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SYSTEMATIC REVIEW

General Medicine

Total body weight estimation by 3D camera systems: Potential high-tech solutions for emergency medicine applications? A scoping review

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Abstract

Background: Weight estimation is required in adult patients when weight-based medication must be administered during emergency care, as measuring weight is often not possible. Inaccurate estimations may lead to inaccurate drug dosing, which may cause patient harm. High-tech 3D camera systems driven by artificial intelligence might be the solution to this problem. The aim of this review was to describe and evaluate the published literature on 3D camera weight estimation methods.

Methods: A systematic literature search was performed for articles that studied the use of 3D camera systems for weight estimation in adults. Data on the study characteristics, the quality of the studies, the 3D camera methods evaluated, and the accuracy of the systems were extracted and evaluated.

Results: A total of 14 studies were included, published from 2012 to 2024. Most studies used Microsoft Kinect cameras, with various analytical approaches to weight estimation. The 3D camera systems often achieved a P10 of 90% (90% of estimates within 10% of actual weight), with all systems exceeding a P10 of 78%. The studies highlighted a significant potential for 3D camera systems to be suitable for use in emergency care.

Conclusion: The 3D camera systems offer a promising method for weight estimation in emergency settings, potentially improving drug dosing accuracy and patient safety. Weight estimates were satisfactorily accurate, often exceeding the reported accuracy of existing weight estimation methods. Importantly, 3D camera systems possess characteristics that could make them very appropriate for use during emergency care. Future research should focus on developing and validating this methodology in larger studies with true external and clinical validation.

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KEYWORDS
3D camera weight estimation, drug dosing, weight estimation

1 | INTRODUCTION

1.1 | Background

During the resuscitative care of critically ill or injured patients, an estimation of their weight is required when weight-based drug therapy is required, and actual patient weight cannot be measured. Measuring weight with scales is not always feasible as it is time consuming and requires patient cooperation as well as a medically stable patient.[1] If a stand-on scale cannot be used due to the patient's clinical condition, some emergency departments (EDs) use scales that are imbedded in patient stretchers. These are costly, difficult to maintain, not universally available, and unproven in terms of accuracy during emergency care.[2,3] An estimation of weight is, therefore, often required.

Numerous studies have described or evaluated different methods of weight estimation in adults. These methods include (1) estimates by patients themselves, family members, and healthcare professionals; (2) formulas based on anthropometric measurements, such as the Lorenz formula; (3) dual length- and habitus-based tapes, such as the PAWPER XL-MAC tape; and (4) high-tech methods, such as 3D camera systems. Of all these methods, 3D camera systems have shown the greatest potential for highly accurate, rapid, easy-to-use estimation of weight.[4] These methods use real-time 3D images and previously trained artificial intelligence algorithms to generate estimates of weight. Existing 3D camera weight estimation methods have used different approaches with different cameras, software, costs, ease-of-use, applicability, and accuracy.

1.2 | Importance

Patient safety organizations have underscored the critical need for precise weight estimation to ensure safe and effective weight-based drug dosing in the ED.[5–8] Consequently, it is of the utmost importance to use the most accurate and easy-to-use method of weight estimation. One weight estimation researcher wrote: "It cannot be considered to be good medical practice to use a weight estimation system that is known to be inaccurate."[9] In adults, many current methods of weight estimation are inaccurate (or not reliable enough for use during emergencies).[4] For example, while patients' self-reported weights are generally the most accurate way to estimate weight, patients may be unable to provide a self-estimate up to 85% of the time.[10] Additionally, even the most accurate anthropometric weight estimation systems, such as the Lorenz method, can have an error of more than 10% in nearly half of the patients in whom it is used.[11]

Weight estimation using 3D camera systems could represent one of the most significant breakthroughs in weight estimation and medication safety in the ED in the past 40 years, potentially rivaling the impact of the Broselow tape in pediatric emergency medicine. Artificial Intelligence-driven 3D camera weight estimation systems could estimate weight safely without patient contact and without user input, allow for accurate dosing of medications, function with speed and efficiency in life-threatening situations, improve care for unconscious or non-responsive patients, minimize human error in high-stress environments, and integrate with other tools such as automatic dose calculators and the electronic medical record. It is crucial to recognize both the potential of the technology to improve emergency care, and the existing knowledge gaps, to effectively develop a framework for future research.

1.3 | Goals of this investigation

Our aim in this scoping review was to review the available literature in which a 3D camera system was used to estimate a patient's weight, with a medical indication as the ultimate purpose. We aimed to describe the performance and accuracy of 3D camera weight estimation systems, the types of cameras used, and the analytical and software methods used in the weight estimation process.

2 | METHODS

This scoping review was based on the PRISMA for Scoping Reviews (PRISMA-ScR) guidelines.[12]

2.1 | Literature search

A literature search was conducted using MEDLINE, EMBASE, IEEE Xplore, and Google Scholar. Eligible studies published between January 2012 and April 2024 were identified using the search strategy shown in Table S1.

2.2 | Eligibility criteria

Studies were included for further evaluation if they were peer reviewed, full length, English language papers containing original data. Studies evaluating any form of 3D camera weight estimation methodology and in any type of participants were eligible for inclusion if an accurate measured weight was used as the standard reference. Studies on weight estimation not relevant to a clinical or hospital setting were excluded (e.g., weight estimation for forensic or non-medical applications).

