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Systematic Review

In-Bed Monitoring: A Systematic Review of the Evaluation of In-Bed Movements Through Bed Sensors

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Abstract: The growing popularity of smart beds and devices for remote healthcare monitoring is based on advances in artificial intelligence (AI) applications. This systematic review aims to evaluate and synthesize the growing literature on the use of machine learning (ML) techniques to characterize patient in-bed movements and bedsore development. This review is conducted according to the principles of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) and is registered in the International Prospective Register of Systematic Reviews (PROSPERO CRD42022314329). The search was performed through nine scientific databases. The review included 78 articles, including 142 ML models. The applied ML models revealed significant heterogeneity in the various methodologies used to identify and classify patient behaviors and postures. The assortment of ML models encompassed artificial neural networks, deep learning architectures, and multimodal sensor integration approaches. This review shows that the models for analyzing and interpreting in-bed movements perform well in experimental settings. Large-scale real-life studies are lacking in diverse patient populations.

Keywords: artificial intelligence; machine learning; prediction; in-bed; monitoring; systematic review

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1. Introduction

Recently, there has been an increase in attention to patient-centric approaches in the healthcare environment, primarily through remote health monitoring [1]. Remote health monitoring allows healthcare personnel to monitor patient health conditions and physiological signs in real time [2]. In addition, electric medical beds have been developed in recent years due to technological progress [3]. These beds are characterized by various features, including alarms, exit sensors in the bed, and integrated accessory controls [3]. They are the so-called "smart beds", where this label describes the interconnection between materials, design and functionality, and user interfaces [3]. Smart beds provide continuous data that can be integrated into the health system to identify risk patterns [4]. Smart beds have been used to prevent episodes such as agitation [5], falls among elderly patients [6], pressure ulcers [7], and sleep disorders [8,9]. Smart beds and their interface offer an opportunity to assess three key objectives, as Karvounis et al. [4] reported: patient monitoring, prevention of falls, and prevention of pressure ulcers.

The growing popularity of smart beds and devices for remote healthcare monitoring is based on the advancement of artificial intelligence (AI) applications [10]. Just lying in a smart bed could provide a significant amount of information. Smart beds are widely used in specific hospital settings, including intensive care units. They have recently found applications in long-term care units and nursing homes to prevent bedsore-related complications [11]. Furthermore, sensors placed in a hospital bed could inform about the position of the patient in the bed [12]. Knowing and consequently anticipating the position of a patient in the bed has been proven helpful in detecting falls in at-risk populations, particularly older people [12]. The large amount of data from these modern devices is dependent on AI support, as traditional database technology cannot store and analyze them [10]. Machine learning techniques are known to be especially suitable for performing data processing tasks, given training examples [13]. Various reviews in the literature on machine learning techniques (ML) and the prevention of pressure injury have shown that ML techniques are widely implemented with promising results [14–16].

This systematic review aims to evaluate and synthesize the growing literature on the use of ML techniques to characterize patient movements in bed.

2. Materials and Methods

This review is reported according to the statement of PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) [17]. It is registered in the International Prospective Register of Systematic Reviews (PROSPERO registration no. CRD42022314329).

2.1. Information Sources and Search Strategy

The search was carried out through the following databases: MEDLINE through PubMed, EMBASE (through Ovid), CINAHL, Scopus, Cochrane, IEEX, arXiv, ACM digital library, and Web of Science. The string search was updated on the seventh of September 2024. The words related to the concept of positions in bed and the other outcomes, bedsore development, and sleep quality, related to the terms related to machine learning techniques and the term "bed". The three groups of concepts were linked with the Boolean operator "AND". Table S1 shows the applied search strategy.

2.2. Eligibility Criteria

The eligibility criteria were based on the PICO (Population, Intervention, Comparison, Outcome) acronym: Participants, Healthy/non-healthy, volunteer/patients; Intervention/exposure; use of smart beds, sensors in the bed; Comparator, wearable devices; Outcome, movement patterns.

Articles with the following characteristics were included in this systematic review: (1) studies in which bed sensors measured parameters such as movements, heart rate, sleep patterns, and pressure ulcers; (2) studies that used any ML technique; (3) studies that used wearable devices based on accelerometry to evaluate movements. Articles (1) in languages other than English, publications (2) with populations other than adults (e.g., animals, children), or (3) letters, commentaries, or reviews without relevant data were excluded.

2.3. Selection Process

The selection of the title/abstract and the full text was performed by two independent reviewers (CB and AC). Any conflicts were resolved through discussion or the judgment of an experienced third-party researcher (HO and CL). The title/abstract and full text were reviewed using the Rayyan free Web tool [18]. Duplicates were manually removed using Rayyan.

2.4. Data Extraction

Data were extracted from all selected publications using a predefined format created in a Microsoft Excel worksheet. The two investigators (CB and AC) independently performed data extraction; they compared the results and resolved any conflict through discussion or involvement of a third investigator (CL or HO).

The following study information was collected: characteristics of the study, authors, year, journal of publication, study design (observational, longitudinal, and simulated designs), setting (home, controlled environment, hospital, and nursing home), experiment duration, and outcome type (in-bed pose estimation, multiple output data, and other specific health indicators); characteristics of the population (volunteers, healthy volunteers, patients), number of participants, number of male and female participants, and age (mean, range); characteristics of the bed, sensor type (bed sensors, wearable devices, arrays of pressure sensors), number of load cells, bed sensor placement (embedded, outside the bed structure), list of in-bed positions (supine, prone, left lateral, right lateral, and other), input data (acceleration data, pressure data, pressure images/maps, and vital sign data), and input data pre-processing; characteristics of the ML techniques applied, ML category (deep learning, shallow learning, and combinations of both), models used (clustering, supervised learning algorithms, and other specific machine learning techniques), and performance metrics (accuracy, F1 score, sensitivity, specificity, and precision).

2.5. Assessment of Risk of Bias

In assessing the quality of the included studies, we utilized the Prediction Model Risk of Bias Assessment Tool (PROBAST) [19]. The tool is structured into four key domains: participants, predictors, outcome, and analysis. Each domain contains multiple signaling questions to guide the assessment. Reviewers use these questions to classify each study as having a ”low”, “high”, or “unclear” risk of bias. Despite some limitations in its applicability to our study design, using PROBAST provided a consistent framework for evaluating study quality across the included studies.

3. Results

This review followed the PRISMA process [20] to select the included articles, as presented in the flow diagram in Figure 1. The search in the various databases retrieved 6009 publications. After checking for duplicates, 4145 items were screened based on title and abstract. This screening led to 3060 studies being removed due to their ineligibility (for example, another outcome), and 78 articles were selected for this review.

