

Review

# Exploring the Role of Artificial Intelligence in Enhancing Nursing Bed Equipment: A Scoping Review

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**Abstract:** Artificial intelligence (AI) has been increasingly integrated into nursing bed equipment to enable continuous patient monitoring, reduce adverse events, and improve the quality of care for bedridden and elderly individuals. Smart nursing beds equipped with sensors and AI algorithms can non-invasively detect posture changes, falls, and physiological abnormalities; however, the scope, technological maturity, and limitations of these systems remain insufficiently synthesized in the existing literature. This study presents a scoping review of AI-based nursing bed equipment, focusing on sensor technologies, application areas, and analytical methods. Four electronic databases—Web of Science, PubMed, IEEE Xplore, and CINAHL—were searched for studies published between January 2010 and July 2024. A total of 5,496 records were identified, and 4,184 unique articles remained after duplicate removal. Following screening in accordance with PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines, 135 studies (3.23%) were included in the final analysis. Pressure sensors were the most frequently used sensing modality (43.0%), followed by RGB (Red–Green–Blue) cameras (11.1%), infrared and thermal imaging sensors (8.9%), and depth cameras (7.4%), while other modalities—including accelerometers, radar, radio-frequency sensors, microphones, and multi-sensor systems—accounted for 37.0% of the studies. The primary application domains were in-bed posture classification and activity monitoring, followed by fall detection, physiological monitoring, and human–machine interaction, with deep learning methods, particularly convolutional and recurrent neural networks, being the most commonly employed analytical approaches. Overall, AI-based nursing bed equipment shows considerable potential to enhance patient safety and care efficiency; nevertheless, challenges related to deployment costs, data privacy, and limited clinical validation remain and must be addressed to enable large-scale adoption and real-world implementation of intelligent nursing bed systems.

**Keywords:** Artificial Intelligence; Deep Learning; Elderly Care; Fall Detection; Machine Learning; Non-Contact Monitoring; Nursing Bed Equipment; Posture Classification; Sensors

## 1. Introduction

Adverse events continue to be a constant problem within healthcare settings, especially in the case of older, bedridden patients who are immobile and long-bed patients. The vulnerability of these people is intrinsic, as it can be characterized by the lack of mobility, the need to be provided with care, and the long-lasting exposure to the risk of pressure injuries, falls, and unnoticed physiological worsening [1]. It has always been demonstrated that adverse events lead to patient morbidity, prolonged hospital stay, and higher healthcare expenditure, which imposes a huge

burden on patients and care providers.

One of the most common and expensive consequences of long bed rest is pressure injuries. Ongoing stress of local body parts may hamper the blood flow, resulting in ischemia, ulceration, and infection of the tissues [2]. Although the nursing practices and mattress construction have improved, the prevalence of pressure injuries in hospitals and long-term care centers is very high. To avoid these injuries, it is necessary to reposition the injured regularly and monitor them faithfully, which is hard to maintain in the care environment with limited resources [3].

Falls are the other significant group of adverse events in bedridden and mobility-impaired patients. Poor monitoring of the bed exit or movement poses a lot of risk to injury, especially among elderly patients. Traditional prevention interventions like bed rails and manual observations are not very protective and are inadequate in terms of providing 24/7 safety, particularly when nurses are not present or when there is a shortage of staff [4].

Other than physical injuries, inadequate observance can slow the realization of physiological abnormalities that include abnormal breathing, sleeping disorders, or cardiac abnormalities. Conventional nursing bed devices provide minimal sensory and analytical power and depend extensively on the periodic manual evaluation [5]. With the increasing pressure on the healthcare system due to the aging population and shortage of workers, manual monitoring becomes more and more unsustainable.

One of the potential solutions to these issues is the use of the concept of artificial intelligence to integrate into the nursing bed equipment. Intelligent nursing beds are able to monitor patient posture, movement, and physiological nondestructive indications in real-time by collecting sensor data and analyzing it through AI-based software. They can produce real-time warnings, facilitate early intervention, and decrease the workload of the caregivers.

The past several years have been marked by a fast growth of the field of research on AI-based nursing bed systems, which use various sensing modalities, i.e., pressure mats, cameras, radar, and wearable or embedded sensors [6]. Nevertheless, the available literature is diverse in regard to technological methods, areas of application and testing environments. To elucidate the existing research tendencies, describe prevailing technologies, and outline the existing challenges, the synthesis of this ever-increasing body of literature is needed.

