Journal of Pain Research

Dovepress
Taylor & Francis Group

Open Access Full Text Article

EXPERT OPINION

Guidelines From the American Society of Pain and Neuroscience for Using Artificial Intelligence in Interventional Spine and Nerve Treatment

Christopher Massey[1], Usman Latif[2], Timothy R Deer[3], Hemant Kalia[4], Maged Guirguis[5], Mark C Bicket[6], Nasir Khatri[7], Reda Tolba[8], Krishnan Chakravarthy[9,10], Ryan Budwany[11], David W Lee[12], Ankur A Patel[13], Alexandra M Moreira[14], Daniel A Jimenez[15,16], Raj G Patel[17], Iden Cowan[17], Sandy Christiansen[18], Derron Wilson[19], Kenneth B Chapman[20,21], Chau Vu[22], Suzanne Manzi[23,24], Sara Nashi[25], Muhammad Waheed[26], Anuj Shah[27], Morad Nasseri[28], Patrick Buchanan[29], Nomen Azeem[30], Erika A Petersen[31], Michael E Schatman[32,33], Alaa Abd-Elsayed[34], Dawood Sayed[2], Sudhir Diwan[35]

[1]Pain Specialists of America, Austin, TX, USA; [2]Department of Anesthesiology and Interventional Pain, The University of Kansas Health System, Kansas City, KS, USA; [3]The Spine and Nerve Center of The Virginias, Charleston, WV, USA; [4]C.R.I.S.P Center for Research & Innovation in Spine & Pain, Rochester, NY, USA; [5]Pain Management Department, Ochsner Health System, New Orleans, LA, USA; [6]Department of Anesthesiology, University of Michigan, Ann Arbor, MI, USA; [7]Insight Health Systems, Flint, MI, USA; [8]Pain Management Department, Cleveland Clinic Abu Dhabi, Abu Dhabi, United Arab Emirates; [9]Division of Pain Medicine, Department of Anesthesiology, University of California San Diego, San Diego, CA, USA; [10]VA San Diego Healthcare, San Diego, CA, USA; [11]PainHealth.ai, NextPain Care, Clearwater, FL, USA; [12]University of California, Irvine/Fullerton Orthopedics, Fullerton, CA, USA; [13]Novant Health Spine Specialists, Winston Salem, NC, USA; [14]Rush University, Department of Anesthesiology, Chicago, IL, USA; [15]Department of Physical Medicine and Rehabilitation, University of Michigan Health-Sparrow, Lansing, MI, USA; [16]Cantor Spine Center, Paley Orthopedic and Spine Institute, Fort Lauderdale, FL, USA; [17]Pain Management, Capitol Pain Institute, Austin, TX, USA; [18]Associate Professor of Anesthesiology and Perioperative Medicine, Oregon Health and Science University, Portland, OR, USA; [19]Goodman Campbell Brain & Spine, Carmel, IN, USA; [20]Department of Anesthesiology, New York University Langone Medical Center, New York, NY, USA; [21]Department of Anesthesiology, the Zucker School of Medicine at Hofstra/Northwell, New York, NY, USA; [22]Evolve Restorative Center, Santa Rosa, CA, USA; [23]Performance Pain and Sports Medicine, Houston, TX, USA; [24]Department of Physical Medicine and Rehabilitation, McGovern Medical School at UT Health, Houston, TX, USA; [25]Interventional Pain & Spine, Trihealth, Cincinnati, OH, USA; [26]Department of Orthopaedic Surgery, Detroit Medical Center/Wayne State University, Detroit, MI, USA; [27]Weill Cornell Tri-Institute, New York, NY, USA; [28]Boomerang Healthcare, Walnut Creek, CA, USA; [29]Spanish Hills Interventional Pain Specialists, Camarillo, CA, USA; [30]Florida Spine & Pain Specialists, Tampa, FL, USA; [31]Department of Neurosurgery, University of Arkansas for Medical Sciences, Little Rock, AR, USA; [32]Department of Anesthesiology, Perioperative Care and Pain Medicine, NYU Grossman School of Medicine, New York, NY, USA; [33]Department of Population Health - Division of Medical Ethics, NYU Grossman School of Medicine, New York, NY, USA; [34]Department of Anesthesiology, University of Wisconsin, Madison, WI, USA; [35]Albert Einstein College of Medicine, Bronx, NY, USA

Correspondence: Christopher Massey, Email chrismasseymd@gmail.com

Introduction: Artificial intelligence (AI) is rapidly evolving and becoming more ubiquitous. Significant advancements have been made in the last few years, driving rapidly increasing adoption. The scale of publications on AI makes it difficult to keep abreast of relevant findings.

Objective: The ASPN Artificial Intelligence Guidelines are designed to help clinicians understand AI and implement it into their practice. This Neuron Project is designed to evolve with the changing landscape of AI.

Methods: An expert panel was chosen to discuss and write the best practice guidelines on AI. The primary authors conducted a literature search on PubMed, cross-referencing key terms in pain management and AI. After a thorough review of the current literature, the information collected was divided into broad categories of potential benefits, potential harms, and ways to ensure the benefits outweigh the potential harms of AI. These guidelines include only the most essential aspects of AI that clinicians need to know and understand before implementing AI into their practice.

Results: Over 12,000 articles were found using the above search results. Many articles were reviews and clinical guidelines. The framework created from these guidelines allowed authors to fill in knowledge gaps and discuss the most critical elements pain clinicians should comprehend about AI.

Received: 8 May 2025
Accepted: 25 July 2025
Published: 20 August 2025

Conclusion: All authors achieved consensus on guidelines for implementing and using AI in pain management following a process of critical review and edits by the entire group of authors. All authors approved final guidelines.

Discussion: The field of artificial intelligence is rapidly growing. As it expands into healthcare, it is necessary to prevent breaches of sensitive data and potential harm to patients. Guidelines that constantly evolve and grow with expanding indications for AI are essential to maximize benefit and prevent harm. This paper is part of ASPN's Neuron Project and is designed to update continuously as this field evolves.

