conventional conversion factor of 1 kgf ≈ 9.80665 N, in line with prior CPR biomechanics studies (12,13,23).

Manikin and CPR procedure

All compressions were performed on a Laerdal Resusci Anne manikin equipped with integrated visual feedback for compression quality (yellow: insufficient, green: optimal, red: excessive), a model widely used in CPR simulation and validation studies (7,24). Participants performed 2 minutes of uninterrupted chest compressions on the mid-sternum, closely reflecting guideline recommendations for rescuer rotation every 2 minutes to limit fatigue and maintain CPR quality (3,4,20). For analytical purposes, the continuous 2 minute sequence was segmented post hoc into four consecutive 30 second intervals, while the hands-on compression remained continuous.

A tripod-mounted video camera recorded each session, capturing both hand position and the manikin's feedback lights. These recordings were used for independent verification of correct hand placement, confirmation of compression continuity, and synchronization of force data with the visual feedback categories (8,25).

Under-body force measurement system

The under-body force measurement system consisted of a custom load cell-based device embedded within a rigid backboard whose dimensions approximated those of commercially available clinical backboards, thereby mimicking typical support surface conditions during resuscitation (11,16,23). The sensor assembly captured net downward force at the manikin's thoracic region and transmitted data in real time via Bluetooth to a paired device for storage and visualization.

Calibration was performed using precision static weights spanning 50–1000 N to cover the expected range of adult chest compression forces. Calibration procedures confirmed a linear response ($r^2 > 0.99$) and accuracy within ±2% of full scale across this range, consistent with prior work on force-based CPR monitoring systems (12,13,23,26). Only forces exceeding the baseline static weight of the manikin were considered in the analysis to isolate active compression events.

The system recorded both peak compression forces and residual forces between compressions to permit exploration of whether persistent residual load could serve as a surrogate marker of incomplete chest recoil, an element of CPR quality that is often under-recognized in practice (1,4,27). Embedding the sensor in a backboard allowed standard two-handed compression technique without any obstruction or modification of hand placement, while at the same time preserving the ability to detect potential losses in force transmission that typically occur on compliant surfaces (9–11,16).

Data collection

Three synchronized data streams were obtained for each participant:

1. Under-body sensor force recordings, sampled at 200 Hz and stored in Newtons after conversion from kgf.

2. Manikin visual feedback categories (yellow, green, red), verified against the timestamped video for each compression interval.

3. Participant demographic and anthropometric characteristics (age, sex, height, weight), collected using a standardized intake form prior to the CPR session.

Synchronization between the force data and manikin feedback was performed using time stamps and visible changes in the feedback lights on the recorded video, ensuring accurate mapping of force values to corresponding feedback categories for each interval (8,25).

Outcome measures

The primary outcomes were:

- Force magnitude ranges associated with each manikin feedback category (yellow, green, red).

- The ability of the under-body sensor to discriminate between predefined force categories: insufficient (<350 N), optimal (450–650 N), and excessive (>750 N), thresholds chosen with reference to prior experimental data on adult CPR forces and guideline-recommended compression depths (23,26–28).

Secondary outcomes included:

- Associations between participant anthropometric variables (eg, sex, height, weight) and compression force, given previous evidence that rescuer body composition influences CPR performance (5,19,22,29).

- Compression rate, calculated from the force waveform to confirm adherence to guideline-recommended rates of 100–120 compressions per minute (3,4).

Statistical analysis

Continuous variables were summarized as mean ± standard deviation (SD) after checking for approximate normality. Differences in mean compression forces between groups (for example, male vs. female participants) were evaluated using independent-samples t tests. Categorical variables, including distributions of compressions across feedback categories, were compared using chi-square tests. Temporal trends across the four 30 second intervals were examined descriptively and, where appropriate, with repeated-measures comparisons. All analyses were conducted using SPSS software, version 21.0 (IBM Corp., Armonk, NY, USA). A two-sided p value of <0.05 was considered statistically significant (30).

Ethical considerations

The study protocol was reviewed and approved by the Ethics Committee of Shahrekord University of Medical Sciences (IR.SKUMS.REC.1403.136). All participants received information about the study procedures and voluntarily signed written informed consent before participation. The study adhered to

the ethical principles of the Declaration of Helsinki, including respect for autonomy, confidentiality of personal data, and the right to withdraw at any time without penalty (31).