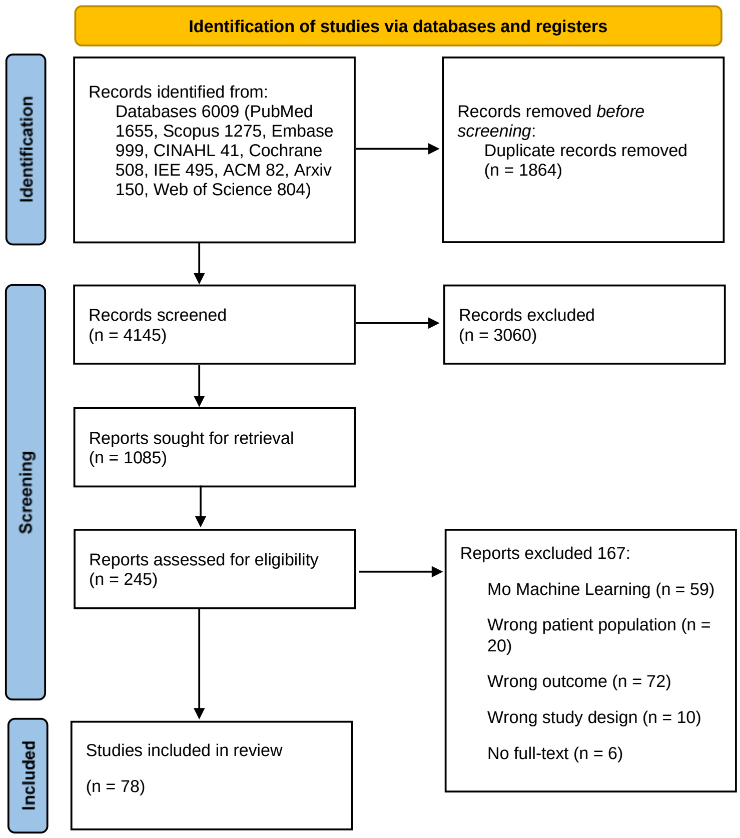

Figure 1. PRISMA flow chart.

3.1. Descriptive Characteristics of the Study

Table 1 reports the descriptive characteristics of the articles included in this review. The 78 articles included in our study were published in journals (41, 52%) or conference collections (37, 48%) after 2018 (53, 68%)—or before it (25, 32%)—and comprised a total of 5647 participants. In many of the studies (65, 75.6%), the data were collected in a controlled environment (such as a laboratory under supervision). For the remaining research, instead, data sets were generated from a variety of settings, including hospitals (8, 9.3%), nursing homes (5, 5.8%), and homes (7, 8.1%).

Table 1. Descriptive characteristics of the included studies.

Author, Year	Study Design	Population Category	Number of Participants	Number of Males	Number of Females	Age Mean	Setting	Sensor Type
Research article								
Albukhari, 2019 [21]	Experimental	Volunteers	7	6	1		Controlled environment	Bed sensors
Alinia, 2020 [22]	Olguın & Pentland, 2006 [23]; Altun, 2010 [24]	Healthy volunteers	30	7; 4	7; 4		Controlled environment	Wearable
Arora, 2020 [25]	Observational; Arriba-Pérez, 2016 [26]	Volunteers	2250				Home	Wearable
Azimi, 2020 [27]	Longitudinal	Elders	9				Nursing home	Bed sensors
Bai, 2023 [28]	Experimental	Dementia nursing home residents	24				Hospital	Bed sensors
Breuss, 2024 [29]	Experimental	Healthy volunteers	21	12	9	28.3 (male) 29.5 (female)	Controlled environment	Bed sensors
Bruser, 2013 [30]	Experimental	Healthy volunteers	10	9	1	63.1	Hospital	Bed sensors
Casas, 2019 [31]	Experimental	healthy volunteers	6	4	2		Controlled environment	Bed sensors
Chica, 2012 [32]	Observational	Patients	20	10	10		Controlled environment	Bed sensors
Cho, 2019 [33]	Experimental	Healthy volunteers	10	7	3		Home	Wearable
Costello, 2021 [34]	Pouyan, 2017 [35]	Healthy volunteers	13				Controlled environment	Bed sensors
Davoodnia, 2022 [36]	Ostadabbas, 2014 [37]; Pouyan, 2017 [35]; Clever, 2018 [38]	Healthy volunteers	30				Controlled environment	Bed sensors
Diao, 2021 [39]	Experimental	Volunteers	16	9	7		Controlled environment	Bed sensors
Duvall, 2019 [40]	Experimental	Healthy volunteers	10				Controlled environment	Bed sensors
Fonseca, 2023 [41]	Experimental	Healthy volunteers	60				Controlled environment (sensor sheets over and under a mattress)	Bed sensors
Gabison, 2022 [42]	Experimental	Healthy volunteers	9	4	5		Home	Bed sensors

Table 1. *Cont.*

Author, Year	Study Design	Population Category	Number of Participants	Number of Males	Number of Females	Age Mean	Setting	Sensor Type
Garcia-Molina, 2024 [43]	Experimental	Healthy volunteers	18	9	9	44.5	Controlled environment; home	Both
Gargees, 2019 [44]	Experimental	Healthy volunteers	56	42	14	29.27	Controlled environment	Bed sensors
Hagihara, 2021 [45]	Experimental	Healthy volunteers	14	2; 5	3; 4		Controlled environment	Bed sensors
Hsiao, 2015 [46]	Experimental	Volunteers	9				Controlled environment	Bed sensors
Hu, 2021 [47]	Experimental	Healthy volunteers	5	3	2	29.2	Controlled environment	Bed sensors
Hu, 2024 [48]	Experimental	Healthy volunteers	22	15	7		Home	Bed sensors
Jung, 2022 [49]	Experimental	Healthy volunteers	15	9	6	25.8	Hospital	Bed sensors
Kawakami, 2017 [50]	Experimental	Patients	3	2	1	76.7	Nursing home	Bed sensors
Kusmakar, 2021 [51]	Observational	Patients; healthy volunteers	80	38	42	47.6	Home	Wearable
Kuwahara & Wada, 2017 [52]	Observational	Healthy volunteers	7				Controlled environment	Bed sensors
Liu, 2021 [53]	Observational	Healthy volunteers	4	2	2	29.75	Controlled environment	Bed sensors
Manners, 2024 [54]	RCT	Healthy volunteers	24	12	12	27.6	Controlled environment	Bed sensors
Matar, 2020 [55]	Observational	Healthy volunteers	12	10	2	27.35	Controlled environment	Bed sensors
Monroy, 2020 [56]	Observational	Healthy volunteers	7	4	3	24.75	Controlled environment	Wearable
Mosquera-Lopez, 2019 [57]	Observational	Patients	14	11	3	48	Controlled environment; home	Bed sensors
Pornpreedawan, 2022 [58]	Experimental	Healthy volunteers	10	5	5	22.5	Controlled environment	Bed sensors
Pupic, 2022 [59]	Observational; simulated	Healthy volunteers	18	10	8	29.8	Controlled environment	Bed sensors
Raschella, 2022 [54]	Observational	Patients	26	19	7	68	Controlled environment; home	Wearable
Rosales, 2017 [60]	Experimental	Elders	4	4	0	91.25	Nursing home	Bed sensors
Stern, 2024 [61]	Experimental	Healthy volunteers	10				Hospital bed, home bed, home bed with foam mattress topper	Bed sensors
Tandon, 2024 [62]	Experimental	Healthy volunteers					Controlled environment	Bed sensors
Tapwal, 2023 [63]	Experimental	COVID-19 patients					Controlled environment; home	Bed sensors
Walsh, 2017 [64]	Experimental	Healthy volunteers	15	12	11		Controlled environment	Bed sensors