Keywords: artificial intelligence, spine, minimally invasive, machine learning, chronic pain

Introduction

History of Artificial Intelligence

The phrase Artificial Intelligence (AI) originated in 1956 at the Dartmouth Summer Research Project Artificial Intelligence conference, where pioneers Allen Newell, Cliff Shaw, and Herbert Simon introduced *Logic Theorist*, which is thought to be the first AI program.[1] Although this early concept showed a promising foundation, AI research faced severe setbacks in the late 1970s into the early 1990s, known as the "AI Winter", due to perceived technological limitations, reduced funding, and insufficient databases.[2]

The earliest applications of AI in medicine were in the 1970's. They included CASNET, which could apply disease information to patients and provide management advice, and MYCIN, which used patient information to provide potential bacterial pathogens and recommended treatments.[2] Starting in the 1990's, the advancement of computing power and machine learning techniques reignited the evolution of AI, which accelerated in subsequent decades with the advent of techniques to integrate unstructured data. With the evolution of these systems, AI has flourished into more mainstream applications such as virtual assistants and healthcare systems. Today, we are faced with balancing the use of ongoing research to integrate these systems into daily practice while ensuring responsible development and utilization of these models.

Technical Fundamentals

AI relies on data and math models. At the core is an extensive data repository that trains and develops algorithms that predict categories or outcomes based on a range of inputs.

Machine Learning

Machine learning strategies broadly fall into the categories of supervised and unsupervised. Data is divided into training, validation, and test data.[3] Training data is used to develop the model, validation data is used to fine tune and validate the data, and test data is unseen data used to evaluate the model. Supervised learning uses labeled data to make predictions based on inputs.[4] Labeled data are data points that are labeled with the category that applies. An example would be data on patients with sacroiliitis who have had SI joint fusion labeled as patients with successful outcomes and those without. Machine learning requires large volumes of data, and a shortage of labeled data in the medical field is a significant obstacle.

The simplest mathematical form of supervised learning is linear regression where a line of best fit is used to predict the values of the dependent variable (Figure 1).[5] It performs well for data with a linear relationship. Logistic regression is used for binary data such as 0 or 1 or True or False. The value of the dependent variable represents the probability of the outcome (Figure 2). However, both methodologies tend to overfit and may not apply to more complex relationships.

Support Vector Machines (SVM) rely on plotting data points and identifying a hyperplane, essentially a line, when in two dimensions, dividing the data between two categories (Figure 3).[6] The optimal hyperplane maximizes the probability of correct classification by maximizing the distance or margin between the hyperplane and any point in the training set.[4] When data is not linearly separable, a kernel function can plot a complex three-dimensional representation such that a hyperplane can exist to separate the categories.

Decision tree algorithms use yes/no questions to sort data into categories.[3] They are prone to overfitting and small changes in training data can significantly change predictions. Random forest algorithms rely on many decision trees built

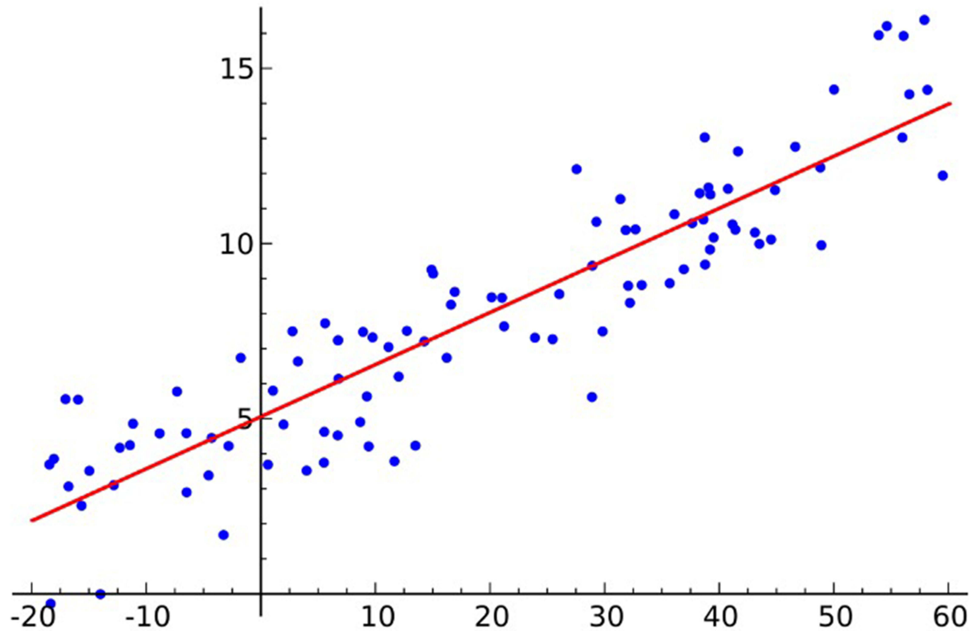

Figure 1 Linear Regression model. A "best fit" line predicts the outcomes of the dependent variables.

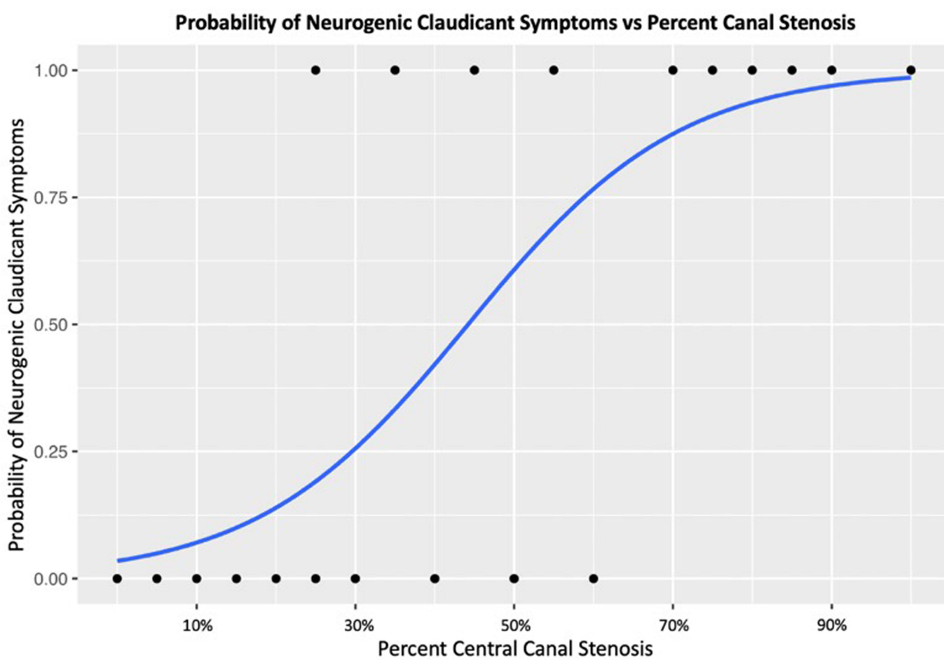

Figure 2 Logistic Regression Model, used for binary data where the dependent variable represents the probability of the outcome.

on training data samples. Each tree provides an outcome which functions like a "vote" for that output. The output with the most "votes" becomes the model's output. These algorithms can handle nonlinear data and implicitly perform feature selection. However, they are computationally expensive.