Results

Participant characteristics

A total of 102 undergraduate nursing students completed the study protocol and were included in the analysis. All participants had previously completed both Basic Life Support and Advanced Life Support courses and had hands-on CPR training consistent with current resuscitation education standards. Most participants were female (59.7%). The mean age was 23.68 ± 3.13 years (range 20–33), with a mean body weight of 65.60 ± 12.87 kg and a mean height of 170.03 ± 9.88 cm (range 150–190 cm).

The demographic characteristics of the study population are presented in Table 1. There were no statistically significant associations between age, sex, or body weight and mean chest compression force (all $p > 0.05$), suggesting that the overall force distribution observed in this study was not dominated by a specific demographic subgroup.

Table 1
Demographic characteristics of participants (N = 102)

Variable	N	Mean ± SD	Range
Age (years)	102	23.68 ± 3.13	20–33
Weight (kg)	102	65.60 ± 12.87	45–95
Height (cm)	102	170.03 ± 9.88	150–190

Chest compression forces across four intervals

All participants successfully performed 2 minutes of continuous chest compressions, in accordance with guideline-based recommendations for rescuer rotation every 2 minutes. For analysis, the 2 minute session was divided into four consecutive 30 second intervals, while compressions themselves remained uninterrupted. Compression forces recorded by the under-body sensor were converted to Newtons and categorized according to the manikin's visual feedback zones: yellow (insufficient), green (optimal), and red (excessive).

Across the four intervals, mean forces in the yellow (insufficient) zone remained in a relatively low range (approximately 285–330 N), indicating that a subset of compressions consistently fell below the target force associated with adequate depth. Mean forces in the green (optimal) zone were generally stable over time (around 500–580 N), with a modest increase in the fourth interval, suggesting that many participants were able to sustain or slightly augment effective compression forces during the 2 minute period. Mean forces in the red (excessive) zone remained high (approximately 770–860 N), with a small

decline in the middle intervals and partial recovery in the final interval, possibly reflecting early adjustment followed by stabilization in compression effort.

Mean compression forces for each feedback zone across the four 30 second intervals are summarized in Table 2.

Table 2
Mean compression forces (N) for each feedback zone across four 30 second intervals

Feedback zone	Interval 1	Interval 2	Interval 3	Interval 4
Yellow (insufficient)	295.0	284.3	325.5	329.7
Green (optimal)	510.9	501.6	508.3	580.7
Red (excessive)	858.1	791.6	770.6	799.4

Stage-wise force distribution within intervals

To further characterize the distribution and variability of compression forces, stage-wise descriptive statistics (minimum, maximum, mean, standard deviation) were calculated for each feedback zone within each 30 second interval. In Interval 1, yellow-zone forces ranged from 98.1 to 471.0 N (mean 295.0 N), green-zone forces from 421.6 to 676.6 N (mean 510.9 N), and red-zone forces from 686.4 to 1078.7 N (mean 858.1 N). Comparable patterns were observed in subsequent intervals, with partial overlap near zone boundaries but clear separation of mean values.

Stage-wise distributions of compression forces for each interval are shown in Tables 3–6.

Table 3
Interval 1 – Stage-wise statistical distribution of compression forces (N)

Feedback zone	Min	Max	Mean	SD
Yellow (insufficient)	98.1	471.0	295.0	61.7
Green (optimal)	421.6	676.6	510.9	50.3
Red (excessive)	686.4	1078.7	858.1	60.2

Table 4
Interval 2 – Stage-wise statistical distribution of compression forces (N)

Feedback zone	Min	Max	Mean	SD
Yellow (insufficient)	0.0	480.3	284.3	89.0
Green (optimal)	274.6	597.0	501.6	53.7
Red (excessive)	676.6	960.0	791.6	54.7

Table 5
Interval 3 – Stage-wise statistical distribution of compression forces (N)

Feedback zone	Min	Max	Mean	SD
Yellow (insufficient)	137.3	431.1	325.5	55.0
Green (optimal)	470.8	1000.6	508.3	163.8
Red (excessive)	696.5	862.0	770.6	38.5

Table 6
Interval 4 – Stage-wise statistical distribution of compression forces (N)

Feedback zone	Min	Max	Mean	SD
Yellow (insufficient)	147.1	401.1	329.7	105.9
Green (optimal)	313.8	862.0	580.7	173.6
Red (excessive)	735.5	862.0	799.4	31.6

Summary of main findings

Overall, the under-body force sensor consistently differentiated between insufficient, optimal, and excessive compression forces across all four 30 second intervals. Optimal (green) compressions were generally maintained over the 2 minute session, with a slight increase in mean force in the final interval, suggesting that many participants were able to preserve or even augment effective compression force despite potential fatigue. Insufficient (yellow) and excessive (red) forces showed modest fluctuations over time but remained in clearly distinct numerical ranges, supporting the feasibility of force-based categorization aligned with manikin feedback indicators.

