Automatic calculation of REBA for animated load handling

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Abstract: Over the years, technological innovation has played a fundamental role in various fields, particularly in production systems, in most modern companies, human resources increasingly work alongside advanced technological support. However, the human factor remains central to operational processes, ensuring workers' needs are met while maintaining efficiency and safety. This study aims to develop a system capable of automatically assessing ergonomic risk through image acquisition. Specifically, it focuses on the automatic calculation of the Rapid Entire Body Assessment (REBA) index, which is particularly suitable for evaluating ergonomic risks associated with handling animated loads. One of the most significant applications of REBA is in the healthcare sector, where nurses and doctors frequently move patients. To validate the technology, ten different poses were performed by ten subjects, and the final REBA index for each pose was compared with an ergonomist's assessment, demonstrating an almost perfect concordance. Additionally, five different tasks were simulated in a laboratory setting, with a second subject acting as the patient. This experiment highlights the significant physical effort required of healthcare staff during patient handling, particularly the strain on the trunk and arms, underscoring the potential ergonomic risks involved in these tasks.

Keywords: Ergonomics, Rapid Entire Body Assessment, Motion Capture, Healthcare, Kinect

1.Introduction

Work-related musculoskeletal disorders (WMSDs) include all musculoskeletal conditions caused or aggravated by work and the conditions in which it is performed (Luttman et al., 2003). Healthcare professionals are particularly exposed to high levels of work-related stress, increased absenteeism, and a heightened risk of developing WMSDs (Strauss et al., 2018). According to the European Working Conditions Survey (EWCS) (Eurofound, 2015), 47% of the workers in healthcare and social work sectors reported back pain and 46% reported upper limb pain in the past 12 months. In this context, it is essential to design work environments that prioritise the well-being of healthcare professionals, assessing the ergonomic risks associated with their posture and movements (Wang et al., 2023). Healthcare professionals frequently perform tasks while standing, often bending, twisting their torso, and engaging in repetitive movements such as lifting, transferring, and repositioning patients (Rezaei et al., 2021). Several studies (Anderson & Oakman, 2016; Rezaei et al., 2021; Ribeiro et al., 2017) have demonstrated that WMSDs among healthcare workers are most prevalent in the upper body, particularly in the back, neck, and shoulders. Although the dangers of WMSDs are widely recognized, ergonomic risk assessments are not regularly conducted across all workplaces. According to the European Survey of Enterprises on New and Emerging Risk (ESENER) (2014 and 2019), the complexity of legal obligations is the most reported barrier. Additionally, the percentage of workplaces reporting a "lack of time or staff" as a challenge increased from 29% in 2014 to 41% in 2019. This shortage of resources makes it difficult to prioritise workplace safety, potentially leading to greater health and safety challenges in the future (European Agency for Safety and Health at Work, 2020). Assessing the ergonomic risk associated with healthcare tasks is crucial for identifying and evaluating occupational injury risks. Traditionally, studies on working postures and movements have relied on self-reported data or observational methods to estimate spinal movements and biomechanical loading (Vieira & Kumar, 2004). Ergonomic posture analysis employs observational assessment methods such as Rapid Entire Limb Assessment (REBA) (Hignett & McAtamney, 2000), Rapid Upper Limb Assessment (RULA) (Mcatamney & Corlett, 1993), and National Institute for Occupational Safety and Health (NIOSH) Lifting Equation (Waters et al., 1993), which use a scoring system to evaluate work-related risks. With advancements in measurements technologies and computerised assessment systems, wearable sensors and motion capture (Mocap) technologies now enable more precise and reliable quantitative assessments (Zhang, 2012). Sensors can be marker-based or marker-less: marker-based systems require physical markers attached to the body, while marker-less systems do not (Yu et al., 2021). Optical depth camera, particularly Kinect devices, are widely used for ergonomic analysis, with several studies focusing on Kinect v1 and v2 for ergonomic risk assessment (Bortolini et al., 2018, 2020; Delpresto et al., 2013; Diego-Mas & Alcaide-Marzal, 2014; Manghisi et al., 2017; Plantard et al., 2015; Vignais et al., 2013). However, research on the newer Azure Kinect remains limited. Recent contributions include:

- Zhang et al. (2022), who conducted a pilot study using Azure Kinect with automated WMSDs risk software.
- Battini et al. (2022), who proposed a real-time ergonomic assessment platform for industrial environments.
- Lolli et al. (2024a, 2024b), who developed tools for calculating NIOSH and RULA scores with Azure Kinect.