Unsupervised learning is a method where algorithms learn from unlabeled data.[6] One purpose is clustering. Imagine that there are multiple phenotypes of patients with spinal stenosis. k-Means clustering could identify multiple subgroups within the patient population.[4] Centroids are plotted, and the sum of squared distances between the data points and centroids is calculated. The number of centroids and locations are varied through progressive iterations until the optimal

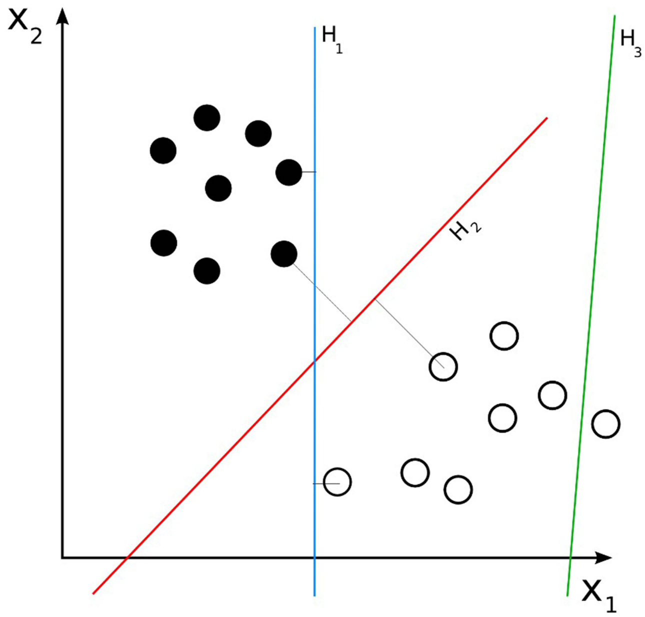

Figure 3 Support Vector Machines. These algorithms are used for classification and regression. They use a line (hyperplane) to delineate between categories.

centroids are identified. Thereafter, any new point will belong to the group associated with the centroid closest to it. A better understanding of the types of patient groups may help with later data exercises to determine if certain groups are better suited to interventions.

Neural Networks

Neural networks are mainly supervised learning.[6] Each input is a node represented by a value and then passed through a connection to a node in the next layer of the neural network after being multiplied by a weight associated with the neuron connecting the nodes and a bias that is added or subtracted from each node. Neural networks consist of an input and an output layer (Figure 4). Deep neural networks contain additional hidden layers between the input and output layers. Training data is used to adjust the weights and biases throughout the neural network with each iteration of training

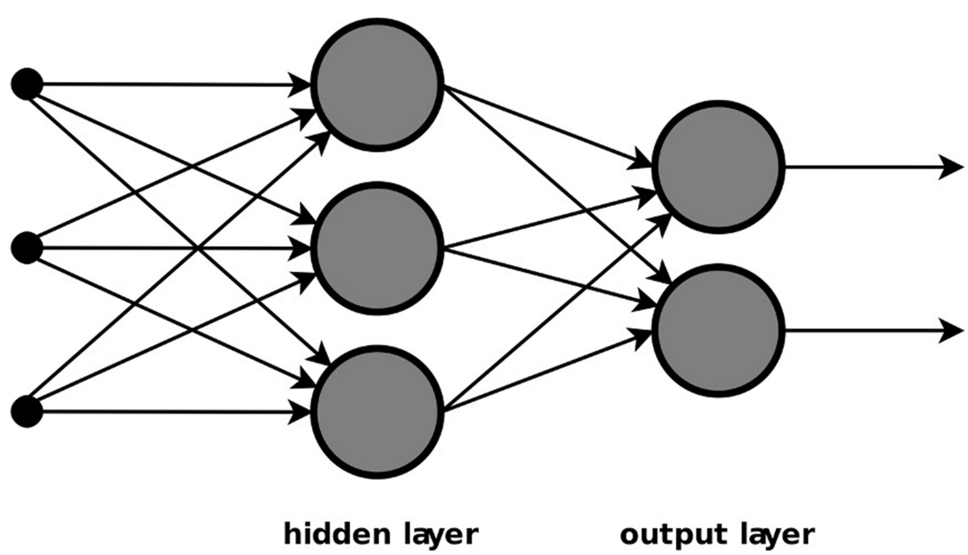

Figure 4 Neural Networks. Each node creates an output that is associated with the next node, which creates another output to the next layer. This occurs at every layer of the network.

Figure 5 AI Model Workflow. Begins with preparing data, followed by training, packaging, and validating the model before deployment. After deploying the model, it must be monitored for accuracy.

data passing through the network. Gradient descent and backpropagation are utilized to massively decrease the time and computational power required to train a neural network.

Reinforcement learning is employed to determine optimal behavior where multiple courses of action are possible in sequential steps.[4] Reward and value functions evaluate the success of various strategies and solve very complex problems, particularly where the outcomes of actions are not always predictable Reinforcement learning is very successful in medicine and has been applied to protein folding problems.

Transfer learning uses a model trained on one task to rapidly develop a model for a second task with less data.[6] Deep learning models frequently employ transfer learning. An example would be using a model that understands spoken words and then using transfer learning to train this model to understand medical terminology. Generative Adversarial Networks (GAN) use a pair of neural networks, a generator and a discriminator to train for tasks.[7] The generator attempts to fool the discriminator by outputting fake data. The discriminator, trained on the desired outcome, evaluates and grades the generator's output to determine if the output data is real or fake. Through repetitive iterations, it is possible the generator will fool the discriminator with fake data.

Large Language Models (LLM) utilize massive volumes of data to learn the meaning of words in various contexts and generate meaningful text.[8] ChatGPT, Gemini, and Grok are well-known examples. OpenGPT is an excellent example of an implementation that can be used for transfer learning to customize for unique applications such as within the medical field.

Creating an AI model starts with preparing data (Figure 5). This encompasses tasks ranging from cleaning up data and addressing missing data to reducing dimensionality. Subsequent tasks consist of training, packing, and validating the model. Deploying models is more complicated than simply uploading the final model. Deployment at scale may require pruning of neural networks for size reduction and optimization of models to reduce the computation power required. The financial and computational costs of AI models can multiply quickly at scale. Finally, models must be monitored to improve performance over time and prevent drift.