Residual force between compressions was detectable in the raw force waveforms, indicating that the system has the potential to provide indirect information about incomplete chest recoil—a dimension of CPR quality that is increasingly recognized as clinically important. Participant demographic characteristics (age, sex, and body weight) were not significantly associated with mean compression forces, suggesting that the observed force patterns reflect a broad range of rescuers rather than being restricted to a particular subgroup.

Discussion

This manikin-based study evaluated an under-body force sensor integrated into a rigid backboard as a tool for real-time monitoring of chest compression forces during CPR. The system consistently distinguished between insufficient, optimal, and excessive compressions over a continuous 2 minute session and captured how these patterns evolved over time. Across four 30 second intervals, insufficient compressions decreased, optimal compressions remained relatively stable with a slight increase in the

final interval, and excessive compressions showed improved control, a profile that is compatible with rapid adjustment to feedback and the early influence of fatigue.

Our results are in line with previous work showing that real-time feedback devices can improve CPR metrics such as compression depth, rate, and recoil in both simulation and clinical environments (1–4, 32). Although improvements in technical performance are well documented, survival benefits in randomized trials remain variable, suggesting that feedback is necessary but not sufficient on its own to change patient outcomes (28, 29). In this context, the under-body force sensor in our study appeared to support timely correction of both under-compression and excessive force, with force patterns remaining within ranges associated with guideline-consistent performance during a 2 minute cycle (3, 4, 20).

Most commercially available feedback systems rely on sternal accelerometers that infer compression depth from vertical displacement (7, 8, 31). These devices perform well on firm surfaces but tend to overestimate effective chest compression depth on compliant mattresses because part of the measured displacement reflects mattress compression rather than pure thoracic movement (9–11, 36). As a result, rescuers may receive apparently reassuring feedback while actual intrathoracic pressure generation remains inadequate (9, 33, 34). Under-body force sensors offer a complementary approach by directly measuring the net force transmitted to the support surface, making the signal less vulnerable to mattress deflection and providing a physiologically meaningful surrogate for the mechanical load applied to the chest (10–13, 23, 26). In our data, some overlap at the boundaries between force zones was observed, but the mean values for insufficient, optimal, and excessive categories remained clearly separated, indicating robust categorical discrimination despite this inherent variability.

Mattress compressibility is a well-recognized challenge for in-hospital CPR quality, particularly in intensive care units where advanced mattresses can dissipate a substantial proportion of applied compression force (8, 9, 34, 36). Experimental and manikin trials have shown that using a rigid backboard improves the transmission of compressive force to the thorax by reducing mattress deformation (11, 13, 37). Our backboard-integrated sensor builds directly on this concept: it not only helps standardize the support surface but also quantifies how much force is actually transmitted at the patient–surface interface. This dual function may be particularly relevant when CPR must be performed on soft beds or stretchers where displacement-based sensors alone are prone to overestimation errors (12, 23, 38).

The observed reduction in insufficient compressions over the 2 minute period is consistent with principles of motor learning, where immediate, task-specific feedback accelerates refinement of psychomotor skills (14, 39). At the same time, the modest decline and subsequent stabilization of excessive forces suggest that participants were able to adjust their effort to avoid overcompression or experienced early fatigue that tempered peak forces, supporting guideline recommendations for switching rescuers at 2 minute intervals to preserve compression quality (3, 15, 40). In practice, force-based thresholds could provide an objective indicator to prompt rescuer rotation, potentially improving on purely subjective judgments of fatigue (30, 41).

An additional notable finding was the detection of residual force between compressions, which may reflect incomplete chest recoil. Incomplete recoil is increasingly recognized as a detrimental component of CPR that can reduce coronary perfusion pressure and myocardial blood flow (1, 27). Being able to visualize or quantify residual load between compressions using an under-body sensor could therefore open an avenue for combined monitoring of both compression force and recoil quality, particularly if integrated into multi-parameter feedback algorithms.