2.3 | Selection of studies

The titles and abstracts of the articles identified by the database search were manually screened by two researchers independently (M.W. and N.G.). The full texts of the selected reviews were then obtained and assessed for eligibility. Any differences in opinion were resolved by discussion and consensus.

2.4 | Critical appraisal of individual sources of evidence (grading of quality of studies)

Every included study was graded for quality of evidence using a modified Newcastle–Ottawa scale (NOS), as has been described previously (see Table S2).[13] Studies were downgraded if significant methodological weaknesses were present, for example, if data presentation was incomplete or if performance outcome data were not appropriately presented or analyzed. An assessment of selective non-reporting or under-reporting of results in the studies was included in the Newcastle-Ottawa scale. Each study could score a minimum of zero stars and a maximum of 10 stars on the modified NOS. On this scale, a study with score from 6 to 10 has high quality, 4 to 5 has a moderate risk of bias, and 0 to 3 a very high risk of bias.

2.5 | Data charting process (data extraction)

Data extraction was conducted by one researcher (T.W.) using a standardized electronic data extraction form and was independently confirmed by another researcher (M.W.) for accuracy.

2.6 | Data items

The following data were extracted: basic study information (region of origin, study population, sample size), study participant characteristics, 3D camera used, analytic method or software used for the weight estimation process, key findings, and the data presented on the performance or accuracy of weight estimation.

2.7 | Data synthesis (map of outcomes)

The findings of this scoping review were synthesized by presenting a descriptive and quantitative summary of the study characteristics using frequencies with percentages. The studies were grouped by the types of 3D cameras used, as well as the overall analytic approach, and summarized according to weight estimation outcomes.

In terms of the quantitative analysis, the main outcomes of interest were metrics representing the performance of the weight estimation system. These included mean error or mean percentage error, which represented the estimation bias; the root mean square error, the mean absolute error, the root mean square percentage error, or the mean absolute percentage error, which quantified the estimation precision; and the percentage of weight estimations that fell within 10% (P10) as well as within 20% (P20) of measured weight, which denoted overall accuracy. We considered the measures of overall accuracy (P10 and P20) to be the most useful indicator of overall performance, as has been described previously.[14–17] If P10 data were not reported, it was imputed, whenever possible, from other reported metrics (mean absolute percentage error or mean percentage error).

3 | RESULTS

No significant deviations from the protocol were noted. The details of the numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, are shown in Figure 1.

3.1 | Characteristics of the included studies

A total of 14 studies were included in this scoping review. The details of the included studies, including the study methodologies, the hardware and software used, and the weight estimation approaches are shown in Table 1. Two-thirds of the studies (9/14 [64%]) were from Europe (all but one from Germany), with three studies (21%) from the United States, and two studies (14%) from elsewhere (one from Indonesia and one from Chile).

Most of the studies (8/14 [57%]) prospectively collected data for data analysis, while six (43%) studies used existing data to develop or evaluate new analytic approaches. Only four of 14 (29%) studies compared 3D camera methods against other methods of weight estimation. The main aim of the study was to evaluate potential methods to estimate weight for drug dosing purposes in six of 14 (43%) studies, for computed tomography (CT) contrast and radiation dosing in five of 14 (36%) studies, for nutritional or body habitus assessment in two of 14 (14%) studies, and other reasons in one of 14 (7%) study.

3.2 | Risks of bias and limitations across studies

The methodological quality of most of the studies was good. Most studies (11/14 [79%]) had a low risk of bias on the Newcastle–Ottawa scale, one study (7%) had moderate risk of bias, and two studies (14%) had a high risk of bias. However, incomplete data reporting or incomplete statistical analysis (5/14 studies [36%]) were common. Only three of 14 (21%) studies presented any form of subgroup analyses and no study provided comprehensive subgroup analyses by sex and weight-status. In addition, two of 14 (14%) studies had a sample size of 100 or fewer

TABLE 1 Details of the included studies.[18–31]