Table 1. *Cont.*

Author, Year	Study Design	Population Category	Number of Participants	Number of Males	Number of Females	Age Mean	Setting	Sensor Type
Waltisberg, 2017 [9]	Observational	Patients	9	6	3	53.6	Controlled environment	Bed sensors
Willemen, 2012 [65]	Simulated	Healthy volunteers	10			22.95	Controlled environment	Both
Conference paper								
Austin, 2012 [66]	Observational	Patients	27	18	9	51	Controlled environment	Wearable
Bajkowski, 2023 [67]	Experimental	Elders	19				Nursing home	Bed sensors
Belay, 2022 [68]	Experimental	Elders	7				Controlled environment	Bed sensors
Breuss, 2023 [69]	Methodological	Healthy volunteers	1				Controlled environment	Bed sensors
Channa, 2020 [70]	Pouyan, 2017 [35]	Healthy volunteers	13			26.9	Controlled environment	Bed sensors
Davoodnia, 2019 [71]	Pouyan, 2017 [35]; Goldberger, 2000 [72]	Healthy volunteers	13				Controlled environment	Bed sensors
Duan, 2021 [73]	Experimental	Volunteers	8				Controlled environment	Bed sensors
Enayati, 2018 [74]	Experimental	Healthy volunteers	58				Controlled environment	Bed sensors
Heydarzadeh, 2016 [75]	Experimental	Volunteers	10				Controlled environment	Bed sensors
Husák, 2021 [76]	Methodological	Healthy volunteers					Controlled environment	Bed sensors
Ibrahim, 2024 [77]	Methodological	Healthy volunteers	15				Controlled laboratory environment	Wearable
Lei, 2024 [78]	Methodological	Healthy volunteers					Controlled environment	Bed sensors
Luo, 2018 [79]	Experimental	Volunteers	10				Controlled environment	Bed sensors
Madokoro, 2014 [80]	Experimental	Volunteers	10				Controlled environment	Bed sensors
Matthies, 2021 [81]	Experimental	Volunteers	11	8	3	31.45	Controlled environment	Bed sensors
Mendez, 2010 [82]	Experimental	Healthy volunteers	11	0	11		Controlled environment	Bed sensors
Metsis, 2011 [83]	Experimental	Volunteers	3				Controlled environment	Bed sensors
Migliorini, 2010 [84]	Experimental	Healthy volunteers	11	0	11		Controlled environment	Bed sensors
Moon, 2023 [85]	Experimental	Bedridden patients	5				Hospital	Bed sensors
Mukai, 2014 [86]	Experimental	Healthy volunteers	11	7	4		Controlled environment	Bed sensors
Oboe Kubota, 2014 [87]	Methodological	Volunteers					Controlled environment	Bed sensors
Perez-Macias, 2017 [88]	Experimental	Volunteers	30	24	6		Controlled environment	Bed sensors
Pouyan, 2014 [89]	Experimental	Volunteers	15				Controlled environment	Bed sensors

Table 1. *Cont.*

Author, Year	Study Design	Population Category	Number of Participants	Number of Males	Number of Females	Age Mean	Setting	Sensor Type
Pouyan, 2015 [90]	Experimental	Volunteers	8				Controlled environment	Wearable
Pouyan, 2017 [35]	Experimental	Healthy volunteers	13			26.9	Controlled environment	Bed sensors
Rangarajan, 2022 [91]	Experimental	Healthy volunteers	5				Tertiary care, university-affiliated hospital	Wearable
Russo, 2021 [92]	Pouyan, 2017 [35]	Healthy volunteers	13				Controlled environment	Bed sensors
Sano & Picard, 2014 [93]	Experimental	Volunteers	15				Controlled environment	Wearable
Sawada, 2022 [94]	Experimental	Healthy volunteers	11				Controlled environment	Bed sensors
Soleimani & Pesch, 2023 [95]	Experimental	Patients at risk of pressure ulcers	13				Controlled environment	Bed sensors
Vázquez-Santacruz & Gamboa-Zúñiga, 2016 [96]	Methodological	Volunteers	1				Controlled environment	Bed sensors
Vyas, 2021 [97]	Observational	Patients	5	2	3	66.2	Hospital	Bed sensors
Wai, 2009 [98]	Methodological	Volunteers					Controlled environment	Bed sensors
Wu, 2023 [99]	Experimental	Healthy volunteers	10	7	3		Controlled environment	Bed sensors
Yoon, 2024 [100]	Experimental	Healthy volunteers	5	3	2		Hospital	Bed sensors
Youngkong, 2021 [101]	Experimental	Volunteers	6	3	3		Controlled environment	Bed sensors
Yousefi, 2011 [102]	Methodological	Volunteers					Controlled environment	Bed sensors

Regarding the participants enrolled in the included studies, in 48 (60.8%) articles, healthy adult volunteers were recruited; similarly, 15 (19%) articles involved volunteers. Furthermore, only five articles involved older people (6.3%), while eleven studies (14%) focused on patients. In the latter case, the diseases considered were Parkinson's [32], sleep disorders [45], obstructive syndrome apnea [29], deteriorated cognitive function [73], atrial fibrillation [43], and heart disease [72]. The age of the participants ranged between 19 [41,51,53,54,57,58] and 99 years [72]. Eleven studies [22,34–42] considered publicly available datasets or simulated data.