General Applications in Medicine

Artificial Intelligence (AI) is revolutionizing medicine with diverse applications. Machine learning algorithms assist in early disease detection, such as identifying cancerous lesions in medical imaging.[9] Natural Language Processing (NLP) enables efficient electronic health record analysis, reimbursement optimization, automated note generation, and patient-doctor communication.[10] AI-powered robotic surgery enhances precision and minimizes invasiveness.[11] Drug discovery has benefited from AI's ability to identify promising compounds and predict their efficacy.[12] Personalized medicine leverages AI to tailor treatments based on patient data.[13] AI's predictive capabilities aid in disease outbreak forecasting and resource allocation. AI-driven digital likeness technology may enable clinicians to scale their patient education and engagement efforts, inside and outside the clinic setting. AI can summarize or even develop scholarly research and aid in peer review.[14] These applications demonstrate AI's transformative potential for healthcare delivery and patient outcomes.

Regulation and Limited Guidance

No federal legislation explicitly limits the use of artificial intelligence (AI) and machine learning (ML), but several documents providing guidance have been presented for the general use of AI/ML. President Biden issued an Executive Order on "Safe, Secure, and Trustworthy Artificial Intelligence" which focused on creating safe and responsible uses of AI.[15] It required AI systems developers to share safety test results with the government if results showed the AI could pose a risk to national security.[15] This was immediately rescinded by President Trump with "Removing Barriers to

American Leadership in Artificial Intelligence" which revoked AI policies thought to hinder American innovation in AI.[16] It also calls for the creation of an Artificial Intelligence Action Plan to "sustain and enhance America's global AI dominance in order to promote human flourishing, economic competitiveness, and national security".[16] This highlights the dynamic nature of legislation surrounding AI based on different administrative goals. The "Blueprint for an AI Bill of Rights: Making Automated Systems Work for the American People" was published by the White House Office of Science and Technology Policy in October 2022.[17] The AI Bill of Rights comprises five principles (Table 1).

Regulation Through the Food and Drug Administration (FDA)

In 2021, the FDA issued the "Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan".[18] (Box 1). Consistent with the action plan, the FDA later issued documents on how adjustments and changes to AI/ML are made safely and effectively (Table 2). The FDA also provides a list of AI/ML-enabled medical devices marketed in the United States.

In March 2024, the FDA published the "Artificial Intelligence and Medical Products: How CBER, CDER, CDRH, and OCP are Working Together", outlining their coordinated approach to AI. Despite these documents, there remains an

Table 1 AI Bill of Rights

Principle	Brief Description
1. Safe and Effective Systems	Systems should undergo pre-deployment testing, risk identification and mitigation, and ongoing monitoring that demonstrate they are safe and effective based on their intended use, mitigation of unsafe outcomes including those beyond the intended use, and adherence to domain-specific standards.
2. Algorithmic Discrimination	Designers, developers, and deployers of automated systems should take proactive and continuous measures to protect individuals and communities from algorithmic discrimination and to use and design systems in an equitable way.
3. Data Privacy	Designers, developers, and deployers of automated systems should seek your permission and respect your decisions regarding collection, use, access, transfer, and deletion of your data in appropriate ways and to the greatest extent possible; where not possible, alternative privacy by design safeguards should be used.
4. Notice and Explanation	Designers, developers, and deployers of automated systems should provide generally accessible plain language documentation including clear descriptions of the overall system functioning and the role automation plays, notice that such systems are in use, the individual or organization responsible for the system, and explanations of outcomes that are clear, timely, and accessible.
5. Human Alternatives, Consideration, and Fallback	You should be able to opt out from automated systems in favor of a human alternative, where appropriate. You should have access to timely human consideration and remedy by a fallback and escalation process if an automated system fails, it produces an error, or you would like to appeal or contest its impacts on you.

Box 1 AI/ML SaMD Action Plan

AI/ML-Based Software as a Medical Device (SaMD) Action Plan
1. Tailored Regulatory Framework for AI/ML-based SaMD
2. Good Machine Learning Practice (GMLP)
3. Patient-Centered Approach Incorporating Transparency to Users
4. Regulatory Science Methods Related to Algorithm Bias and Robustness
5. Real-World Performance (RWP)

Table 2 FDA Documents on How AI/ML Changes Are Made

FDA Documents on ML/AI Changes
Good Machine Learning Practice for Medical Device Development: Guiding Principles (October 2021)
Marketing Submission Recommendations for a Predetermined Change Control Plan for Artificial Intelligence/Machine Learning (AI/ML)-Enabled Device Software Functions (April 2023)
Predetermined Change Control Plans for Machine Learning-Enabled Medical Devices: Guiding Principles (October 2023)

overall paucity of guidance and regulations regarding developing and deploying these technologies, specifically within the medical field.

Regulation Through The US Department of Health and Human Services (HHS)

HHS released a Strategic Plan for the Use of Artificial Intelligence in Health, Human Services, and Public Health outlining their vision to be a leader in innovating and adopting responsible AI to advance American health and well-being.[19] The framework and roadmap ensures HHS fulfills its obligation to the nation and pioneers the responsible use of AI.

The Strategic Plan is organized into seven domains, including five primary domains and two functional areas:

Primary Domains:

1. Medical Research and Discovery
2. Medical Product Development
3. Healthcare Delivery
4. Human Services Delivery
5. Public Health

Functional Areas:

1. Cybersecurity and Critical Infrastructure Protection
2. Internal Operations

Each domain chapter follows a consistent structure, discussing stakeholders, opportunities, trends, potential use cases and risks, and an action plan.

HHS supports a coordinated public-private approach to improving quality, safety, efficiency, accessibility, equitability, and outcomes in health and human services through innovative, safe, and responsible development and use of AI.[19] The plan focuses on four key goals:

1. Catalyzing health AI innovation and adoption
2. Promoting trustworthy AI development and ethical use
3. Democratizing AI technologies and resources
4. Cultivating AI-empowered workforces and organization cultures.

The Strategic Plan acknowledges both AI's potential benefits and risks in health and human services. It emphasizes the importance of responsible adoption, addressing bias, privacy, and security issues. The plan also highlights the need for collaboration among various stakeholders, including government agencies, academic institutions, industry partners, and patients, to ensure AI's successful and ethical implementation in healthcare and related fields. ASPN endorses this strategic vision, and this Neuron Project provides the first societal framework to support its adoption.