While these works mainly target industrial or clinical settings and focus on specific ergonomic metrics, this study introduces a novel tool integrating Azure Kinect with the REBA methodology, specifically designed for assessing ergonomic risks in healthcare professionals. The tool was validated by comparing automated REBA scores with expert assessment on ten static postures and further tested in simulated clinical tasks to evaluate its applicability in real-word healthcare context. The paper is structured as follows: Section 2 outlines the materials and methods, including the REBA calculation process, data acquisition, and validation. The results resent validation outcomes and application in simulated clinical tasks. The conclusions summarise key findings, benefits of automation, and future research directions.

2.Materials and methods

2.1 Automatic calculation of REBA

The automatic ergonomic risk assessment using the REBA method (Hignett & McAtamney, 2000) was conducted based on Azure Kinect data. Using the Azure Kinect SDK (Microsoft, 2021), 32 body joints were tracked. By leveraging the 3D coordinates of these joints, relevant angles were measured through a geometric informatics model developed in Python. To perform the automatic REBA analysis, postures were recorded using the depth camera and subsequently processed. The steps involved in the automatic REBA calculation are illustrated in Figure 1.

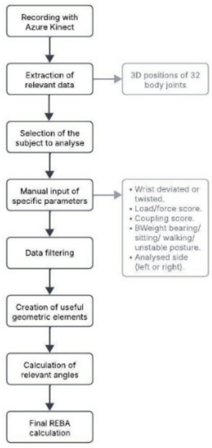

Figure 1: Workflow for automatic REBA calculation.

The process begins with recording movements using Azure Kinect. Relevant data from one or multiple tracked subjects are extracted, with the system allowing selection of the subject to analyse, minimising confusion between individuals. Key joint angles from the selected subject are then calculated to determine the final REBA score, indicating the associated risk level (see Table 1).

Table 1: REBA action levels (Hignett & McAtamney, 2000).

Action level	REBA score	Risk level	Action	Description
0	1	Negligible	No necessary	Acceptable if short duration
1	2-3	Low	May be necessary	Further investigation may be needed
2	4-7	Medium	Necessary	Changes may be required
3	8-10	High	Necessary soon	Changes required soon
4	11-15	Very high	Necessary now	Immediate changes required

To determine the angles, a geometric model was developed to detect relevant geometric elements. The movements computed by Python code are presented in Table 2, based on the criteria outlined by Hignett & McAtamney (2000).

Table 2: REBA posture scoring criteria Hignett & McAtamney (2000)**.**

REBA Group	Movement/Position	Range	Score
A	Trunk twist/side flexion	>0°	+1
A	Trunk flexion	0°-20° 20°-60° >60°	2 3 4
A	Trunk extension	0°-20° >20° >60°	2 3 4
A	Neck flection	0°-20° >20°	1 2
A	Neck twist/side flexion	>0°	+1
A	Legs position*	Bilateral weight bearing/walking/sitting Unilateral weight bearing/Feather weight bearing/Unstable posture	1 2
A	Leg flexion	30°-60° >60°	+1 +1
B	Upper arm flexion	<20° 20°-45° 45°-90° >90°	1 2 3 4
B	Upper arm extension	<20° >20°	1 2
B	Upper arm abduction/rotation	>0°	+1
B	Shoulder raised	>0°	+1
B	Upper arm supported	-	-1
B	Lower arms flexion	60°-100° <60°	21
B	Lower arms extension	>100°	2
B	Wrist flexion/extension	0°-15° >15°	1 2
B	Wrist deviation/twist *	>0°	+1

*Parameters marked with an asterisk () were not calculated automatically but were manually entered.

2.2 Experimental protocol

The main objective of the study was to develop and validate the automatic calculation of REBA by comparing the proposed method with the traditional assessment conducted by an ergonomic expert. To achieve this, ten static poses were performed by ten participants (six males and four females) with different physical characteristics (mean age: 26.26±4.3 years, mean height: 177.2±9.3 cm, mean weight: 71.7±11.8 kg). the selection of static poses for validation was inspired by Kim et al. (2021), who aimed to validate OpenPose-based system for RULA/REBA calculation. The poses are illustrated in Figure 2.

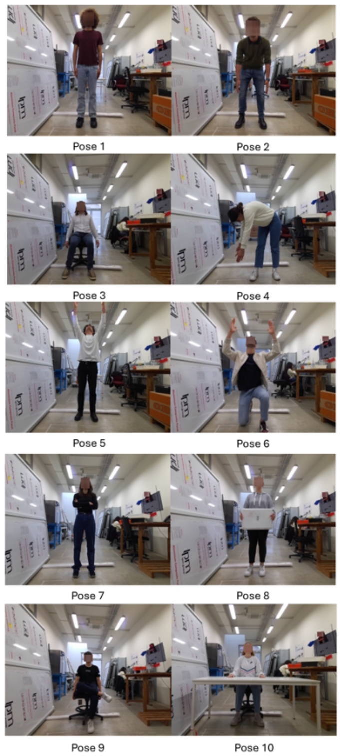

Figure 2: Static poses performed during the experiments.