3.2. Characteristics of the Collected Data

Experiments in this review lasted less than 0.5 h in 14 studies [21–24,28,35,36,38,40,44,50,52,55,60] or up to months when investigating sleeping patterns [71,72]. The input data were classified into kinetic data, pressure data, pressure image or map, and vital sign data (Tables 2 and S2). As expected, before analysis, these input data underwent a preprocessing phase (70, 90%), which, in most models, involved signal manipulation (46, 58%), feature extraction (24, 31%), and analysis of the principal component (15, 19%) (Table S3).

Table 2. Summary of the characteristics of the machine learning technique (MLT) used in the included articles.

Characteristic		**Overall**	**Other**	**Position Estimation**	**Sleep and Vigilance**	**Vital Signs**
		N = 78	N = 31	N = 481	N = 191	N = 81
Type of input data	Acceleration data	6 (7.7%)	1 (33%)	2 (4.2%)	3 (16%)	0 (0%)
	Multiple input data	12 (15%)	0 (0%)	7 (15%)	5 (26%)	0 (0%)
	Other	5 (6.4%)	0 (0%)	1 (2.1%)	4 (21%)	0 (0%)
	Pressure data	29 (37%)	2 (67%)	21 (44%)	2 (11%)	4 (50%)
	Pressure image/map	1 (1.3%)	0 (0%)	1 (2.1%)	0 (0%)	0 (0%)
	Vital sign data	17 (22%)	0 (0%)	16 (33%)	1 (5.3%)	0 (0%)
Input data pre-processing	No	8 (10%)	0 (0%)	0 (0%)	4 (21%)	4 (50%)
MLT category	Deep learning	29 (37%)	2 (67%)	22 (46%)	3 (16%)	2 (25%)
	Shallow learning	39 (49%)	1 (33%)	21 (44%)	12 (64%)	5 (63%)
	Both	10 (13%)	0 (0%)	5 (10%)	4 (21%)	1 (13%)
MLT type	Boosting methods	5 (6.4%)	0 (0%)	3 (6.3%)	0 (0%)	2 (25%)
	Discriminant analysis	1 (1.3%)	0 (0%)	0 (0%)	1 (5.3%)	0 (0%)
	KNN-based	6 (7.7%)	0 (0%)	5 (10%)	1 (5.3%)	0 (0%)
	Linear models	1 (1.3%)	0 (0%)	1 (2.1%)	0 (0%)	0 (0%)
	Naive Bayes	1 (1.3%)	0 (0%)	0 (0%)	1 (5.3%)	0 (0%)
	Other	32 (41%)	2 (67%)	24 (50%)	3 (16%)	3 (38%)
	Random Forest	9 (12%)	0 (0%)	6 (13%)	2 (11%)	1 (13%)
	SVM-based	22 (28%)	1 (33%)	9 (19%)	10 (53%)	2 (25%)
	Unsupervised Learning	1 (1.3%)	0 (0%)	0 (0%)	1 (5.3%)	0 (0%)
Accuracy more than 95%	Yes	36 (47%)	2 (67%)	29 (62%)	2 (11%)	3 (38%)

Abbreviations: MLT = machine learning technique.

3.3. Smart Bed Characteristics

The participant data were acquired from wearable devices (11, 13.4%) and bed sensors (67, 81.7%), and four of them from both (4.8%). The study utilized various sensor technologies to monitor pressure distribution and related parameters. The majority of the devices used were load cells, accounting for 32.1% of the cases, followed closely by arrays of pressure sensors, representing 27.2% (Figure 2). The load cells are specialized transducers that convert mechanical force or weight into an electrical signal. In the context of bed monitoring, load cells are often integrated into the bed frame or mattress to measure changes in weight distribution and provide quantitative data on patient movements, postural changes, and restlessness during sleep.

These pressure sensors consist of an array of pressure-sensitive elements distributed across the bed's surface. They function by detecting changes in pressure distribution when a patient lies on the bed, providing valuable information about the patient's movements and positioning during sleep or rest. A small percentage of studies used multiple sensors (6.2%) and EMFi sensors (3.7%), highlighting some diversity in sensor choice. Additionally, a few studies employed specific devices like hydraulic bed sensors (3.7%) and piezoelectric sensors (2.5%) (Table 1).

The number of sensors that made up the arrays was between 15 [25] and 3560 [27], with 2048 being the most common size [50,51,53,54,57,58,62,75]. Hydraulic sensors use fluid-filled chambers or tubes to measure pressure variations, providing information on patient movements and body positioning. Pad sensors typically consist of pressure-sensitive pads or mats placed on the bed surface to detect pressure distribution and movement patterns. Oscillosensors use oscillatory motion or vibration detection mechanisms to monitor patient movements and sleep disturbances.