Methods

The American Society of Pain and Neuroscience (ASPN) established a multidisciplinary panel to develop expert consensus on the application of artificial intelligence (AI) within pain management. This panel consisted of leading pain medicine physicians, anesthesiologists, physical medicine and rehabilitation physicians, and neurosurgeons, augmented by promising residents and fellows with significant interest in the field. Critical focus areas were identified and subsequently refined by the lead and senior authors, alongside a group of section editors. Authors were then organized into teams to conduct comprehensive literature reviews and develop their respective sections. To ensure impartiality, all authors disclosed financial conflicts of interest and were required to recuse themselves from any discussions or content related to their competing interests. In instances where a conflicted author possessed unique expertise in a specific area, a non-conflicted author assumed the ultimate editorial oversight for the submitted material.

The main objective of the panel was to create a systematic guideline process to outline the current literature on artificial intelligence (AI) in relation to the practice of pain medicine. This paper provides a primer on AI to the pain practitioner to help them understand AI to utilize in their practice. A literature search was conducted using PubMed to evaluate the current literature regarding AI relevant to pain practitioners. Search terms included key words such as "pain", "pain medicine", "pain management", "analgesia", "opioid", and other relevant terms cross-referenced with "artificial intelligence", "machine learning", "deep learning", and "neural network". Two reviewers screened results to remove articles that were not relevant to our review. For example, articles discussing AI that were not primarily focused on pain management and vice versa. A deep dive into the literature to evaluate the quality of presented evidence was not performed, as it was deemed outside the scope of this paper. Broad categories of articles were created using the available data and reference papers, broad categories of articles were created. These categories give a general idea of the goals and use cases for articles discussing AI in pain management.

With these broad categories in mind, senior reviewers met and discussed important aspects of AI that practitioners must understand before implementing AI in clinical practice. These aspects include understanding the potential benefits of AI, the potential harms of AI, and how to ensure the benefits of AI outweigh the risks. With these aspects clearly defined, authors were divided into groups, and another literature search was conducted to review the current literature regarding the benefits and harms of AI. Authors utilized their literature searches to complete each section within the framework.

The guideline development process commenced with section editors and lead authors collaboratively outlining key principles for each focus area. An initial comprehensive draft of guidelines was then consolidated, with lead and senior authors integrating analogous themes and eliminating redundant content. This list of candidate guidelines underwent an iterative, multi-cycle refinement process by the entire author group, leading to a streamlined, heavily edited collection of guidelines that had reached a convergence of shared expert opinion. The final, votable guideline list was subsequently distributed for unanimous approval from all contributing authors.

Results

Over the past 20 years, the number of publications regarding AI has increased exponentially. Searching "artificial intelligence" in PubMed before 2000 produces just over 3000 results. From 2021 until the time of writing, over 71,000 articles have been published discussing artificial intelligence (Table 3). We found over 12,000 articles pertinent to pain

Table 3 Number of PubMed Search Results for "Artificial Intelligence" (as of Oct 30, 2024)

Prior to 2000	3069
2001-2010	13,305
2011-2020	21,211
2021-Present	71,835

 https://doi.org/10.2147/JPR.S529465

management and artificial intelligence using our search terms. Most articles about chronic pain and artificial intelligence were not clinical studies but are reviews offering guidance to clinicians.[20–22] The remaining articles cover broad topics in pain management, utilizing AI to improve the field. Major topic categories include aiding in the diagnosis of pain, monitoring, management, outcomes, and enhancing research capabilities.

We found no significant articles offering broad understanding and guidelines applying artificial intelligence in pain medicine. This paper fills those gaps and gives the clinician the tools to understand and use AI in their daily practice.

The AI healthcare market has experienced explosive growth in recent years, with projections indicating continued rapid expansion. According to a recent report, the global AI in Healthcare market was valued at USD 20.9 billion in 2024 and is estimated to reach USD 148.4 billion by 2029. This represents a compound annual growth rate (CAGR) of over 38% during the forecast period.

Key factors driving this remarkable growth include:

- Increasing adoption of AI technologies in medical imaging, diagnostics, and drug discovery
- Rising demand for personalized medicine and improved patient outcomes
- Growing investments in AI healthcare startups and research initiatives
- Advancements in machine learning algorithms and computing power
- Expanding applications in telemedicine and remote patient monitoring.

While estimates vary slightly between sources, the consensus points to a market poised for significant expansion. One report projects AI in the healthcare market to surpass USD 187.95 billion by 2030, highlighting the immense potential for AI to revolutionize healthcare delivery and management in the coming years.[23–25]

Conclusions/Recommendations/Consensus Guidelines for AI in Pain Medicine

Benefits of Artificial Intelligence - Enhancing Healthcare

AI in Diagnosis and Treatment Planning

Treatment Algorithms and Patient Selection

Common healthcare professional challenges include accurate identification of patients benefiting from a specific therapy and the time required to review a patient's history. Specific time constraints or unfamiliarity with interpreting different image modalities can lead to an over reliance on radiology reports, which may not discuss crucial pathologies relevant to chronic disease states that have established FDA-approved treatments. Additionally, administrative and payor-related regulations can lead to unsuccessful authorization of beneficial therapies.

Artificial Intelligence (AI) and Machine Learning (ML) technologies evolve and "learn" through data feeding, a process that allows models to update and refine their algorithms, leading to more accurate and effective learning over time. When used as a support tool, these technologies help implement personalized treatment algorithms based on different types of variables within those data flows. Examples include genetic variants, patient history, relevant physical exams, imaging analysis, ICD codes, labs, and medication regimens. This feature not only has the potential to engender more appropriate patient management but also liberate clinicians' time, allowing for enhanced patient care.[26]

Given the significant promise of these technologies, several companies have focused on building machine learning into medical decision making. They are creating tools to support clinicians, as well as algorithms designed to function independently of them.

Medical Imaging Interpretation

One of the most promising applications of ML within healthcare is in the field of radiology. For instance, ML has been successfully used to detect and predict lung malignancy in 8000 cases, outperforming non-thoracic radiologists.[27] Artificial Intelligence (AI) algorithms, especially those based on deep learning, can analyze complex medical images, identify patterns invisible to the human eye, and provide accurate diagnoses. This significantly enhances the efficiency

 https://doi.org/10.2147/JPR.S529465

and accuracy of medical imaging interpretation, reducing the workload of clinicians interpreting various imaging modalities, while potentially improving patient outcomes. ML can substantially enhance the radiology workflow when combined with Electronic Health Records (EHRs) and clinical decision-making processes. It could potentially automate dose estimation, improve examination quality control, and expedite the turnaround for radiographic images and interpretation.[28] This would boost efficiency and enhance precision in identifying pertinent positive findings.