In line with this, this review is a systematic review of studies concerning AI-enabled nursing bed equipment, especially in terms of sensor types, purposes of application, and methods. This work will help develop a systematic overview of existing evidence that will guide future research and help develop safe, effective, and deployable intelligent nursing bed systems.

Although AI algorithms offer hope to help nursing beds, they can have constraints in the context of being able to adapt to specific patients. Such systems do not always provide a personalized adjustment of the system to the unique health conditions, preferences, and any further changes in the health condition of the patient. As an example, patients diagnosed with several comorbidities or experiencing swiftly evolving conditions can not be as advantageous in terms of standardized monitoring systems. AI models that incorporate patient-specific information over time could increase the accuracy of the system, as well as offer more tailored interventions.

## **2. Related Work**

The use of artificial intelligence to operate the nursing bed equipment has been steadily growing over the last ten years as more and more studies explore the application of the technology as an opportunity to ensure continuous monitoring of patients, aging, and the insufficient capacity of the nursing workforce. The available literature is mainly centered on the methods of using AI algorithms alongside other sensing methods to identify the changes in posture, track physiological indicators, and avoid negative outcomes (falls and pressure injuries). The subsections below summarize the previous literature based on the prevailing sensing abilities and uses.

### **2.1. Nursing Bed Systems Based on Pressure Sensors**

The most popular sensing technology that has been integrated into AI-enabled nursing bed equipment is the use of pressure sensors. To measure spatial pressure distributions created by the human body, these systems often use pressure pads, pressure mats, or sensor arrays in mattresses or bed frames to measure and record the pressure distribution [7]. The resulting pressure maps can give a lot of insight into body position and dynamics as well as contact forces.

Preliminary research showed that it was possible to use pressure sensor data to classify in-bed posture and

identify the activity. The support vector machines, decision trees, and k-nearest neighbors machine learning techniques were originally employed to categorize sleeping positions, as well as posture changes. As the computational power increased, deep learning methods (especially convolutional neural networks) have become more and more common as they can more accurately predict high-dimensional pressure maps [8].

In addition to classifying the posture, the pressure sensors have been applied to estimate physiological parameters based on ballistocardiogram signals and, thus, non-invasively monitor the heart rate and respiratory activity. The predictive use of pressure sensors to determine bed-exit intention and fall risks based on temporal variations in pressure distributions has also been studied in a number of works. Although they do work, the systems using pressure sensors are challenged by the cost of the hardware, the optimization of sensor density, and the long-term viability of these systems in actual care environments.

## 2.2. Vision-Based Surveillance with Commonplace Cameras

Another significant group of sensing technology in an intelligent nursing bed system is the use of ordinary cameras. The systems make use of computer vision to track patient posture, identify bed-exit behavior, and identify falls. The installation of the cameras could be above the bed, beside the bed, or on the walls that surround the bed to give a clear view of the movement of the patients.

Convolutional neural networks, pose estimation models and object detection algorithms are usually used in AI-driven vision-based frameworks to process visual data. These methods have shown good results in identifying complex body positions and risky behavioral anticipation, like unassisted bed exits. Furthermore, other researchers have also dealt with gesture- and eye-movement-based interfaces so that patients in bed could take a more active role in the functions of the bed [9].

Nevertheless, the use of cameras in surveillance raises a lot of privacy issues, especially in sensitive care settings. The visual data can reveal recognizable characteristics of patients, which may be treated with an unwilling attitude by the users and caregivers. Consequently, researchers have suggested anonymization methods like skeletal representation, silhouette extraction, and region-based analysis to reduce the threat to privacy [10]. In spite of such attempts, the issue of privacy continues to be a major obstacle in the broader adoption of the normal camera-based nursing bed systems.

## 2.3. Infrared (IR) and Thermal Imaging Procedures

The Infrared (IR) and thermal images technologies are technologies that have been looked into more and more as privacy-preserving replacements to regular cameras. These are systems that record heat radiation as opposed to visual outlook and they are able to detect posture and movement even in the night or low-light environments and minimize the chance of personal identification.