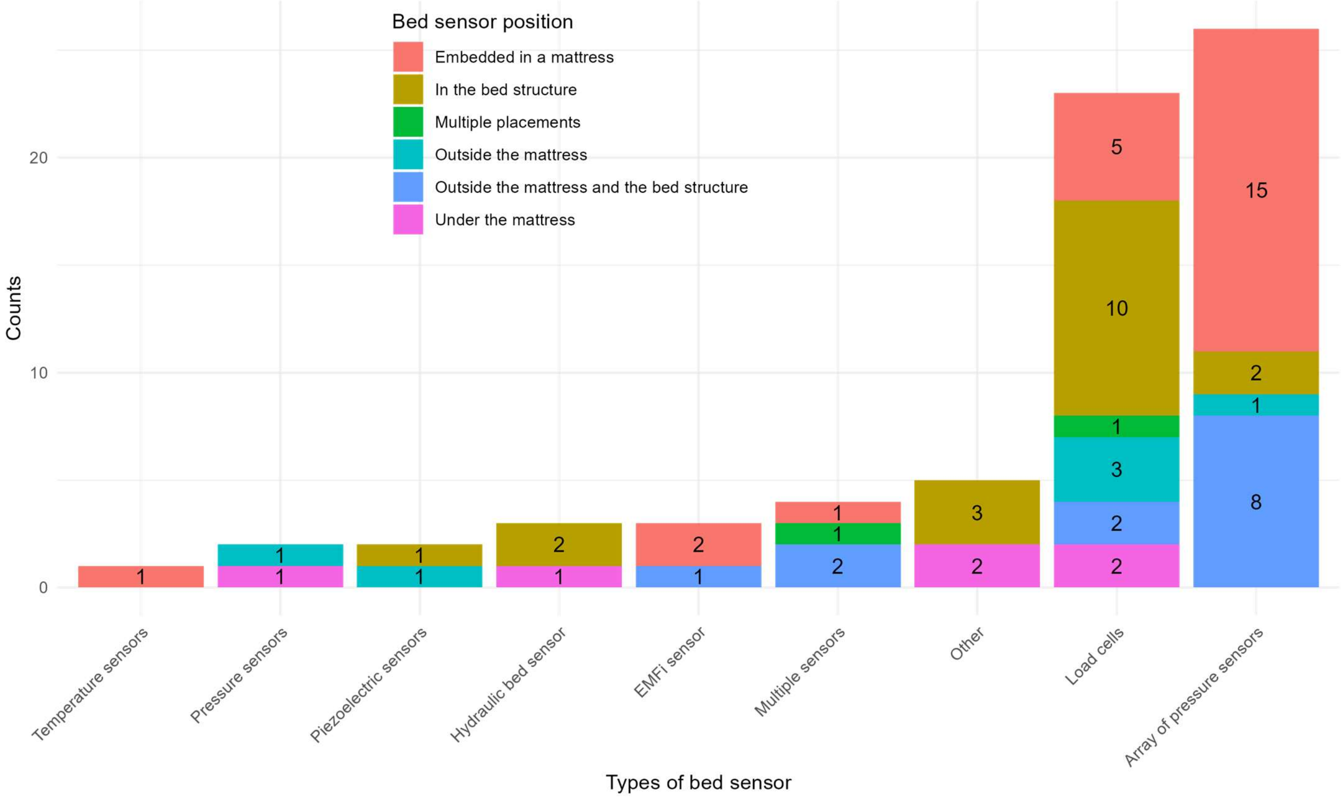

Figure 2. Type of bed sensors (columns) and their positions (colors). In the y-axis are reported the number of studies, while the x-axis categorizes the types of sensors.

Most sensors were embedded into a mattress (25, 30.9%), followed by those integrated into the bed structure (18, 22.2%). Some were placed outside the mattress and bed structure (13, 16.0%), while others were positioned outside the mattress (6, 7.4%) or under the mattress (6, 7.4%). A few studies involved multiple placements (2, 2.5%). Notably, eight entries (9.9%) had missing information on sensor placement (Figure 2).

3.4. In-Bed Movements

In 53 articles (68%), participants were instructed to perform a set of movements or acquire specific positions while lying in bed. The most popular postures detected were supine (47, 60%), prone (21, 27%), and lateral (47, 60%) (Table S4). Regarding the positions, we categorize the primary static ones (prone, supine, and lateral). When using the term "movements", we refer to all distinct types of movement considered by the authors in the articles, whether static or dynamic. The in-bed movements, as considered by authors, ranged from three [25,31] to twenty-eight [41]. Postures such as supine (lying on the back), lateral (lying on the side), prone (lying face down), and various transitional movements between these positions contribute to the diversity of in-bed movements captured by the sensors. The differences in in-bed movements between different postures can be attributed to several factors, including changes in weight distribution, pressure points, and muscle activation patterns associated with each posture. For example, in the supine position, movements can primarily involve changes in body position and adjustments for comfort, whereas, in the lateral or prone positions, movements can include rolling, turning, or repositioning to alleviate pressure or discomfort.

3.5. Machine Learning Techniques Applied

Among the 78 articles, we considered a model for each outcome and MLT for 142 models (Table S4). Deep learning models were used primarily featuring CNNs for in-bed position estimation. Shallow models appeared in seven cases (32%), mainly using SVM, KNN, and decision trees, often paired with feature extraction and clustering methods. For sleep outcome, deep learning models (e.g., CNNs) were used in five cases (56%) with preprocessing steps such as SMOTE and signal manipulation. Vital sign monitoring featured in five cases (13%), where shallow models dominated with four instances (80%), including Random Forests, Naive Bayes, and clustering techniques like KMCA and FCM. Table S3 describes the characteristics of the models included and their reported performance.

Accuracy was used as an evaluation indicator to assess the performance of the ML model; we considered the accuracy of the number of correctly identified positions. Pressure images and pressure data are the most frequently used types of input data for in-bed monitoring applications, particularly in pose estimation and bedsore prevention (Figure 3). Pressure data and pressure image/map data are associated with higher accuracy rates in detecting and predicting various outcomes. The varying sizes and colors of the bubbles further illustrate the different levels of accuracy achieved across various applications, with warmer colors indicating higher accuracy.