Author, date, location	Study population	Participant characteristics	Camera technology	Method of weight estimation	Analytic method or software	Accuracy data	Notes
Velardo et al. 2012, France	NHANES 1999 to 2005 datasets, $N = 28,000$. Volunteers for testing of actual 3D camera system, $N = 15$.	Age: >20 years. Sex: not reported. Weight: not reported. BMI: not reported.	Microsoft Kinect 1	Biometrics obtained from 3D image silhouette—regression equation to predict weight. User input required: none.	MATLAB Neural network toolbox to obtain estimators. OpenNI framework, Primesense, OpenCV, PCL. ANN (single hidden layer) to create algorithm for weight estimation.	Weight: MAPE 3.6% in 10/15 human test subjects, using 3D camera. No data reported for females.	Gender recognition was included using neural network classifier on anthropometric measurements (80% accurate). No results reported for other 5/15 subjects. Internal validation: none.
Nguyen et al., 2014, USA	University student and staff volunteers, $N = 190$.	Age: 18–60 years. Sex: not reported. Weight: not reported. BMI: not reported.	Microsoft Kinect 1	Feature fusion models—including linear dimension features, area features, and sideview shape from 3D camera. User input required: none.	RANSAC for video processing. SVR-LibSVM with Gaussian Radial Basis Function for weight estimation.	Weight: MAE 4.6 kg (F), 5.6 kg (M). MAE 5.4 kg when autodetection of gender was used.	Gender estimation—88%–92% accuracy. The 3D camera system was more accurate than observer estimates. Internal validation: fivefold cross-validation.
Pfitzner et al., 2015, Germany	Convenience sample of emergency department patients, $N = 110$.	Age: 19–86 years. Sex: male 53.6%. Weight: 49–117 kg. BMI: 18–40 kg/m^2.	Microsoft Kinect 1 & Optris PI400 (thermal camera)	The approach involves patient segmentation, body volume estimation, and body weight estimation using a fixed coefficient for body density. User input required: gender.	RANSAC, point cloud geometry.	Weight: MPE 1.02 (95% LOA −15.8 to 17.9) P10 79.1%	The 3D camera method was more accurate than physician estimates and similar to the Lorenz method, but less accurate than patient self-estimates. Internal validation: none.
Pfitzner et al., 2016, Germany	Convenience sample of emergency department patients, $N = 69$.	Age: 18–87 years. Sex: not reported. Weight: 49–129 kg. BMI: 19–48 kg/m^2.	Microsoft Kinect 1 & Optris PI400 (thermal camera)	The approach used for weight estimation involves sensor fusion of an RGB-D sensor and a thermal camera, pre-processing and segmentation of the sensor data, extraction of 10 features for machine learning-based weight estimation. User input required: gender.	Multiple features extracted from cloud point data. ANN (single hidden layer) to create algorithm for weight estimation. ANN trained using a dataset recorded in real emergency scenarios.	Weight: MPE −0.7 (95% LOA −13.5 to 12.1) P10 89.9%	The 3D camera method was more accurate than physician estimates and the Lorenz method, but less accurate than patient self-estimates. Internal validation: none.

(Continues)

TABLE 1 (Continued)

Author, date, location	Study population	Participant characteristics	Camera technology	Method of weight estimation	Analytic method or software	Accuracy data	Notes
Benalcazar et al., 2017, Chile	Volunteers N = 185 (LMS method) Volunteers, N = 34 (ANN method)	LMS model: Age: 3–23 years. Sex: male 100%. Weight: 11–114 kg. BMI: not reported. ANN model: Age: 3–18 years. Sex: male 100%. Weight: 17–88 kg. BMI: not reported.	Microsoft Kinect 1	The area of the person in the normalized image was computed, and this parameter was used to estimate the weight of the person. User input required: information on hairstyle and clothing.	Both LMS and ANN fitting techniques were explored for the weight estimation model. The Levenberg Marquardt back-propagation method was used for training.	Weight: LMS MAPE 10.7% ANN MAPE 5.8%	The increase in accuracy between LMS and ANN was due to the change in evaluation of hair and clothing. Internal validation: k-fold cross-validation.
Pfitzner et al., 2017, Germany	Convenience sample of trauma room patients, N = 127. Volunteers from public event, N = 106.	Age: not reported. Sex: male 41.2%. Weight: 49–129 kg. BMI: not reported.	Microsoft Kinect 2	The features used for weight estimation include volume, surface area, number of points, density, eigenvalues, sphericity, flatness, linearity, compactness, kurtosis, alternative compactness, distance to person, contour length, contour area, convex hull length, convex hull area, gender, and temperature features. User input required: gender.	RANSAC for video processing, artificial neural network for weight estimation.	Weight: MPE 0.3 (95% LOA −10.1 to 10.7) P10 94.8%	The Kinect 2 was more accurate than the Kinect original and was perhaps underappreciated in the paper. Internal validation: none.
Pfitzner et al., 2018, Germany	Various sources, N = 299 (reanalysis of previous depth data with new methodology).	Age: not reported. Sex: male 67.5%. Weight: 49–129 kg. BMI: not reported.	Microsoft Kinect 1, Microsoft Kinect 2, Optris PI400)	New approach was used in which deep learning was used for the weight estimation process. Features are extracted from the person's point cloud, including geometric features, features based on eigenvalues, statistical features, and features from the silhouette of a person. These features are then used as input to different algorithms, such as clustering, a 3-layer feedforward neural network, and an ANN, to estimate the body weight. User input required: gender.	CNN, ANN, RANSAC	Weight: P10 95.3% for lying subjects, P10 91.3% for walking subjects and P10 100% for walking subjects.	This paper is closer to being a summary of other tests than being a standalone paper, although new modeling is used. The only new data are for walking subjects. Internal validation: none.

(Continues)

TABLE 1 (Continued)