Thermal imaging devices have been specifically useful in identifying unusual movements, e.g., seizures or falls, and tracking bedside activity in sleep [11]. Convolutional neural networks, recurrent neural networks, and hybrid architectures that are used to detect both spatial and temporal patterns are the AI methods used in thermal data. Thermal systems have better strength in low-brightness conditions and user-friendliness as they are less intrusive than visible-light cameras.

However, thermal imaging equipment can be costlier than regular cameras, and can also have lower spatial resolution. These constraints may influence the accuracy of posture classification and limit the use of posture classification in a cost-conscious health care environment.

## 2.4. Depth Cameras and In-Depth Sensing

Depth cameras give a three-dimensional space as the distance data is captured instead of color or texture. Depth sensors are usually fitted on the top of a bed to ensure that nursing beds monitor patient posture, skeletal motion as well as bed-exit behavior. Structured-light or time-of-flight cameras have been extensively used as devices to do so [12].

The depth camera systems based on AI are frequently combined with the convolutional neural networks and recurrent models to learn temporal Markov switches in posture. One major benefit of depth sensing is that it is resistant to changes in lighting conditions and partial hiding of objects by blankets or bedding. Also, depth images have an added advantage of providing even more privacy protection than a regular camera because there are no

detailed facial/appearance-related features.

In spite of these merits, depth cameras are poorly calibrated and need to be installed in a special manner so as to be accurately covered. Another unfavorable effect could be the deterioration of their performance in busy places or when other patients are observed within the spatial area of the sensor [13].

## **2.5. Non-Contact Non-Physiological Radar and RF (Radio-Frequency) Sensor Physiological Monitoring**

Radar and radio-frequency (RF) sensory systems have become potent in non-contact physiological detection in nursing bed systems. They are sensors that respond to minute body motions due to breathing, heartbeat or change of posture by examining reflected electromagnetic signals.

Research using radar and RF sensors has shown promising outcomes of non-contact measurements of heart rate, respiratory rate, sleep apnea and exit behavior. Convolutional neural networks, recurrent neural networks and signal decomposition algorithms are typical examples of AI algorithms that are commonly used to identify meaningful patterns in radar and RF data [14].

The main benefits of these systems are a high level of privacy and a low level of intrusion. Nevertheless, radar systems and RF systems can be more expensive in terms of hardware and are typically more expensive in terms of signal processing and deployment, which limits their applicability in a general clinical environment.

## **2.6. Multi-Sensor Fusion Hybrid Systems**

In order to overcome the single-modality sensing constraints, some works have suggested multi-sensor systems that combine information on multiple sources, including pressure, cameras, infrared and microphones. These hybrid methods will focus on the strengthening of robustness, precision, and situational awareness through the integration of data streams complementary to each other.

The sensor fusion techniques which are artificial intelligence-based such as feature-level sensor fusion and decision-level sensor fusion have been demonstrated to enhance performance in posture, fall and physiological monitoring tasks. Multi-sensor systems are specifically useful in a complicated environment in which single sensors might be impacted by occlusion, noise, or environmental interference [15].

Multi sensor arrangement however complicates the system, adds cost and maintenance needs. The development of scalable and cost-effective fusion architecture is still a research issue.

Besides the mentioned research, recent outputs like Kau et al. (2023) [5] also offer crucial information regarding introducing AI technologies into the medical apparatus, nursing bed systems included. Researcher concentrate on the creation of assistive technology, depending on robotics and AI in medical practice, however, with specific attention to motor disability care, which is quite topical in terms of sensor technologies and AI approaches. Kau et al. (2023) [5] consider the systems based on pressure sensors to determine the quality and state of sleep and show how AI can be used to enhance patient monitoring without invasive patient interventions. These research works are consistent with the growing relevance of AI and multi-modal sensor systems in smart healthcare devices.

## **2.7. The Research Trends and Gaps**

On the whole, current studies present a high potential of AI-powered nursing bed devices to enhance patient safety and quality of care. The focus of the modern literature consists of pressure sensors and vision-based systems; non-contact technologies like radar, RF sensing are also on the rise in the field because of their privacy benefits. Although there is technological advancement, the majority of the studies are confined to experimental or pilot studies with a small number of studies, having been validated in a real-life clinical setting.