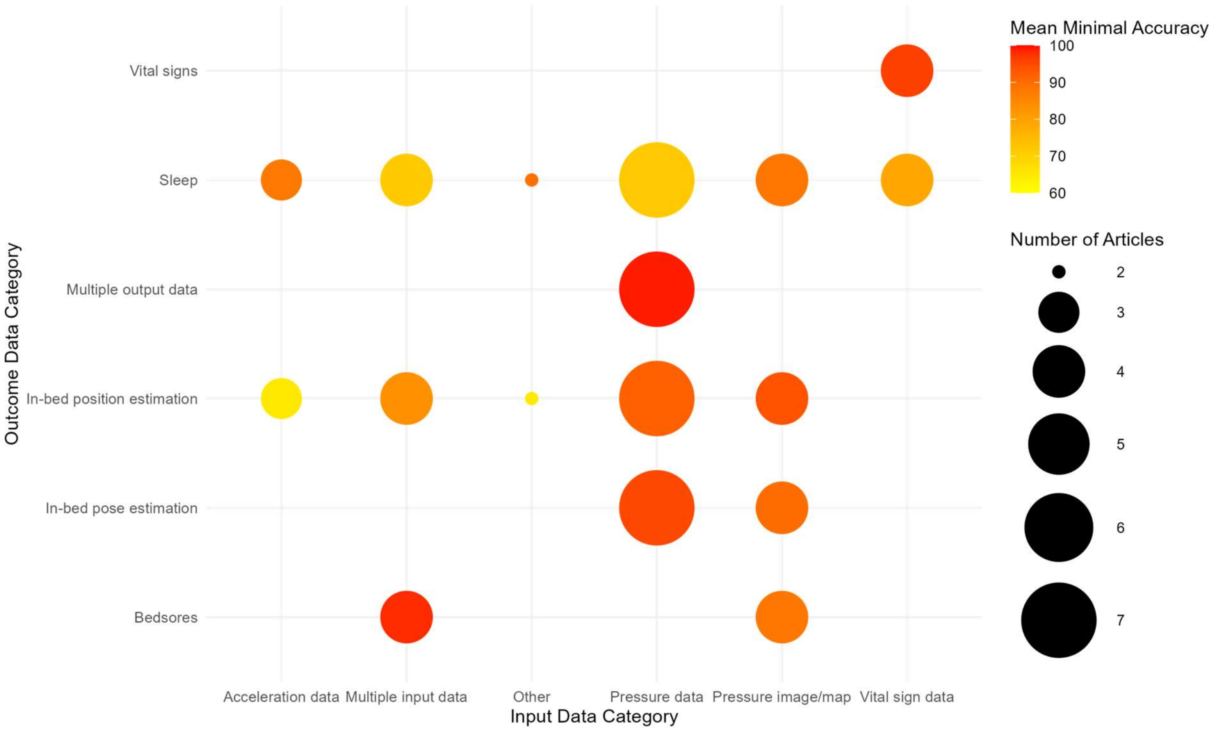

Figure 3. Bubble chart of the mean minimal accuracy (color) of the best model divided by outcome (vital signs, sleep, multiple output data, in-bed pose estimation, bedsores) and type of input data (acceleration data, multiple input data, other, pressure data, pressure image/map, vital sign data).

The best-performing models in each article exhibited an accuracy range from 31% (as seen in the AdaLSTM in Alinia et al. [22]) to 100% (Feed Forward Neural Network in Davoodnia et al. [36] and RF in Youngkong et al. [101]). Globally, 36 models (34%) reached an accuracy of more than 95%.

Figure 4 shows if the models have used pre-processing techniques or not. The bar chart highlights that the majority of studies, regardless of the machine learning approach used, apply preprocessing techniques. Specifically, thirty-six of the shallow learning studies (51.4%), twenty-five deep learning studies (35.7%), and nine of the combined shallow and deep learning studies (12.8%) utilized preprocessing. This underscores the importance of preprocessing in improving the performance of in-bed patient monitoring systems.

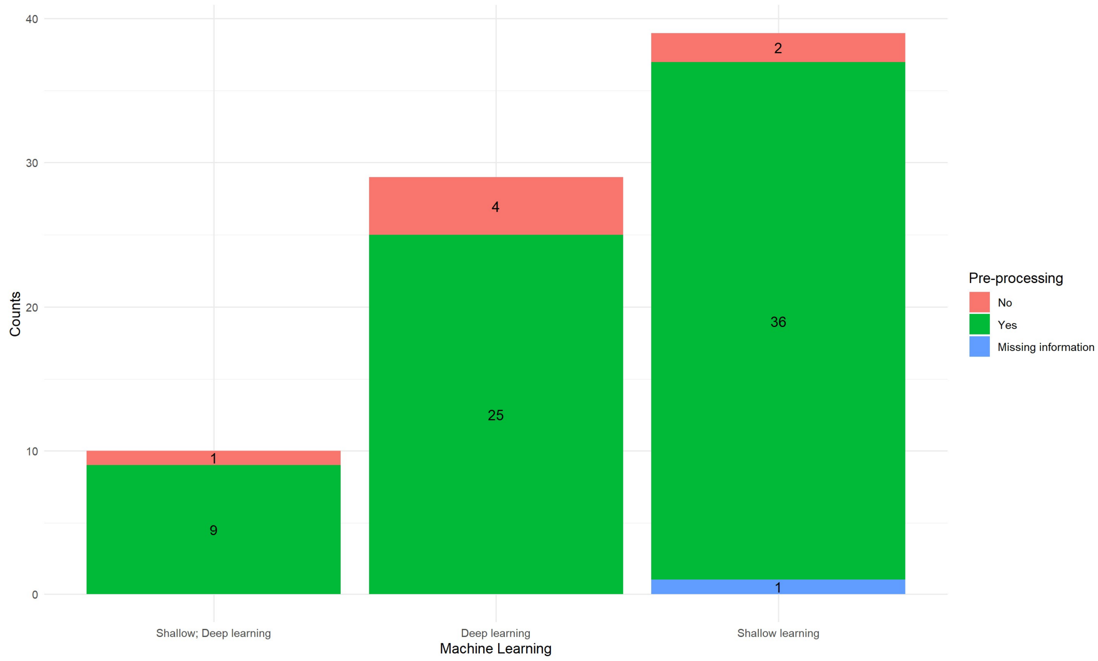

Figure 4. Preprocessing techniques in in-bed patient monitoring studies with machine learning approach.

In Table S3, the information on pre-processing is reported. The most commonly used preprocessing methods were feature extraction methods, accounting for 20 occurrences (28.57%). This was followed closely by signal manipulation methods with 23 occurrences (32.86%). Principal Component Analysis (PCA) was used in 12 instances (17.14%). Additionally, image processing techniques appeared three times (4.29%), while data cleaning and augmentation were employed in three cases (4.29%). Other methods comprised six instances (8.57%).

3.6. Risk of Bias Assessment

Overall, about 40% of the studies are rated as "Unclear", indicating uncertainty in their overall quality, while around 35% are rated as "High", suggesting notable concerns. Only about 25% have a "Low" rating, reflecting a lower risk of bias in their overall assessment. This distribution suggests that many studies may have methodological limitations affecting their overall reliability.

4. Discussion

This review focuses on the use of sensor devices and bed sensors to primarily classify movements in the bed, the onset of bedsores, or sleep quality. In detail, we focus on the types of ML models implemented so far in the field.

ML models were classified into deep learning models and shallow models. As suggested by Chollet et Allaire, shallow learning models use one or two hidden layers [13] or are non-neural-network ML models (e.g., SVM or RF). In contrast, deep learning considers numerous hidden layers [78]. In this present review, we show that deep learning and shallow learning were used to detect outcomes in the bed, which is the main outcome considered in this work. Among shallow learning models, the best models achieve the best accuracy, ranging from 71.95% to 99.93% for different outcomes. DL models also demonstrate competitive performance, with the best accuracy ranging from 31.05% to 100%. Similarly to other studies [103], we observed higher accuracy rates in controlled simulated settings (up to 95.43%) compared to real-world clinical environments (around 86.80%). This discrepancy emphasizes the challenge of achieving high detection accuracy in practical applications, a point that is not always fully addressed in the existing literature.