Author, date, location	Study population	Participant characteristics	Camera technology	Method of weight estimation	Analytic method or software	Accuracy data	Notes
Bigalke et al., 2021, Germany	Not reported. $N = 60$ for training, $N = 49$ for testing.	Age: not reported. Sex: not reported. Weight: 44–105 kg. BMI: not reported.	Not reported*	The approach used for weight estimation in this study was deep learning techniques applied to 3D point cloud data without relying on hand-crafted features. They adopt the concept of basis point sets (BPS) to encode the input point cloud into a low-dimensional feature vector, which is then passed to a neural network trained for weight regression. User input required: none.	RANSAC for image isolation, DBSCAN, ADAM optimizer, PointNet, fully connected neural network	Weight: MAE 4.2 (0.12) kg MAPE 6.4 (0.2) % P10 78.6%	Many "not reported" items. Internal validation: split sample.
Dane et al., 2021, USA	Convenience sample of outpatient CT scan patients, $N =$ 363 for training, $N = 90$ for testing.	Age: 59.8 (14.9) years. Sex: not reported. Weight: 34–107 kg. BMI: not reported.	FAST 3D camera (Siemens Healthineers)	The 3D camera captured the patient's body surface landmarks using infrared imaging. The patient's body was divided into different regions (head, thorax, abdomen, arm, and leg) based on the 3D patient geometry. From the estimated 3D patient body mesh, various geometry-based features such as volume and length of each body region were computed. These features were used for weight estimation. User input required: none.	Deformable Patient Avatar (digital twin) with Deep Image Network. The weight estimation was modeled as a weighted sum of all the geometry-based features, and the weight coefficients were estimated using a Bayesian Ridge regression model. This process was performed using Scikit learn.	Height: MAPE 2.0% (1.4) Weight: MAPE 5.1% (4.3) 9.2% underweight ($n = 7$) 5.4% normal weight ($n = 57$) 4.6% obese ($n = 22$)	Poorer estimations in underweight patients. Incomplete accuracy data reporting. Internal validation: split sample.
Geissler et al., 2021, Germany	Random patients undergoing CT scanning, $N = 221$ for training, $N =$ 101 for testing.	Age: 21–92 years. Sex: not reported. Weight: not reported. BMI: 27.3 (SD 5.5) kg/m^2.	Microsoft Kinect 2	Digital twin or avatar fitted to observed depth data, sized according to height. User input required: none.	Not reported.	Height: MAE 2.5 (1.9) cm Weight: MAE 4.4 (3.9) kg 35% of patients had estimate error >5 kg	Worse estimates in obese patients, but height estimates not affected. Weight estimates much worse than patient self-estimates, but much better than staff estimates. Internal validation: split sample.

(Continues)

TABLE 1 (Continued)

Author, date, location	Study population	Participant characteristics	Camera technology	Method of weight estimation	Analytic method or software	Accuracy data	Notes
Mameli et al., 2021, Italy	Volunteers. $N = 94$ for training, $N = 9$ for testing.	Age: not reported. Sex: male 63.1%. Weight: 40–100 kg. BMI: not reported.	Orbec Astra S2	"Top View Weight Estimation Approach", VRAI Weight estimation dataset. Deep learning model trained directly off 3D depth data. User input required: none.	Deep Neural Networks (VGG16, ResNet, Inception DenseNet, EfficientNet)	Weight: MAE | MSE ResNet 4 kg | 36 kg Inception 3 kg | 11 kg DenseNet 1 kg | 4 kg EfficientNet 1 kg | 2 kg	Top view (bird's eye view) of standing participants was the only 3D image used in this study. Internal validation: split sample.
Naufal et al., 2021, Indonesia	Volunteers, $N =$ 147.	Age: 5–70 years. Sex: not reported. Weight: 14–90 kg. BMI: not reported.	Microsoft Kinect 1	3D images segmented and converted to 2D images. This image area was correlated with weight. User input required: N/A.	MATLAB-based software	Weight: Only correlation was used. No valid method of assessing accuracy.	Height estimation accuracy to within 1% Internal validation: none.
Tamersoy et al., 2023, Germany	Volunteers plus patients undergoing CT or MRI imaging, $N =$ 1850.	Age: not reported. Sex: not reported. Weight: 45–120 kg. BMI: not reported.	3D camera not specified	The method treats the estimation of patient height and weight as separate single-value regression problems, eliminating the need for error-prone intermediate stages such as volume computations. A 3D patient avatar or digital twin image is fitted to the acquired depth images, which is then used for part-volume based weight estimation. User input required: none.	ResNet 18 ADAM optimizer	Height: P5—98.4% P15—99.9% Weight: P10—95.6% P20—99.8%	Extremely high weight estimation accuracy. May possibly be overfitted model. Internal validation: 23-fold cross-validation.
Shahzadi et al., 2024, Germany	Consecutive patients undergoing MRI, $N = 148$.	Age: not reported. Sex: not reported. Weight: 45–120 kg. BMI: not reported.	myExam 3D Camera Siemens Healthineers	Details not reported. Unspecified features from depth data used in separate prediction models for height and weight. Model was trained on an unspecified dataset of images. User input required: none.	ResNet18 for initial training. SMAPE as a loss function and ADAM optimizer.	Height: P5 100% MAPE 1.7 (1.2)% Weight: P10 85.1% P20 95.9% MAPE 5.6 (5.5)%	Without blanket P10 93.8, P20 100%. Height estimations also slightly better. Predictions were still good in patients with Class 2 obesity. Internal validation: 23-fold cross-validation.

Abbreviations: ANN, artificial neural network; ADAM, adaptive moment estimation; BMI, body mass index; CNN, convoluted neural network; CT, computed tomography; DBSCAN, density-based spatial clustering of applications with noise; LibSVM, library for support vector machines; LMS, least mean squares; LOA, limits of agreement; MAE, mean absolute error; MAPE, mean absolute percentage error; MATLAB, MATrix LABoratory; MPE, mean percentage error; MRI, magnetic resonance imaging; NHANES, National Health and Nutrition Examination Survey; P10, percentage of estimates within 10% of actual weight; PCL, Point Cloud Library; RANSAC, RANdom SAmple Consensus; SVR, support vector regression.