Some of the gaps include little longitudinal assessment, limited testing with various patient groups, unanswered privacy issues, and high cost of deployment. These gaps are critical in realizing AI-based nursing bed systems that need to be translated, based on research prototypes, into an actual healthcare solution.

Besides the existing studies, the recent articles like Kau et al. (2023) [5] and Jaichandran et al. (2022) [7] can offer significant understanding of implementing AI technologies in the health equipment, including nursing bed systems. Kau et al. (2023) [5] discuss such a solution to the problem of posture recognition and fall detection in the nursing bed that relates to the usage of advanced sensor technologies and AI to ensure patient safety. Jaichandran et al. (2022) [7] study the role of multi-sensor fusion to improve the accuracy and reliability of AI-based monitoring

systems in the long-term care setting. These works are in tandem with the existing tendencies in sensor technologies and data analytics and indicate that the multi-modal sensing and the state-of-the-art AI approaches are ever more integrated into the smart healthcare devices.

### 3. Methods

#### 3.1. Search Strategy

An extensive search in the literature was carried out to find the studies that used artificial intelligence (AI) technologies in nursing bed equipment. They were searched in 4 databases: Web of Science, PubMed, IEEE Xplore and CINAHL. The search included articles published between 1 January 2010 and 30 July 2024, which is the time when AI-based healthcare technologies started to evolve at a fast pace.

Titles and abstracts were searched with search terms and combined keywords that were associated with healthcare settings and beds with AI-related terms [16]. Search terms were core (consisted of nursing OR care OR hospital OR medical) and Bed and a general list of AI-related terms, which were artificial intelligence, machine learning, deep learning, neural networks, computer vision, and algorithm-specific words. Additional relevant studies were also filtered through the reference lists of included articles to have complete coverage.

#### 3.2. Eligibility Criteria

The Population-Concept-Context (PCC) framework was used to select the studies.

- Population: Long-term bedridden patients, hospitalized patients and elderly patients.
- Concept: Research that entails offering, creating, assessing, or implementing AI technologies embedded within nursing bed machines.
- Context: The hospital settings, the long-term care and the home-care settings [17].

Peer-reviewed journal articles and conference proceedings written in English were only included. Articles were not included as they were review articles (systematic reviews, scoping reviews or meta-analyses), editorials, opinion papers, or when it was impossible to access the full-text. Studies that implied AI-based equipment in the nursing bed were not included in the research as well.

#### 3.3. Study Selection Process

The retrieved records were all exported to EndNote to remove any duplicates and then exported to the Rayyan web-based screening solution. Article titles and abstracts would be screened by two reviewers independently to determine relevance. The studies were classified in terms of included, excluded, and uncertain. All possible eligible studies were screened on a full-text basis. It was also seen that disagreements encountered in the screening process were solved by discussing them before a consensus was reached amongst the research team [18].

The PRISMA 2020 guidelines were used in the study identification and selection to guarantee transparency and reproducibility.

**Figure 1** demonstrates the PRISMA flow diagram that summarizes the identification, screening, and eligibility assessment and inclusion of studies.

#### 3.4. Data Extraction

Each of the included studies was analyzed to obtain the necessary information using a structured data-charting form. The elements of extracted data were as follows:

- Bibliographic data (authors, year of publishing, place of publication).
- Care setting and target population.
- Nursing bed equipment and sensor technology type.
- Location of sensors with regard to the bed.
- Algorithms and methodology of AI.
- Data source and data type.
- Main purpose of application (e.g., posture classification, fall detection, physiological monitoring).
- Other reported considerations are ethical or privacy [19].

The research team worked together on data extraction so as to provide consistency and accuracy.