To compare the REBA scores obtained from the automatic and traditional methods, the Mean Absolute Error (MAE), and Cohen's kappa coefficient (Cohen, 1960) were applied following the Landis & Koch (1977) scale to evaluate the accuracy of the automatic REBA calculation. The second phase of the experiments involved applying the automatic REBA calculation to simulated healthcare tasks performed in a laboratory setting. These tasks were performed by 27-year-old female participant, who acted as a caregiver moving another subject (simulating patient). The specific analysed tasks were:

- Patient transfer process, following the guidelines of Han et al. (2023).
- Wound dressing task in a stooped posture (standing), based on(Szeto et al. (2013).
- Wound dressing task in a upright posture (sitting) (Szeto et al., 2013).
- Patient transfer tasks, inspired by Man et al. (2022), analysing both the initial and final phases of the transfer process.
- Mobility and mobilization techniques, including six subtasks derived from (Zhang et al. (2022).
- Bed-to-wheelchair transfer, incorporating three subtasks based on (Matsumoto et al. (2016).

All tasks and their corresponding references are detailed in Table 3.

Table 3: Tasks performed to simulate clinical activities.

Task	Description	Reference
1	Patient transfer process	(Han et al., 2023)
2	Wound dressing task in a stooped posture (standing)	(Szeto et al., 2013)
3	Wound dressing task in a upright posture (sitting)	
4a	The start of a patient transfer process	(Man et al., 2022)
4b	The end of a patient transfer process	
5a	Sitting to standing mobility practice	(Zhang et al., 2022)
5b	Bed to chair sitting pivot transfer	
5c	Side-lying to sitting position transfer.	
5d	Shoulder mobilization (dorsal glide)	
5e	Hip mobilization (posterior glide)	
5f	Lumbar rotation mobilization	
6a	Patient lifting from the bed	(Matsumoto et al., 2016)
6b	Rotation on the wheelchair side	
6c	Safe positioning on the wheelchair	

To summarise experimental process, Figure 3 provides a visual representation of the different acquisitions.

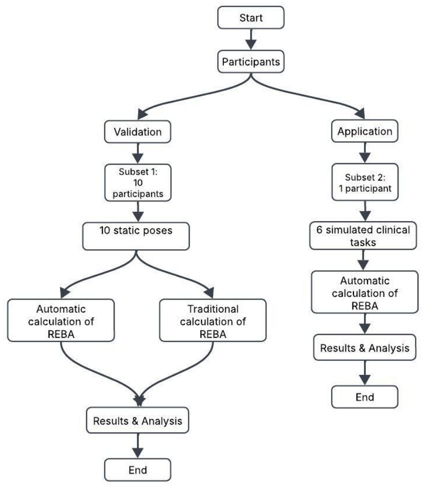

Figure 3: Graphical representation of experiments.

3. Results

The findings of this study are presented in two sections: the validation of the automatic REBA calculation and its application in simulated clinical tasks.

3.1 Validation of automatic REBA

To assess the accuracy of the automatic REBA calculation, ten participants performed ten static poses. The final REBA scores were determined using both the automatic system and the traditional expert evaluation. Additionally, key body segment angles-trunk, neck, right leg, upper and lower right arm, and right wrist- were analysed. The Mean Absolute Error (MAE) between the two methods for each pose is summarise in Table 4. The expert assigned a single score per pose, while the automatic system captured subtle variations across participants, causing score differences.

Table 4: Comparison of REBA scores between automatic and traditional methods, including MAE.

POSES	Automatic REBA	Traditional REBA	MAE
1	1.3±0.67	1±0	0.3±0.67
2	3.3±1.16	4±0	0.9±0.99
3	2.6±0.70	1±0	1.6±0.70
4	5.9±1.52	5±0	1.3±1.16
5	6.2±0.63	7±0	0.8±0.63
6	6.5±1.58	5±0	1.9±0.99

7	1.5±0.53	1±0	0.5±0.53
8	1.3±0.48	1±0	0.3±0.48
9	4.0±1.25	2±0	2±1.25
10	2.5±1.18	1±0	1.5±0.18

A graphical representation of the differences in REBA scores between the two methods is illustrated in Figure 4.

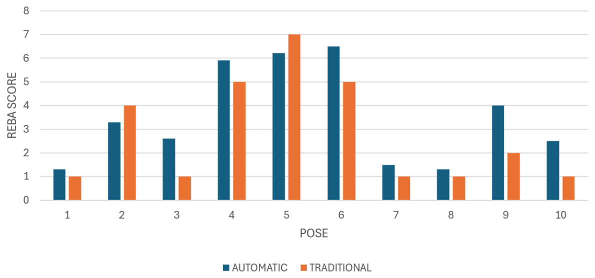

Figure 4: Graphical representation mean REBA scores.