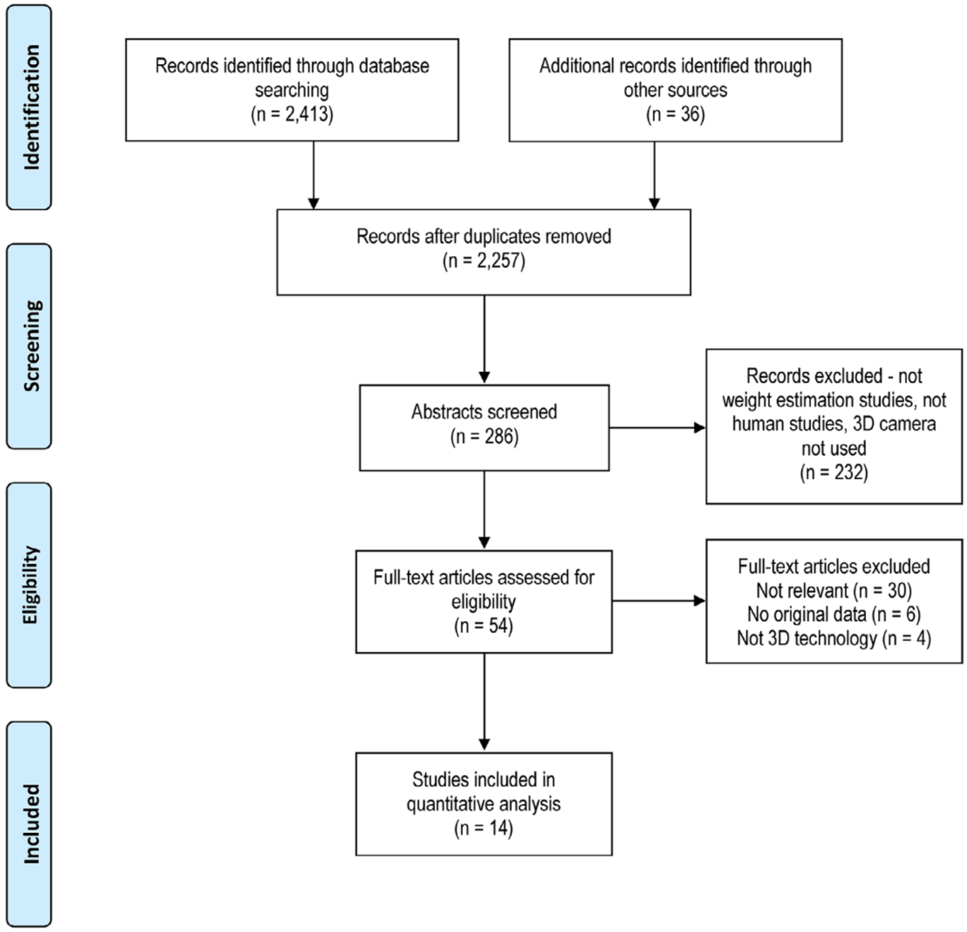

FIGURE 1 The Preferred Reporting Items for Scoping Reviews (PRISMA-ScR) flow chart for article identification and selection.

participants, and only three of 14 (21%) studies had a sample size of greater than 300 participants. These findings are summarized in Figure S1.

Eight studies (57%) employed some form of appropriate internal validation of the developed model: split sample analysis in four studies and cross-validation in four studies. No 3D camera weight estimation system had a true external validation process.

3.3 | Camera technology and hardware

The original Microsoft Kinect 1 camera was used in seven of 14 (50%) studies, and the Microsoft Kinect 2 camera was used in three of 14 (21%) studies. A Siemens FAST 3D camera, a Siemens myExam 3D camera, and an Orbbec Astra camera were used in one study each (7%). The type of 3D camera used was not reported in two studies (14%).

3.4 | Fundamental approach used in the weight estimation methodology

Multiple differences approaches were used to process 3D images and obtain a weight estimate from the depth data (see Table 2). Deep learning methods were used in the image preprocessing phase in four of 14 (29%) studies, and in the weight estimation phase in nine of 14 (64%) studies. Most methods (9/14 [64%]) required no user input to facilitate the weight estimate calculations, with the exceptions of the methods of Pfitzner and colleagues, which required gender as a manual input, and the method of Benalcazar et al , which required information on clothing and hairstyle.

3.5 | Accuracy of weight estimates

Unfortunately, only half of the studies (7/14 [50%]) provided comprehensive data on the performance of the weight estimation systems. Accuracy data (P10—the percentage of estimates within 10% of actual weight) could be imputed in four additional studies. The accuracy data for each study are shown in Figure 2. Every study for which data were available exceeded the minimum acceptable accuracy standard of P10 > 70%.[14,32] This standard, originally used for pediatric weight estimation systems, has been adopted by researchers in adult weight estimation.[15] The standard was statistically designed to ensure that the error rate for critical drug dosing remains below 5%.[13]

In the four studies in which direct, paired comparisons were made against other weight estimation systems, the following findings were

TABLE 2 Analytical approach to total body weight estimation in adults.