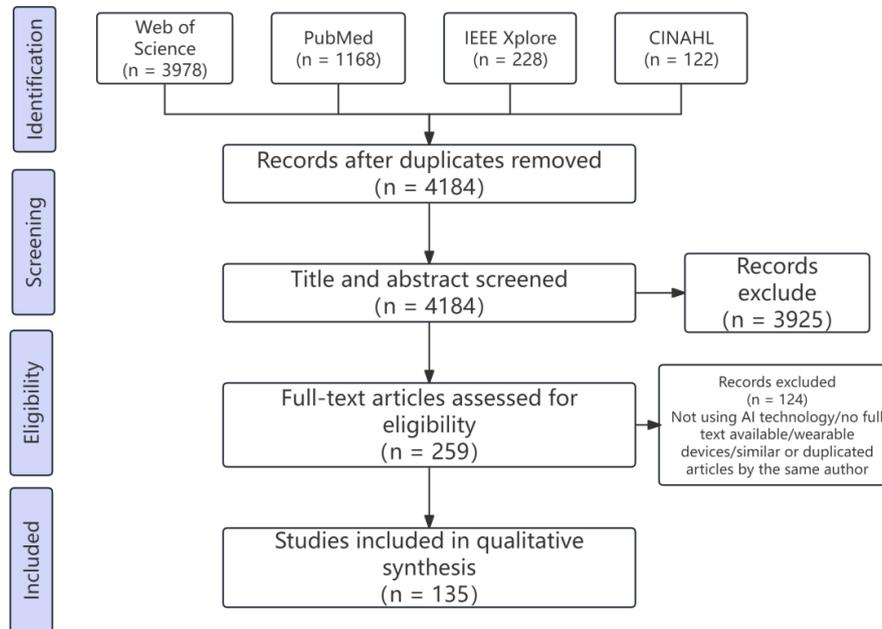


Figure 1. PRISMA Flowchart.

### 3.5. Data Synthesis

Qualitative content analysis with descriptive statistical analysis was used to extract data and synthesize it. The identification of the research gaps and the prevalent research trends, the most frequently used technologies, and their variety were achieved by grouping studies by their sensor type, application objective and AI methodology. This method of synthesis allowed for a comparative study of AI-based nursing bed systems in a variety of sensing modalities and care settings [20].

## 4. Proposed Work: Theorizing AI-Assisted Nursing Bed Equipment

In spite of the fact that this is a scoping review paper, a systematic conceptual framework is suggested to combine the current literature and explain the ways of introducing artificial intelligence technologies into the equipment of the nursing bed. This framework grouped the previously done work based on sensor modality [21], data characteristics, AI methodology, and purpose of application, as opposed to isolated implementations. This generalization brings out prevailing design trends and opens loopholes that need further studies.

### 4.1. Framework Overview

The conceptual framework of the proposed AI-based nursing bed system involves the following 4-layered pipeline:

- Sensing Layer.
- Data Processing Layer.
- AI Analytics Layer.
- Decision Layer and Application Layer.

This hierarchical design indicates the way the raw physical data is gradually converted into meaningful clinical information.

## 4.2. Sensing Layer

The physical interface between the intelligent nursing bed system and the patient is the sensing layer. Available literature indicates that sensor selection is an underlying factor in determining the quality of the data, privacy implications, and system viability.

The sensors applied in nursing bed equipment may be generally divided into contact and non-contact modalities:

Mechanical interaction between patient and bed surface is directly measured by contact sensors, including pressure pads, load cells, accelerators and vibration sensors. These sensors offer spatial or temporal data with high resolution and are especially useful in posture classification, movement detection, as well as ballistocardiogram-based physiological monitoring.

Cameras, infrared and thermal cameras, radar, RF sensors, and microphones are non-contact devices that observe the patient's behavior and physiological symptoms. These modalities are becoming widely popular because they are more comfortable and cause less disturbance to the movement of patients [22].

The other important factor is sensor placement. The sensors can be inserted in the mattress, on the frame of the bed, on the walls around the bed, or on the overhead of the bed. Research shows that embedded and under-mattress sensors have better user acceptance and overhead sensors have better coverage with high privacy concerns.

## 4.3. Data Processing Layer

The data provided by nursing bed sensors has a wide range of structure, dimensionality and time resolution. The data processing layer will be dealing with converting the raw sensor data to an analyzable format.

The noise filtering, normalization, segmentation and feature extraction are common preprocessing steps. The data of pressure sensors are usually in the form of two-dimensional pressure maps or time-series signals, whereas the visual systems deal with image frames or skeletal representations. Complex time-frequency signals are produced by radar, RF, and acoustic sensors and can only be analyzed by the signal decomposition and transformation [23].