With the advent of digitized images and the availability of massive imaging datasets, coupled with advancements in computer vision, machine learning performance is anticipated to surpass human accuracy.[29] These algorithms are not subject to fatigue, and model accuracy continues to improve as these algorithms are fed with uninterrupted data.

These algorithms could also be particularly beneficial in medical imaging interpretation for preoperative and intraoperative planning. For example, in a sacroiliac joint fusion, massive datasets can analyze multiple anatomic variables simultaneously to determine the precise positioning for the implantation of allograft or titanium screws. Based on treatment success variables, postoperative imaging model datasets can also enhance implant positioning.

Improving Treatment Equity

Not all treatment plans are created equally, with disparities in treatment quality that can be attributed to various factors such as clinician inexperience, patient selection challenges, issues with workflow algorithms, or implicit bias. Implicit biases are subconscious prejudices that can be difficult to recognize and standardize against. They contribute to disparities in health care access, quality of care, and overall health outcomes.[30]

Given that ML models are fundamentally data-driven, model design may incorporate these biases and should thus be scrutinized for their presence. To counter such biases, data for algorithms should be balanced and acquired from a wide range of diverse populations to reduce health care disparities and improve patient outcomes.[31]

Prediction of Outcomes

ML applications have demonstrated effectiveness in disease prediction utilizing diverse data types, medical imaging, and clinical outcome prediction.[32–34] These sophisticated technologies can process and analyze vast amounts of data, identifying patterns and making remarkable predictions. This predictive power can significantly influence medicine and clinical decision-making processes.[35] By offering insights into the success rates of different treatment types, ML applications may assist doctors in determining the most effective treatment plan. For patients, especially those faced with various treatment options, these evidence-informed data points are critical to provide a reasonable estimate of success, enabling patients to make more informed and confident decisions about their health.

Staying Up to Date with Current Literature

In the rapidly evolving landscape of medicine, the immense complexity of emerging therapies demands a solution to comprehend better the volume of evidence generated daily. The surge in data-driven treatment solutions necessitates integrating incorporating AI more than ever. AI plays a pivotal role in various aspects of healthcare, particularly in diagnosis and treatment recommendations. These are primarily based on a comprehensive review of the latest literature. AI tools that process and interpret vast amounts of data will offer invaluable service in summarizing published studies by learning from patterns and adapting based on feedback.

ML excels in managing many predictors, often surpassing the number of observations and amalgamating them in nonlinear and highly interactive ways. This capability enables us to utilize new data types, the volume or complexity of which would have previously rendered them unmanageable for analysis.[36] The learning component of these systems is critical as they can be trained to continually enhance their diagnostic precision and clinical decision-making recommendations aligned with the most recent data.

Treatment and Treatment Optimization

Electrical Delivery Individualized

For spinal cord stimulation, clinicians currently collaborate with device specialists to adjust parameters such as waveform, frequency, amplitude, and others to tailor electrical flows in stimulation. This practice inherently leads to variability between the programming of these parameters without a mechanism to reliably determine the optimal stimulation settings for every component. The use of AI/ML in spinal cord stimulation presents a significant opportunity to refine practice among the increasing numbers of SCS implants annually.[37] One of the most common medical applications of AI/ML is neural network "learning" (ie, being trained) by processing examples containing "inputs" and "results".[38] When considering its application in SCS, inputs may include stimulation parameters, patient data (age, sex, BMI, comorbidities, spinal anatomy), diagnosis, and pain pattern. Results may include longitudinal outcomes such as pain scores and patient-reported outcome measures (PROMs). Ultimately, such use of AI/ML would predict and inform optimal settings for the delivery of stimulation for each individual patient, minimizing variability in current practice.

Medication Delivery Individualized

Similar limitations exist in medication delivery for pain management. The trialing and titrating of medications varies from clinician to clinician, and may lead to delayed progress, excess burden on healthcare systems, side effects, and inferior outcomes. Using of AI/ML to process existing data (inputs and results) may predict optimal medication(s) and dose for each specific patient and calculate the risk of side effects, misuse, and inefficacy. High-quality, high-volume data would allow for incremental learning and refinement of such computational algorithms to drive improved patient outcomes.[38]

Virtual Reality

Virtual, augmented, and mixed reality have several applications in interventional and surgical specialties.[39] One application is their use in training. Some interventional pain management fellowships may not provide adequate exposure to neuromodulation and advanced innovative procedures in the field.[40] These technologies allow trainees to interact with a virtual or mixed environment to practice operative techniques and sharpen interventional skills, improving accuracy, faster operative time, and reducing complication rates.[39] Another application of these technologies is their intraoperative use. AR/MR projects graphics onto real-world surfaces for enhanced intraoperative guidance. With the use of patient preoperative imaging, these technologies have been shown to assist in the precise placement of percutaneous sacroiliac joint screws, reduce fluoroscopy and operative time, as well as facilitate accurate spinal instrumentation.[39,41,42] As the footprint of sacroiliac joint fusion/stabilization, interspinous process devices, and spinal arthrodesis expands in interventional pain management, the application of AR/MR intraoperatively with VR presents an opportunity to improve techniques, outcomes, and patient safety.

Identification of Complications

The use of AI-driven models to predict and identify complications also has growing use-cases and substantial promise. For example, an AI model trained on the data of 3034 patients and 35 unique input variables to predict surgical site infection after posterior spinal fusion had a positive predictive value of 92.6%.[43] Applying AI to predict complications after endovascular aneurysm repair led to a model with 100% sensitivity for post-operative complications.[43] Such use can readily apply to interventional pain management, where patient data and inputs may be utilized to create similar predictive models for post-operative complications such as infection, lead migration, wound dehiscence, and other significant outcomes. Higher-risk patients could then be considered for closer postoperative surveillance, thus avoiding potential delays in care. Furthermore, advancements in patient-wearable devices may help provide AI models with key inputs to identify complications such as lead migration, lead fracture, or implantable pulse generator (IPG) failure in real-time. Patient-wearable data may provide input variables for AI models targeting activity, steps, and heart rate.[44] AI/ML could then synthesize the complex relationships in changes and variations between such inputs and others over time to create a model for real-time complication detection.