Authors	What 3D camera data are used and what image preprocessing is used?	How is weight estimate obtained from 3D camera data?
Velardo et al, 2012	Biometric data measured from 3D image: height, arm length, arm circumference, waist circumference, leg length, and leg circumference.	A regression equation is used to estimate weight from the 3D camera-measured biometric input data. Gender is predicted from the biometric data (80%) accuracy.
Nguyen et al, 2014	The "sideview shape" (or anterior body contour) depth data are extracted from the point cloud data.	Height and sex are determined from the depth data. Height, sex, and depth data are then used in a support vector regression model to predict weight.
Pfitzner et al, 2015	Point cloud data used to obtain 3D body surface area and body length.	Body volume is calculated from the depth data. Using an assumed constant value for density (1.04 kg/m^3), a weight estimate is then calculated from volume.
Pfitzner et al, 2016	Point cloud depth data used as a source to extract 10 shape parameters (features).	An artificial neural network is trained to predict weight using 10 extracted features.
Benalcazar et al, 2017	A 3D image is used to create a 2D silhouette, from which 2D surface area is calculated.	Both least mean square and artificial neural network methods are used to generate weight estimates.
Pfitzner et al, 2017	Point cloud depth data used as a source to extract 23 shape parameters (features).	An artificial neural network is trained to predict weight using 23 extracted features.
Pfitzner et al, 2018	Point cloud depth data used as a source to extract 19 shape parameters (features).	An artificial neural network is trained to predict weight using 19 extracted features.
Bigalke et al, 2021	Point cloud data encoded into a k-dimensional surface mesh using basis point sets.	Deep learning used to estimate weight from point cloud mesh data.
Dane et al, 2021	Point cloud encoded into 3D surface mesh. This image is segmented, and lengths and volumes of thorax, abdomen, head, arms, and legs calculated.	Segmental lengths and volumes are used in a Bayesian Ridge regression model to estimate height and weight.
Geissler et al, 2021	Point cloud encoded into a 3D surface mesh.	A virtual patient model, an "avatar" or digital twin is fitted into the depth data from a library of avatars with known volumes and weights. This avatar is adjusted iteratively to match the depth data. Weight is then estimated from the segmental volumes of the avatar.
Mameli et al, 2021	Top view depth data of standing participants converted to point cloud data.	Deep convolutional neural networks are used to obtain a weight estimate directly from the top view depth data.
Naufal et al, 2021	A 3D image is used to create a 2D silhouette, from which 2D surface area and height is calculated.	Simple regression is used to predict weight from silhouette area.
Tamersoy et al, 2023	Unspecified features are extracted from the 3D cloud data based on segmental volumes. Feature extraction performed using an encoder–decoder deep network.	Height and weight estimated in separate models using deep neural networks.
Shahzadi et al, 2024	Unspecified features are extracted from the 3D cloud data based on segmental volumes. Feature extraction performed using an encoder–decoder deep network.	Height and weight estimated in separate models using deep neural networks.

notable: first, the 3D camera systems were always more accurate than guesstimates by healthcare providers (four studies); second, the 3D camera systems were always less accurate than participant self-estimates of weight (three studies). Comparative data were not available from the studies in which the 3D cameras achieved exceptionally high accuracy results.

3.6 | The suitability of 3D camera weight estimation systems for emergency and critical care

There were 4 of 14 (29%) studies conducted in an environment designed to simulate an ED setting, and five of 14 (36%) studies conducted in, or with data from, a radiological suite. However, no study evaluated an estimation method during the provision of actual or simulated emergency care.

4 | LIMITATIONS

There were several limitations to this review. First, papers in the non-medical literature are less well indexed and searchable than in the medical literature. It is therefore possible that some relevant studies were missed. Second, the studies were from a very narrow range of geographical locations, which could limit the generalizability of the findings. Third, the small sample sizes, the variable data reporting and