The most significant discrepancy was observed in Pose 6, particularly in the leg scoring (MAE = 2.7±0.64). this was likely due to the frontal positioning of the Kinect, which led to occlusions affecting the accuracy of leg tracking. A more precise measurement of leg angles could be achieved by positioning the Kinect at a lateral angle relative to the subject. The primary goal of ergonomic risk assessment using REBA is to categorise the action level associated with a task. To evaluate the agreement between the automatic and traditional assessment, Cohen’s kappa coefficient (Cohen, 1960) was applied following the Landis & Koch (1977). The calculated kappa value was 0.58, indicating moderate agreement. Additionally, the observed proportion correct coefficient was 0.71. a contingency table summarising the classification of action levels between the two methods is provided in Table 5.

Table 5: Contingency table comparing automatic and traditional ergonomic action level assessment.

Automatic action level assessment	**Traditional action level assessment**			
	0	**1**	**2**	**3**
0	30	0	0	0
1	19	10	5	0
2	1	0	31	0
3	0	0	4	0

The results indicate a slight tendency for the automatic system to overestimate action levels. For example, in Pose 3, the expert classified the posture as having negligible risk (action level 0), while the automatic system identified it as low risk (action level 1). This difference can be attributed to the precision of the automatic assessment, which detects even minor deviations in trunk angle that may not be visually apparent. While the expert assumed the trunk was perfectly in a seated position, the automatic system identified slight flexion or extension, highlighting its ability to capture slight posture variations.

3.2 Implementation of automatic REBA in simulated clinical tasks

To assess the effectiveness of automatic REBA evaluation in a clinical setting, a participant performed six simulated activities, each with its corresponding subtasks, while another individual acted as a patient. The results of the automatic REBA assessment are presented in Table 6.

Table 6: Automatic ergonomic risk assessment of simulated clinical tasks.

TASK	REBA score	Action level	Risk level	Action
1	12	**4**	**Very high**	Necessary now
2	5	2	Medium	Necessary
3	4	2	Medium	Necessary
4a	1	0	Negligible	No necessary
4b	11	**4**	**Very high**	Necessary now
5a	5	2	Medium	Necessary
5b	9	3	High	Necessary soon
5c	10	3	High	Necessary soon
5d	5	2	Medium	Necessary
5e	8	3	High	Necessary soon
5f	9	3	High	Necessary soon
6a	9	3	High	Necessary soon
6b	11	**4**	**Very high**	Necessary now
6c	11	**4**	**Very high**	Necessary now

The results indicate that most simulated clinical tasks fall into the high or very high ergonomic risk levels. To further analyse the contributing factors, a detailed analysis of specific body segment scores was conducted. Table 7 presents the individual scores for the trunk, neck, right leg, right upper arm, right lower arm, and right wrist for the tasks classified as very high risk. Notably, all tasks within this category involve patient transfer, a physically demanding activity requiring significant lifting efforts.

Table 7: Detailed REBA scores for high-risk tasks.

TASK	1	4b	6b	6c
Trunk score	**4**	**4**	2	3
Neck score	2	1	1	2

Right leg score	2	2	3	3
Right upper arm score	**4**	**4**	**4**	3
Right lower arm score	2	2	2	1
Right wrist	3	2	3	2
REBA	12	11	11	11

The data highlights that the trunk and right upper arm have the most significant impact on the classification of tasks as very high risk. This is expected, as patient transfer tasks require substantial upper-body effort to support the patient's weight. To further illustrate these findings, Figure 5 visually represents the postures associated with the most ergonomically hazardous tasks.

Figure 5: Visual representation of high-risk tasks.

The images clearly depict trunk flexion exceeding 20° or even 60°, often combined with the trunk rotation, leading to a REBA trunk score of 4. Additionally, the right upper arm is consistently flexed, shoulders are raised, and no external support is available, further increasing strain and risk.

4. Conclusions

This study developed and validated an automated method for ergonomic risk assessment using Azure Kinect, focusing on healthcare workers and the REBA score. The system uses geometric modelling to calculate joint angles and REBA scores, showing moderate agreement (kappa = 0.58) with expert evaluations. The automated system detects subtle postural deviations not easily observed by humans. Application to simulated clinical tasks revealed significant postural strain, especially during patient transfers, which posed a very high risk. The automated approach improves assessment accuracy, efficiency, and reduces costs by eliminating the need for markers or professional ergonomists. Limitations include a small validation sample, limited camera positioning tests, and use of non-healthcare participants. Future research should increase sample size, test in real clinical environments, and explore integration into real-time monitoring systems to support ergonomic risk management and enhance worker safety.

ACKNOWLEDGEMENTS

Partially funded by the European Union - Next Generation EU, Mission 4 Component 1, CUP E93C22001860006.

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