Among deep learning models, a common approach used in these studies is the application of artificial neural networks (ANNs). For example, Chica et al. [21] propose a real-time recognition system that uses ANNs to classify patient intentions based on sequences of pressure maps. Similarly, Hu et al. [26] present an ANN-based model to classify posture in the bed using pressure sensors on the bed sheets. ANNs allow these models to learn and recognize patterns in the pressure data, enabling accurate classification of different postures or behaviors.

Another approach mentioned in the references is the use of deep learning models. Deep residual networks [22] and deep learning [23] are used for sleep posture recognition and sleep stage classification, respectively. Deep learning models, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have successfully processed sequential data, making them suitable for analyzing time-series data collected from sensors.

In addition, some studies combine different sensor modalities and machine learning techniques to enhance the accuracy of posture recognition and behavior detection. For example, in the study by Pupic et al. [31], they considered the bed reaction and the skin–bed interface forces to detect the position of the patient and monitor the skin pressure to prevent pressure injury.

Both deep and shallow learning models offer distinct advantages: deep models excel in complex pattern recognition with large datasets, while shallow models are more feasible for real-time, resource-limited clinical settings. Combining both approaches can optimize patient monitoring and outcomes.

The studies considered in this review use different types of sensors, such as pressure sensors, bed sensors, load cells, and wearable devices. Several studies used pressure-sensitive sensors attached to the bed or patients' clothing to detect sleep posture, bed-exit intention, and in-bed postural changes. Chica et al. [21] developed an artificial neural network (ANN) that can recognize patient intentions from sequences of pressure maps in real time. Kuwahara and Wada [27] developed a deep learning algorithm that predicts bed leave using a pressure-sensitive sheet-type sensor base. Similarly, Gargees et al. [44] used a hydraulic bed sensor to classify the stages of sleep using deep learning. Hsiao et al. [25] developed a body posture recognition and turning recording system for bedbound patients. Matar et al. [28] used an ANN to classify posture in the bed using bedsheet pressure sensors. Hu et al. [26] developed a patient-specific real-time sleep posture recognition system using a pressure-sensitive conductive sheet and transfer learning. Furthermore, Metsis et al. [38] and Walsh et al. [33] used bed pressure mats to recognize sleep patterns using machine learning. Finally, some studies used sensors to monitor pressure changes to prevent pressure ulcers and sleep apnea. Monroy et al. [30] used inertial sensors attached to clothing to monitor postural changes in the bed to avoid pressure ulcers. Pupic et al. [31] used bed reaction forces and monitored skin–bed interface forces for the prevention and management of pressure injuries. Waltisberg et al. [8] used non-contact pressure-based sensors to discriminate between sleep and wakefulness.

The market for in-bed patient monitoring has seen some commercialized products, such as smart beds and wearable devices integrated with sensor technologies. These products are designed to monitor vital signs, detect exits from the bed, and assess sleep patterns, improving patient care and safety. However, widespread adoption is hindered by several factors. A significant challenge is that most studies have been conducted on prototypes rather than on real hospital beds, which limits the generalizability of the findings to actual clinical settings. Additionally, high costs, technological limitations, regulatory hurdles, data privacy concerns, and the need for user acceptance and training further impede commercialization. Overcoming these challenges requires increased funding, collaborative efforts, standardization of protocols, advancements in technology, regulatory support, and public engagement to build trust and facilitate broader implementation. Large-scale real-life studies across diverse patient populations are still lacking due to logistical challenges, high costs, and ethical and privacy concerns. To improve this scenario, several steps can be taken: increased funding and resource allocation, fostering collaborations between institutions and countries, developing standardized protocols for data collection and analysis, leveraging advanced technologies like electronic health records (EHRs) and AI, and ensuring robust data protection measures to build public trust.

The range of movements considered in the included studies varied significantly, from three to seventeen distinct dynamics. This level of detail in movement categorization is more comprehensive compared to previous reviews, which often did not differentiate as clearly between static and dynamic movements [103]. This variability suggests a lack of standardization in the categorization and measurement of movements, which could impact the comparability of results across studies. Additionally, the ability of sensors to accurately detect and classify different postures and movements may differ, indicating the need to discuss the precision and limitations of the various sensor types used. Movements associated with different postures, such as supine versus lateral, have different characteristics due to differences in weight distribution, pressure points, and muscle activation. This aspect warrants further investigation to understand how well sensors capture these nuances. Furthermore, movements made for comfort adjustments versus those made to alleviate discomfort or pressure could provide insight into patient well-being and the effectiveness of sensors. Understanding these distinctions could enhance the interpretation of data collected from monitoring in the bed. Finally, discussing the implications of these findings for clinical practice is crucial. For instance, understanding typical movements in different positions could help design better intervention strategies for bedridden patients, improving patient care.

This review, which includes a variety of study designs, highlights the significant efforts made to predict events affecting patient outcomes. However, only nine studies were conducted on actual patients, and these involved relatively small sample sizes. Studies in controlled environments often do not account for the variability in movements and conditions present in real hospital settings, such as the use of pillows or the presence of bed rails. Additionally, we identified significant heterogeneity in the machine learning (ML) models used across studies, with notable differences in input data types, preprocessing methods, and model architectures. This variability makes it challenging to compare results between studies, as differences in sensor types, data granularity, and movement categorizations lead to inconsistent findings. For example, models trained in controlled environments with healthy volunteers may not generalize well to clinical settings, where patient conditions and behaviors are more diverse. Furthermore, the lack of standardized performance metrics complicates the evaluation of model accuracy and limits the ability to determine which models are truly robust across different populations. To address these issues, future research should prioritize standardized data collection, preprocessing, and reporting practices, along with the development of benchmark datasets that reflect real-world variability. Standardization would facilitate the comparison of results and improve the generalizability of findings across diverse clinical environments.

This review, considering that it includes all kinds of studies, shows that there is a great effort to try to predict events that can affect patient outcomes. However, there are only nine studies conducted in actual patients, involving only a few patients. Studies in a controlled environment do not consider the same variability in movements available in a real-hospital setting. Most studies must provide information on the use of a pillow and the presence/absence of bed rails.

5. Conclusions

This review highlights significant heterogeneity in the diverse range of ML models used to recognize and classify patient behaviors and postures. These models include artificial neural networks, deep learning architectures, and approaches that combine different sensor modalities. Each model has advantages and may be more suitable for specific applications based on the available data and the desired classification tasks.

Looking towards the future, in-bed patient monitoring through bed sensors holds promising prospects. Trends indicate a growing integration of advanced machine learning algorithms, both deep and shallow, to enhance accuracy and functionality. Continuous improvements in sensor technology and data processing capabilities will lead to more sophisticated monitoring systems that can provide real-time insight into patient movements and vital signs.