This layer is very important to the system's performance. Poor preprocessing can seriously obstruct AI accuracy, especially in real-life situations where noise, occlusion and environmental disturbances are inevitable.

## 4.4. AI Analytics Layer

The AI analytics layer is the heart of the intelligence of nursing bed systems. The currently existing studies utilize a wide variety of artificial intelligence methods which may be divided into three groups:

### (1) Non-Neural Network Machine Learning

Support vector machines, decision trees, random forests, k-nearest neighbors and logistic regression are algorithms that are often applied to structured and low-dimensional data. These approaches are interpretable and less complex to compute; thus, they can be deployed on embedded systems and can be used in cost-sensitive deployments [24].

### (2) Deep Learning Models

Deep neural networks and in particular convolutional neural networks and recurrent neural networks are dominating on the tasks that require high-dimensional data like images, pressure maps and time-series signals. Hybrid systems that use Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) are particularly effective in posture and time behavior prediction.

### (3) Hybrid and Fusion Models

Multi-sensor systems are also becoming heavily based on hybrid artificial intelligence frameworks that integrate outputs or determinations of two or more data streams. These models make the systems more robust and accurate but add complexity to the system design and training [25].

A choice of an algorithm is strongly connected to sensor modality and application requirements. Deep learning methods can be used with high-resolution spatial data, and simpler signals can see comparable performance with more traditional machine learning methods.

#### 4.5. Application and Decision Layer

Application layer converts AI outputs into actionable data to caregivers, patients, or bed automated control devices. As per the literature reviewed, the applications can be classified into four major categories:

- The classification of postures and monitoring of activities, in order to prevent pressure injuries and musculoskeletal complications.
- Fall and bed-exit detection which is aimed at the early warning and prevention of injuries.
- Physiological measurements, such as respiration, heart rate, sleep quality and disease-specific measurements.
- Human-machine interaction, where the patients could manage the bed functions by gesture, movements or voice command [26,27].

This layer may have alert systems, a visual dashboard or automated bed changes. These applications can become effective not only based on the accuracy of AI but also on usability, interpretability, and the ability to integrate into clinical processes.

#### 4.6. Design Trade-Offs and System Constraints

The suggested framework identifies a number of trade-offs that are apparent in the existing systems:

- Accuracy vs. Cost: The high-density sensor arrays and other advanced sensing technologies enhance the performance, but these systems are very expensive [28,29].
- Privacy vs. Observability: Sensors with vision will provide more contextual data but the privacy is compromised, non-visual sensors have more privacy, at the cost of understanding.
- Complexity vs. Deployability: Multi-sensor fusion enhances robustness but complicates installation, maintenance and scalability.

These trade-offs are vital in designing realistic nursing bed systems that can be used in the real-life healthcare setting.

#### 4.7. Future System Design Implications

This proposed model is structured to give an organized reference in developing AI-enabled nursing bed equipment since the existing research has been consolidated into one framework. It shows the importance of efficient sensor designs, analytics that do not compromise privacy, and AI models that are clinically proven. The future systems must put more emphasis on scalability, acceptance by the user, and the ability to blend into the care routines than purely seeking technical performance [30,31].

Although deep learning models like CNN and RNN (Recurrent Neural Networks) are promising in high dimensional data analysis, the models need a lot of labeled data to operate successfully. In healthcare, the challenge of getting adequate quality, labeled data may present a problem because of the patient privacy concerns, the variability of patient conditions, and the lack of data on specific conditions. The future avenue of research might involve solutions such as data augmentation, transfer learning, or multi-institutional partnerships to address this problem and increase the usefulness of deep learning in a wider range of patients.

### 5. Results and Discussion

#### 5.1. Introduction to Inclusion in the Studies

This review included 135 studies that were published in the years 2010–2024 after using the PRISMA-guided selection process. The analysis of the studies as a whole focuses on the implementation of the artificial intelligence approach into the nursing bed equipment that may be used to monitor the posture, identify falls, and measure physiological parameters. The majority of the studies were experimental or prototype, but there was little large-scale clinical validation of any kind. Even so, the variety of sensing modalities and methods of analysis is the evidence of the fast development of the smarter bed technologies in nursing.