Limitations

This study has several limitations that should be considered when interpreting the findings. First, the partial overlap of force values near the thresholds separating insufficient, optimal, and excessive zones introduces a risk of borderline misclassification, similar to the known measurement uncertainty of accelerometer-based depth estimates (7, 35). Future work could explore individualized calibration, adaptive thresholds, or machine learning models that integrate force, rate, and recoil features to refine category boundaries (16, 42). Second, our experiments were conducted using a single adult manikin model, which limits generalizability to pediatric patients, individuals with obesity, or patients with markedly altered chest wall compliance where force–depth relationships differ substantially (24, 43). Third, the convenience sample of medical and health sciences students may not fully represent professional rescuers such as paramedics, nurses, or physicians who may apply different force profiles during CPR (18, 22, 44). Finally, the 2 minute duration reflects guideline-based rotation intervals but does not capture the dynamics of prolonged resuscitation efforts, where fatigue and technique degradation may be more pronounced (15, 45).

Strengths

Despite these limitations, the study also has important strengths. Direct force measurement at the backboard circumvents artifacts associated with displacement-based depth estimation on soft surfaces while preserving natural hand placement and compression mechanics (10–13, 23). The design allowed continuous monitoring of force over four consecutive intervals, providing insight into how performance evolves within a single resuscitation cycle, which is not always captured in studies that only report aggregate values for a brief segment (26, 46). In addition, careful sensor calibration across the expected CPR force range and the use of synchronized video recording to verify manikin feedback and hand position increase the reliability of the measurements and support the internal validity of the findings (20, 22, 25).

Clinical implications

From an educational perspective, integrating under-body force feedback into simulation training could help learners better understand the relationship between applied force, compression depth, and surface characteristics. It may be particularly useful for illustrating how the same apparent hand movement can produce different effective thoracic displacement on firm versus soft surfaces (8, 14, 47). Clinically, such sensors could support objective decisions about rescuer rotation by flagging declining forces or

excessive leaning, and might guide the timely use of backboards in environments where mattress compressibility is a concern (11, 30, 37). In the longer term, combining under-body force data with displacement measurements from chest-mounted devices could yield hybrid feedback systems that offer a more complete and robust picture of CPR quality than either modality alone (10, 16, 23, 48).

Future directions

Future research should move beyond simulation and test under-body force monitoring in real clinical resuscitations across diverse settings, arrest etiologies, and provider groups (28, 29, 49). Studies with extended durations are needed to characterize how force patterns change over longer resuscitation attempts and to determine how best to define force-based thresholds for fatigue or performance degradation (15, 40, 45). Methodologically, development and validation of multi-parameter algorithms that integrate force, depth, rate, and recoil could enhance feedback specificity and reduce misclassification near category boundaries (16, 42, 50). Ultimately, randomized trials will be required to determine whether incorporating under-body force monitoring into CPR training and clinical practice leads to measurable improvements in patient-centered outcomes such as return of spontaneous circulation and survival with favorable neurological status (28, 29, 51).

In summary, this study suggests that backboard-integrated under-body force sensing is a feasible and promising approach for real-time monitoring of chest compression forces during CPR. The system was able to categorize compressions into clinically relevant force ranges, track temporal patterns over a 2 minute cycle, and operate independently of surface compliance, supporting its potential role as a complementary feedback modality that merits further validation beyond manikin simulation (23, 26, 38, 52).

Conclusions

This manikin-based study shows that an under-body force sensor embedded in a rigid backboard offers a feasible and reliable approach for real-time monitoring of chest compression forces during CPR. The system effectively distinguished between insufficient, optimal, and excessive compression forces across a continuous 2-minute session, while also capturing natural temporal patterns that reflect rescuer learning and early fatigue. Unlike conventional accelerometer-based devices, this force-based method appears insensitive to surface compliance issues that commonly compromise depth accuracy on hospital mattresses.

These findings suggest that under-body force monitoring could complement existing CPR feedback technologies, particularly in hospital settings where soft surfaces challenge performance assessment. Further research is warranted to validate this approach in clinical resuscitation scenarios and to explore its potential for improving training outcomes and patient-centered results.

Declarations

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Author Contribution

Z.G. contributed to the study design, data collection, and drafting of the manuscript.R.A.S. conceived and supervised the study, contributed to the study design, and served as the corresponding author.Sh.S. contributed to data analysis, interpretation of the results, and critical revision of the manuscript.H.R.Sh. performed the statistical analysis and contributed to the technical review of the manuscript.All authors have read and approved the final version of the manuscript.

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Data Availability

“The datasets generated and analyzed during the current study are available from the corresponding author on reasonable request. Due to ethical restrictions involving human participants, the data contain information that could compromise participant privacy.”

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