Overall, the studies demonstrate the potential of sensor technology and machine learning algorithms to monitor patient sleep posture, intention to leave the bed, postural changes in the bed, sleep patterns, and prevention of pressure ulcers and sleep apnea. The generalizability of the findings is limited by the fact that many studies were conducted in controlled environments or with small sample sizes. Furthermore, few studies involved real-world clinical settings, which restricts the applicability of the findings to broader patient populations. Future research should aim to validate these findings in more diverse, real-world settings.

However, several critical challenges must be addressed to realize these advancements. The high cost of these technologies remains a significant barrier to widespread adoption. Efforts to reduce production costs and develop cost-effective solutions will be crucial. Additionally, the integration of these systems with existing hospital infrastructure poses technical challenges that require robust, interoperable designs.

To address these issues, a structured roadmap can guide future developments (Figure 5). Establishing standardized protocols for data collection and utilizing high-resolution, unobtrusive sensors can enhance accuracy and patient comfort, ensuring more reliable monitoring systems. Developing and refining machine learning algorithms that balance accuracy and computational efficiency is essential. These algorithms should be optimized for real-time processing and low-power consumption, making them practical for various settings. Implementing robust data encryption and privacy-preserving techniques is necessary to protect patient data and comply with regulations. Furthermore, extensive validation studies in clinical environments will ensure the effectiveness and reliability of these technologies. Fostering interdisciplinary collaboration between engineers, healthcare professionals, and researchers will help develop holistic solutions. Providing comprehensive training for healthcare providers and patients is also crucial to maximizing the benefits of smart-bed technologies. Ethical and privacy concerns surrounding patient data need to be rigorously addressed to build trust and compliance with data protection regulations. Engaging healthcare providers and patients through education and training will be essential to ensure acceptance and the proper use of these technologies.

Ethical and privacy concerns surrounding patient data also need to be rigorously addressed to build trust and compliance with data protection regulations. Engaging healthcare providers and patients through education and training will be essential to ensure acceptance and proper use of these technologies.

In conclusion, while the potential for in-bed patient monitoring technologies is substantial, overcoming these barriers will require coordinated efforts from researchers, industry stakeholders, regulatory bodies, and healthcare providers. By addressing these challenges, we can pave the way for more personalized and proactive healthcare solutions that significantly improve patient care and outcomes.

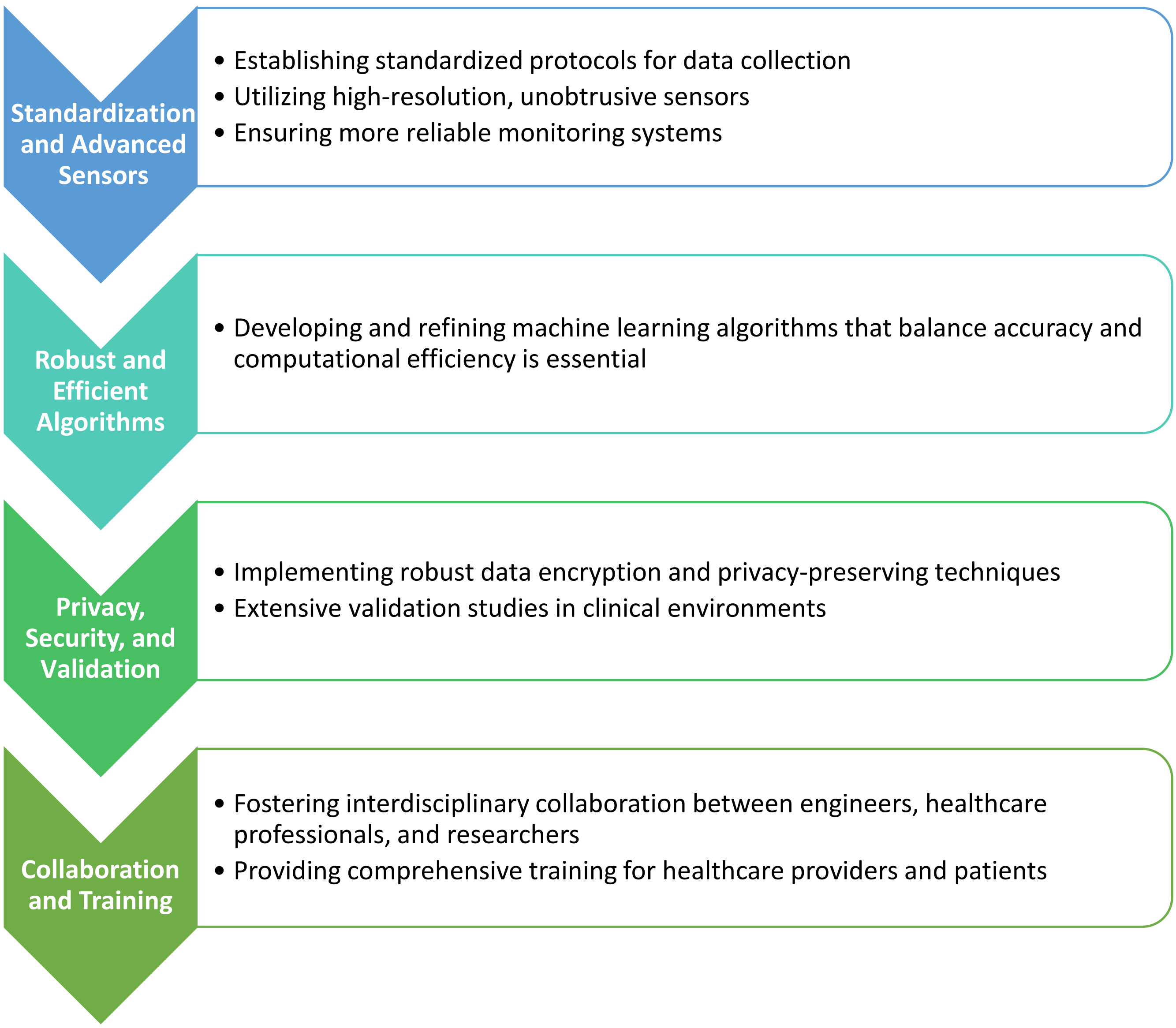

Figure 5. Roadmap for Future Smart-Bed Technologies.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/informatics11040076/s1, Table S1: Search strategy for PubMed, Table S2: Summary of the 79 studies included according to the outcome, Table S3: Characteristics of the machine learning models, Table S4: Characteristics of the study considering smart beds.

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