Injections

Integrating AI/ML with fluoroscopy also presents several opportunities for optimizing injection-based interventions. The potential reduction in radiation exposure has been highlighted in several studies.[45–47] For example, in a study comparing

AI-equipped fluoroscopy with conventional fluoroscopy in endoscopy, AI-enabled fluoroscopy significantly decreased radiation exposure by using ultrafast collimation targeting the area of interest.[46] In oncology and pathology, deep learning analysis of the critical features of disease in imaging has accelerated more accurate and earlier detection of cancers.[48,49] Incorporating such deep learning with AI-enabled fluoroscopy systems in interventional pain management has many potential applications. This includes real-time detection and confirmation of contrast spread in the intended treatment area during an injection and high-sensitivity detection of unwanted spread (ie intravascular, intrathecal). In this manner, utilization of AI can optimize outcomes and safety with fluoroscopy-based treatments.

Safety

AI and Opioid Safety

For opioid management, Large Language Models (LLMs) may efficiently synthesize and retrieve information from an expansive corpus of medical literature, clinical guidelines, and patient records, contributing to better decision-making. With more optimized opioid dosing and therapeutic outcomes, opioid-associated risks including abuse and overdose can be better mitigated to deliver safer, more effective care.[50]

Patient education is critical to safe opioid use. AI chatbots educating patients with materials tailored to their specific needs may reduce opioid use post-operatively and increase patient satisfaction. Applications of AI chatbots have already augmented the patient experience while maximizing provider time.[51] Several studies have examined LLM application in post operative pain and demonstrated positive outcomes in opioid-related adverse events.[51] These applications are useful for practitioners without specialized training who manage post operative pain. Additionally, these models are being used in opioid abuse treatment and show promise in predicting retention with treatment.[52]

For opioids, wearable technologies providing biometric data interpreted by AI can now use cardiac and respiratory sensors to assess opioid use, overuse, and overdose, including designs with a naloxone auto-injector.[53] While still early in development, LLM applications with real-time biometric responses to pain medications and/or interventions have the potential to fundamentally alter opioid safety in both acute and chronic pain settings.

Patient Engagement

Workflow Efficiency

Pain management clinicians frequently grapple with time-consuming administrative tasks, including documentation in EMRs and ensuring accurate coding for billing purposes. These challenges impede workflow efficiency and have financial implications for healthcare organizations. Integrating AI technologies offers promising solutions to address these challenges, enabling clinicians to devote more time to patient care while optimizing practice management processes.[54]

AI integration with EMRs holds immense potential in streamlining workflow processes for pain management clinicians. Natural Language Processing (NLP) algorithms can automate the documentation process by extracting relevant information from clinical notes, reducing the time spent on manual data entry. Furthermore, AI-powered decision support systems can analyze patient data in real-time, providing clinicians with actionable insights and personalized treatment recommendations. By automating repetitive tasks and offering intelligent decision support, AI integration enhances workflow efficiency, allowing clinicians to focus on delivering high-quality patient care.[55]

Improving Coding Accuracy with AI-Assisted CPT Coding

Accurate coding is crucial for pain management practices to ensure proper reimbursement and compliance with regulatory requirements. However, the complexity of CPT coding often leads to errors and inconsistencies, resulting in revenue loss and compliance risks. AI-assisted CPT coding tools leverage machine learning algorithms to analyze clinical documentation and recommend appropriate codes based on the procedures performed and the documentation provided. These tools improve coding accuracy and facilitate compliance with billing regulations, reducing the risk of audits and revenue loss.

Research

Large language models (LLM) have been suggested to aid in clinical research.[56] LLM-based chatbots can assist with preliminary research design, including providing an overview of the evidence, defining a research question and hypothesis, and calculating the needed sample size for a powered study. During the clinical trial, LLM chatbots may assist with patient-trial matching, coding free-text narratives, and detecting cognizant consent. Following data collection completion, LLMs may even execute statistical analysis of data and technical writing of the manuscript. However, it is essential to note, that despite the LLM providing answers or solutions to these research tasks, this does not necessarily mean the answer is correct or appropriately conducted. Thus, at present, chatbots do not replace scientific training and experience but rather should be regarded, at most, as a starting point that requires validation.[57]

Optimize Healthcare Administration

Pain management clinicians face unique challenges in healthcare administration, including navigating prior authorizations, optimizing scheduling, and promoting their services effectively in competitive markets. Inefficient administrative processes can result in delays, increased costs, and reduced patient satisfaction. Consequently, there is a growing need to explore innovative strategies for optimizing healthcare administration in pain management settings.

Optimization of Prior Authorizations

Prior authorizations are often required for medications, procedures, and therapies in pain management practices, adding administrative complexity and delaying patient care. Implementing electronic prior authorization (ePA) solutions and utilizing AI-powered tools can streamline the authorization process, reduce paperwork, and expedite approvals. By integrating ePA systems with electronic health records (EHRs) and leveraging AI algorithms to predict authorization requirements, pain management clinicians can minimize administrative burdens and enhance patient access to timely treatments.[58]

Streamlining Scheduling Processes

Efficient scheduling is crucial for optimizing patient flow, minimizing wait times, and maximizing resource utilization in pain management clinics. Utilizing scheduling software with customizable features, automated appointment reminders, and real-time patient tracking capabilities can improve scheduling efficiency and patient satisfaction. Moreover, implementing telemedicine options for follow-up appointments and leveraging patient portals for self-scheduling can further streamline the scheduling process, offering convenience and flexibility to patients while reducing administrative overhead for clinicians.[59]

Effective Marketing Strategies

Artificial Intelligence holds immense potential to transform marketing strategy development in pain management practices, enabling personalized patient engagement, targeted outreach, and service optimization. By harnessing AI-driven insights, practices can enhance patient satisfaction, loyalty, and outcomes while optimizing resource allocation and revenue generation. However, addressing data privacy, interpretability, and ethical use challenges is crucial for successfully integrating of AI into pain management marketing strategies. Nonetheless, the opportunities presented by AI offer a pathway to more effective and patient-centric pain management practices in the digital age.