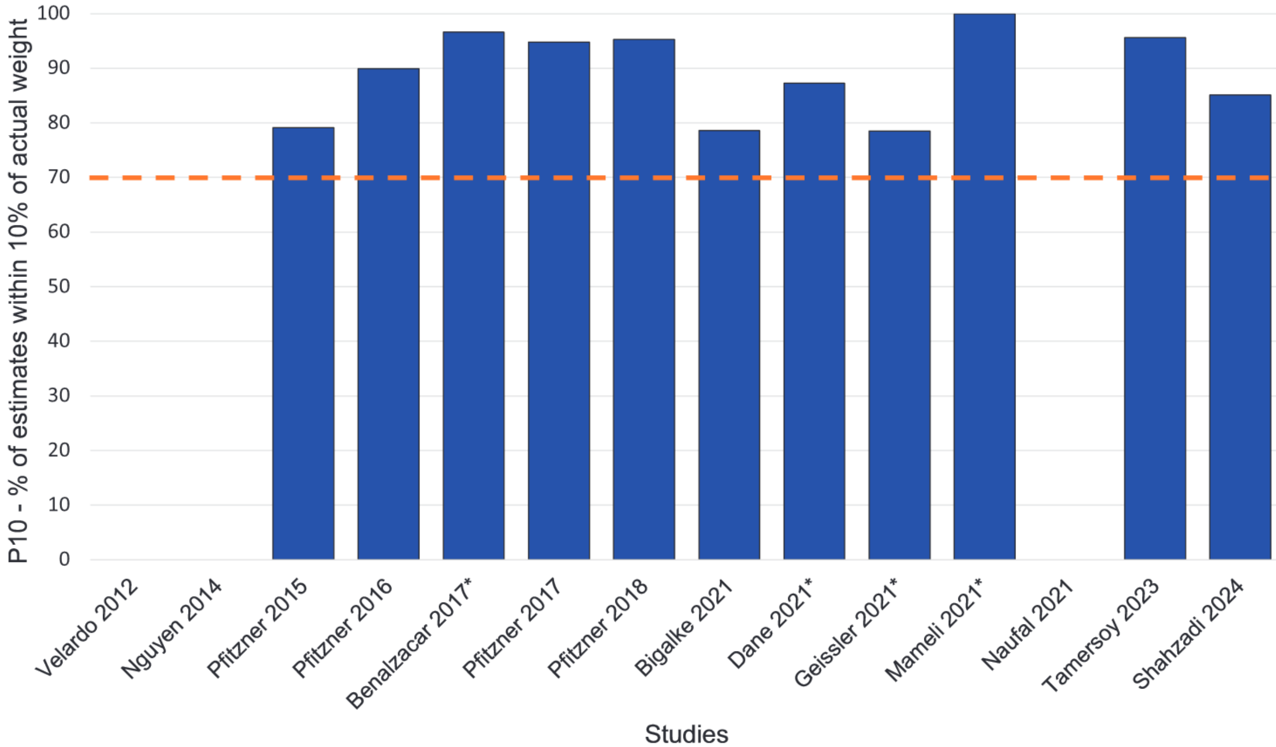

FIGURE 2 The accuracy data (P10—percentage of estimates within 10% of actual weight) for each of the 3D camera weight estimation systems. The studies marked with an asterisk (*) identify studies for which P10 data was imputed. The red dashed line indicates the minimum acceptable performance threshold of P10 = 70%.

statistical analysis, especially of subgroups of BMI, limited any comparisons between different 3D camera weight estimation systems. The need to impute data was also a limitation. Furthermore, few studies included a sufficiently diverse sample of participants with different ages, ethnic groups, height and weight ranges, and weight status (eg, underweight, healthy weight, overweight, and obese). Finally, none of these systems had received true external validation, which remains a significant deficiency that needs to be addressed in future research.

5 | DISCUSSION

The current understanding of 3D camera-based weight estimation in adults, including its potential role during emergency care, has significant gaps. For example, when faced with a critically ill or injured patient in need of urgent weight-based drug therapy, but without any recorded weight, could a 3D camera system be used for estimating their weight? The significance of our review lies in its exploration of the currently available information on this topic. Our aim was to offer information and guidance to clinicians and researchers in this matter of important patient safety. The importance of the topic lies in providing information to guide future clinical emergency medicine research in this new field. This research has a significant potential to make an enormous contribution to advancing patient safety in the ED. It could be argued that high-tech research should be focused on obtaining actual measured weights (eg, weigh capable stretchers), rather than methods of estimating weight. There are two counterarguments here. First, in-stretcher scales are expensive, difficult to operate accurately in emergencies, not universally available, and have unproven accuracy during actual clinical care. Second, in-stretcher scales cannot provide estimates of ideal body weight or lean body weight (which could be predicted by 3D camera systems), which may be required for optimizing drug doses in patients with obesity. In addition, ideal body weight is an essential metric to allow for the calculation of mechanical ventilation settings for low tidal volume ventilation. This would be frequently required and could be of equal importance to drug dose scaling.

We identified and reviewed all the published literature on 3D camera weight estimation methods that could potentially be used during emergency medical care of adult patients. While some methods were primarily intended for nutritional assessment, others were devised and intended to guide acute medical interventions (e.g., to guide dosage of thrombolytic therapy in patients with acute ischemic stroke).

5.1 | Quality of the studies

Although a few studies had inadequate data reporting and statistical analysis, most of the studies were methodologically sound. This provided a good evidence basis from which to draw preliminary conclusions. The lack of true external validation studies was a significant limitation in the field of 3D weight estimation, however.

5.2 | Camera technology

The studies in this review made use of several different types of 3D cameras: structured light systems (eg, Microsoft Kinect 1 and Orbbec Astra) and time-of-flight systems (eg, Microsoft Kinect 2). These camera systems are relatively old and, in some cases, no longer manufactured. Newer cameras have native software to perform many image processing tasks automatically: intrinsic and extrinsic calibration to ensure accurate depth measurements and color-depth alignment, automatically correct lens distortion, generate 3D point clouds from depth data, convert depth images to 3D coordinates automatically, detect and track human skeletons in real time, automatically detect and track objects or faces within the camera's field of view, provide bounding boxes or other positional data for detected objects, apply noise reduction and smoothing filters to depth data, and perform edge detection and other image processing tasks. These newer 3D cameras are, therefore, likely to be better than those already tested. Existing research relating to the cameras themselves has been sparse, and future work needs to evaluate the most appropriate hardware system for use for weight estimation and in potential clinical emergency medicine applications. Table S3 provides a description of the different types of 3D cameras and their characteristics.

5.3 | Analytical approach to weight estimation

The analytical approaches to weight estimation have evolved significantly in successive studies over the last decade. The earliest system described the use of a 3D camera to obtain biometric data, which could be used in an equation derived from an anthropometric dataset.[18] Subsequent studies used depth data to calculate total body volumes (and, later, segmental body volumes), which are converted to weight estimates using density constants.[20,21,23,24] The most recent methodologies have used deep learning to match a digital twin from a library of trained images against the point cloud data of a captured 3D image.[15,31] This is perhaps the most flexible method, with the highest potential for accuracy. The use of deep learning both in image processing and in the weight estimation process has substantially improved the accuracy of weight estimates.