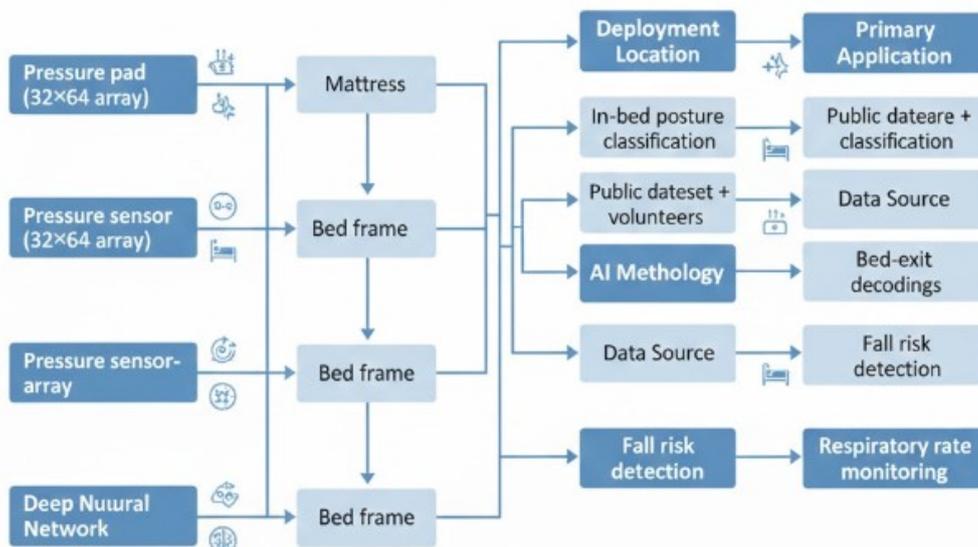
## 5.2. Nursing Bed Systems on the Basis of Pressure Sensors

The most common sensing modality featured in studies was pressure sensors. Such systems generally use pressure pads, pressure mats or sensor arrays in mattresses or bed frames to record spatial pressure distributions that the human body produces. The pressure data obtained were explored with the help of machine learning and deep learning to distinguish the posture, keep track of movements, and forecast bed-exit behavior.

**Table 1** and **Figure 2** present the summary of the representative pressure sensor-based studies, where sensor configuration, AI methodology, data source, and purpose are highlighted. Convolutional neural networks and other neural network architectures take over this category because of the ability they have to process high-dimensional pressure maps. The pressure sensors were also found to be versatile in other studies that used pressure-derived ballistocardiogram signals to estimate respiratory and cardiac activity.

**Table 1.** Representative Pressure Sensor-Based AI Applications in Nursing Bed Equipment.

Sensor Type	Deployment Location	AI Methodology	Data Source	Primary Application
Pressure pad (32 × 64 array)	Mattress	CNN	Public dataset + volunteers	In-bed posture classification
Pressure sensor array	Under mattress	SVM, KNN	Volunteers	Sleep posture recognition
Pressure mat	Mattress surface	CNN + LSTM	Volunteer recordings	Bed-exit intention prediction
Pressure sensors	Bed frame	Random Forest	Patients	Fall risk detection
Pressure-sensitive sheet	Mattress	Deep Neural Network	Mixed dataset	Respiratory rate monitoring



**Figure 2.** Representative Pressure Sensor-Based AI Applications in Nursing Bed Equipment.

Even though pressure sensor systems are effective, they also have significant challenges. High-resolution sensor arrays are very expensive and long-term viability of pressure mats is an issue in real-life care settings. Furthermore, several studies were based on the data gathered on healthy volunteers, but not on patient populations, which can be a limitation to clinical generalization.

## 5.3. Discussion

The prevalence of systems based on the pressure sensor can be explained by the fact that they offer continuous and non-invasive monitoring without raising serious privacy issues. In comparison, camera-based methods, pressure sensors are usually more acceptable to the users and caregivers because they do not gather recognizable visual data. The above benefit places pressure sensors as a viable basis for the intelligent nursing bed system, especially in long-term care facilities.

The selection of AI methodology also has a strong connection with characteristics of data. Deep learning methods, particularly convolutional neural networks are preferred when pressure maps of higher resolution are avail-

able whereas standard machine learning methods can be used with lower-dimensional or feature-engineered data. CNN-LSTM models, which are hybrid models between spatial and temporal learning, have better results in predicting bed-exit behavior and posture transitions [32,33].