5.4 | Accuracy of weight estimation by 3D camera systems

In this review, each of the 11 weight estimation systems for which P10 data was available exceeded the minimum required accuracy threshold for a weight estimation system (P10 > 70%), as has been described previously.[13,32] In fact, the lowest P10 was just below 80%, and four systems had a P10 > 95%. Overall, these performance data are remarkably good. To put this in context, a recent meta-analysis of weight estimation systems in adults showed that only patient self-estimates of weight approached this degree of accuracy but were inconsistent across studies.[4] In addition, self-estimates of weight were often not able to be provided by the sickest patients. In studies conducted during actual emergency medical situations, the number of patients unable to provide a self-estimate may be as high as 70%–85%.[10] The evidence is thus clear that methods of weight estimation that do not rely on self-estimates must always be available.[4] The data from this scoping review show that 3D camera systems could potentially fulfill this role if their performance holds up in larger scale clinical studies. Another consideration is that patients with severe obesity (Class 2 and 3 obesity) are less able to self-estimate their weight accurately than patients with normal weight.[33–35] Since there is some evidence that 3D camera systems can estimate weight very accurately in this subgroup of patients, it could become preferable to use a 3D camera estimate rather than a self-estimate in such patients.[15] A 3D camera could also provide a measurement of a patient's girth which could determine whether they could be accommodated for advanced imaging with CT/MRI systems.

Other noteworthy factors were that accurate weight estimation was achieved with several different 3D cameras, as well as with different processing and analytical approaches. This strongly supports the validity of the underlying principles, and predictable biological associations between body size, shape, and body weight. In addition, accurate weight estimation was even possible when patients were clothed or covered with light blankets.[36]

5.5 | Appropriateness for use during ED or prehospital emergency care

The appropriateness of 3D camera weight estimation systems for use during emergency care was not explicitly studied, although several of the studies specifically intended their systems to be used for this purpose.[20,21,23,24,37] There are several factors that make fully evolved 3D camera systems ideal for use during emergency medical care. First, they are quick. A weight estimation can be calculated in <1 s, even with the use of deep learning systems in both the image preprocessing and the weight estimation algorithms.[23] Second, they are highly automated. The system can automatically select the optimum image to use for the processing (useful for when patients are moving or uncooperative). No user input is required for the weight estimation: sex and height, which have significant associations with weight, can be estimated using deep learning. Third, the system can compensate for patient posture and patient movement. Irrespective of whether the patient is supine, prone, or lateral, an accurate weight estimate can be obtained. Finally, light clothing or coverings do not interfere with weight estimation, as 3D camera systems can "see beneath the covers" using deep learning digital twin-based analyses. The problems described by Benalcazar et al., with clothing and hairstyles confounding weight estimates, were largely rendered irrelevant by more advanced machine learning approaches to generating weight estimates.[22]

5.6 | Future directions

This is an important and exciting field for future research. The 3D camera systems need to be studied in larger samples, including representative numbers of underweight and obese patients, as well as pregnant patients, and patients from diverse population groups, to ensure generalizability. These methodologies also need to be evaluated in clinical environments, including during emergency care. Future research will also need to examine the suitability of these systems for detecting serial changes in weight while in hospital (e.g., with fluid retention or loss). This has never been evaluated for any type of weight estimation system. Likewise, the research needs to include children. Future innovations could also include the estimation of ideal body weight and lean body weight to allow for precision weight-based dosing (and tidal volume calculations) for all patients. At present, establishing these weights is complex and requires additional measurements and calculations. They are thus not routinely employed by emergency physicians.

6 | CONCLUSIONS

The weight estimation accuracy of 3D camera-based systems represents a significant advancement in the field of automated measurement and analysis. These systems utilize precise depth sensing and 3D modeling to capture the volume and dimensions of objects or individuals with high accuracy. By integrating advanced algorithms and machine learning techniques, 3D camera-based systems can convert depth data into reliable weight estimates. When properly optimized, 3D camera-based weight estimation can achieve accuracy comparable to traditional weighing methods, providing a non-contact, efficient, and versatile potential solution for use during emergency care. However, it was clear from this review that additional, high-quality prospective research is urgently needed in this field, as a matter of prioritizing patient safety during emergency care.

AUTHOR CONTRIBUTIONS

Conceptualization: Mike Wells, Lara Nicole Goldstein, Borifoje Furht, and Richard Shih. *Data collection*: Mike Wells, Terran Wells, and Niloufar Ghazi. *Data analysis*: Mike Wells and Lara Nicole Goldstein. *Critical review and evaluation of results*: Mike Wells, Lara Nicole Goldstein, Borifoje Furht, Abhijit Pandya, Gabriella Engstrom, Muhammad Tanveer Jan, and Richard Shih. *Primary authorship of the paper*: Mike Wells. *Review and editing of the paper*: Mike Wells, Lara Nicole Goldstein, Terran Wells, Niloufar Ghazi, Borifoje Furht, Abhijit Pandya, Gabriella Engstrom, Muhammad Tanveer Jan, and Richard Shih.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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