Nonetheless, there are a number of weaknesses that prevail in the studies reviewed. The evaluation under controlled conditions was conducted on many systems and the elderly or clinically complex patients' population was not fully tested. Also, the high density of sensors and the maintenance of large-scale systems are impediments to large-scale implementation. The future studies should aim at optimizing sensor configurations, extending clinical validation, and evaluation of long-term system reliability in the real clinical setting [34,35].

Even though AI-based system of nursing beds demonstrated positive results in the laboratory conditions, its efficiency in the non-experimental healthcare facilities has barely explored. The effectiveness, reliability and scalability of the systems should be established through more clinical trials and long-term studies to be conducted in various medical facilities. These studies will help in establishing the barriers in the practical world such as integration with the current care practices, acceptance by the users and the cost of the running of the implementation of such systems.

## 6. Conclusion

This scoping review summarized the recent studies concerning the usage of artificial intelligence in nursing bed equipment and the influence of intelligent sensing and data-driven analytics on redefining patient monitoring and care delivery. The analyzed articles show that AI-powered nursing beds can aid in uninterrupted, non-invasive monitoring of patient posture, movement, and physiological activity and respond to the most important safety issues like falls, pressure injuries, and unnoticed worsening of health of people in bed.

Pressure sensors were identified in the literature as the most widely used sensing modality, because of their reliability, applicability, and the high privacy-preserving nature of the sensing modality. Vision-based systems such as ordinary cameras, infrared imaging and depth sensors provide better contextual knowledge and accuracy in posture and behavior recognition, with non-contact systems like radar, RF sensors and microphones giving a promising alternative to physiological monitoring with limited intrusion of the patient. The efficiency of these systems is directly connected with the choice of suitable AI methodologies and deep learning models are predominant in the processes that require high-dimensional data and traditional machine learning methods are also efficient in the structured sensor signals.

Although the use of AI as a nursing bed equipment driver has been promoted to encourage its usage in practice, several issues still restrict the practical use of AI in nursing bed devices. The barriers to high system costs, privacy, limited clinical validation and the use of healthy volunteers to test the system and patient populations are ongoing. There are also numerous papers that concentrate on individual technical performance measures without paying full attention to usability or integration into clinical processes or system sustainability.

Subsequent studies must focus on conducting large-scale clinical studies, cost-effective sensor designs, and system designs that are privacy-conscious to guarantee aspects of practical deployability. The user-centered design should also be stressed, so that the intelligent nursing bed systems are easy to use by the caregivers as well as the patients. Having addressed all these issues, AI-assisted nursing bed appliances will be able to leave the status of an experimental project and be implemented on a larger scale as a potentially useful healthcare solution capable of providing more secure patient care, reducing the number of interested caregivers, and providing better and more efficient and personalized care.

## Author Contributions

Conceptualization, L.M. and C.S.T.; methodology, L.M.; software, Y.Z.; validation, J.Y., N.A. and Z.F.; formal analysis, L.M.; investigation, L.M. and Y.Z.; resources, C.S.T.; data curation, Y.Z.; writing—original draft preparation, L.M.; writing—review and editing, C.S.T. and Z.F.; visualization, J.Y.; supervision, C.S.T.; project administration, C.S.T. All authors have read and agreed to the published version of the manuscript.

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## Institutional Review Board Statement

Not applicable. This study is a scoping review based on previously published literature and does not involve human participants or animals.

## Informed Consent Statement

Not applicable.

## Data Availability Statement

No new data were created or analyzed in this study. Data sharing is not applicable to this article.

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## Conflicts of Interest

The authors declare no conflict of interest.

## Abbreviation

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
BCG	Ballistocardiogram
CNN	Convolutional Neural Network
DNN	Deep Neural Network
DT	Decision Tree
ECG	Electrocardiogram
FNN	Feedforward Neural Network
GBDT	Gradient Boosting Decision Tree
KNN	K-Nearest Neighbors
LDA	Linear Discriminant Analysis
LSTM	Long Short-Term Memory
ML	Machine Learning
MLP	Multilayer Perceptron
NB	Naive Bayes
NN	Neural Network
OSA	Obstructive Sleep Apnea
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machine

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