New Drug Product Development

Regarding basic and translational science, LLM may accelerate drug discovery by predicting the structural target, location of binding, pharmacodynamic properties, pharmacokinetic properties and dosages associated with therapeutic benefit versus toxicity.[60] Once the medication is developed, clinicians and patients can use LLM to identify drug-drug interactions[60] and more rapidly advance through the phases of clinical trials. Several biomedical companies are already employing LLM in product development.[60]

Potential Harms of AI

Artificial intelligence has amassed significant attention and excitement due to its potential applications in enhancing the medical community and optimizing healthcare for both clinicians and patients. However, we must consider potential pitfalls, harms, and limitations in leveraging AI. By acknowledging these challenges, we can ensure that AI is used safely, meaningfully, and equitably while preserving the integrity and humanity of healthcare delivery. This section examines potential concerns regarding the use of AI in medicine:

Hallucinations/Errors

One inherent risk associated with AI is the possibility of generating hallucinations or errors in data processing. AI algorithms, particularly machine learning models, rely heavily on data input for training and decision-making. The quality of AI output is contingent upon the quality and comprehensiveness of the data used to train the model. Machine learning algorithms are therefore only as proficient as the data they are exposed to. This raises the concern for bias, reporting inaccuracies, and data inadequacies. One example is IBM's Watson supercomputer, aka Watson, which uses AI algorithms to generate treatment recommendations for cancer patients. However, the data used to create Watson was based on a few hypothetical cases with oncologist input. Recommendations made by Watson were sometimes erroneous and had the potential to harm a patient if executed.[61]

AI tends to fabricate or extrapolate data to fill in gaps in existing knowledge. This is known as data hallucination. Data hallucination can lead to erroneous conclusions, particularly if not reviewed for accuracy. AI has also been known to fabricate references that do not exist. For instance, Alkaissi & McFarlane utilized ChatGPT to generate a paragraph on homocysteine-induced osteoporosis.[62] While the AI generated an articulate and seemingly well-rounded discussion on the topic, a closer review revealed inaccuracies in some conclusions. Further, when asked to provide references to support the AI-generated content, ChatGPT supplied citations that did not exist, with PubMed IDs corresponding to unrelated papers.[62]

Such hallucinations and errors in AI can propagate misinformation and false assumptions, ultimately compromising patient care and the integrity of scientific knowledge.

Over-Reliance on AI

Another significant concern surrounding AI is over-reliance on automated systems which can have far-reaching consequences. In medicine, diagnoses are often complex and not black and white, usually requiring deductive reasoning and experience to delineate. For instance, two patients with the same type of pain may describe it very differently as pain perception of pain is colored by many components including cultural and emotional dimensions. It is unclear how AI will account for these more subjective elements.

Over-reliance on AI can also lead to diminished patient-clinician relationships as reduced human interaction can cause patients to feel alienated. Wu et al, conducted over 3000 patient surveys and found that the perception of clinician empathy and trust in the clinician's benevolence significantly influenced the patient's evaluation of the patient-clinician relationship.[63] Trust, communication, and empathy are cornerstones in medicine and cannot be diminished in delivering compassionate, patient-centered care.

Studies regarding applications of artificial intelligence in medicine are difficult to regulate due to the complexity of the data. Additionally, with the increasing popularity of generative AI to write scientific narratives, properly evaluating presented data is more critical than ever. A study using deep learning to improve the diagnosis of spinal foraminal stenosis has been retracted for discrepancies in scope, data, and inappropriate citations.[64]

Another concern is inequitable resource allocation. Vulnerable populations with low technological literacy or socio-economic status may face barriers to accessing AI-driven healthcare services. These innovative services may disproportionately be utilized amongst privileged groups, widening health inequity.[65]

Ethical Considerations

Determining accountability becomes paramount when considering failures within AI and ML systems, posing a significant ethical quandary. China and Hong Kong's prohibition of AI in medical decision-making underscores the urgency of addressing accountability. The absence of universal guidelines in healthcare AI usage fosters moral and ethical debates, prompting ongoing research by organizations like the FDA and NHS to establish standards. However, regulatory approval and legal frameworks for AI and ML actions remain challenging for authorities and courts.[66]

Model Bias

Bias within the medical realm can be analyzed from three perspectives: data-driven, algorithmic, and human biases. In healthcare AI, such biases can have a negative impact by perpetuating societal prejudices ingrained within datasets. Consequently, patient groups historically underrepresented, such as gender and ethnic minorities, risk misdiagnosis, exacerbating existing disparities.

Future endeavors should prioritize establishing AI standards in healthcare that prioritize transparency and data sharing, all while safeguarding patient privacy. Adopting open science methodologies can promote fairness in healthcare AI. These encompass: (1) involving participants in AI algorithm development and embracing participatory science; (2) promoting responsible data sharing and inclusive data standards to ensure interoperability; and (3) facilitating code sharing, including algorithms capable of synthesizing underrepresented data to mitigate bias.[67]

Data Privacy

One inherent concern with AI and healthcare is the large amount of sensitive data required for AI models to analyze patient data and potentially predict treatment outcomes effectively. The inherent complexity of medical reasoning and the underlying heterogeneity of datasets necessitates extensive data sets to build reliable models. The challenge with AI in healthcare is related to acquiring a large dataset, and more importantly, to the sensitive nature of this data. AI requires access to sensitive electronic medical records, imaging scans, laboratory results, and other personal data to generate recommendations. Laws to protect patient confidentiality such as HIPAA, have been in effect for nearly three decades. However, these laws were enacted long before the advent of AI in modern-day healthcare. Conflict over ownership of health data has also emerged with AI, where patients are thought to deserve to own and control their own data, but often other members of the healthcare and AI systems make claims for control of the information.[68]

The concern is ensuring integrity and patient confidentiality are maintained using AI models. This was also a concern during the transition from paper charts to electronic health records (EHR). Although EHRs have undoubtedly revolutionized healthcare in many ways, the electronic nature of these records makes them susceptible to significant breaches. A 2020 US Department of Health and Human Services report states that approximately 578 healthcare institutions experienced data breaches, impacting over 41 million individuals.[69] One study suggested that up to half of the US population may have had their medical records compromised.[70] The concern is even more amplified when appreciating that this same vulnerable data may need to be moved into other storage environments and aggregated across multiple institutions to reach the necessary scale. Larger datasets represent an enormous trophy for bad actors.

Another potential harm of AI in healthcare is the lack of transparency concerning acquisition, distribution, usage and interpretation of data. The "black box" phenomenon is a well-documented criticism of AI models. Artificial intelligence's inability to explain or justify its complex conclusions can add unwanted ambiguity to an already sensitive matter: a patient's health. As clinicians, we need to know not just the "what" but also the "why" and "how", which can be difficult to ascertain at times with this type of technology. Additionally, data that is too much for a non-AI model might be too little for a specific AI algorithm. Therefore, building a comprehensible explanation of an AI model is often impossible. There is growing work in "E xplainable AI", which is a technique to help humans understand and trust AI systems s. Finally, although there remains a push towards an increase in regulatory oversight on AI data distribution, the rapid advancement of AI has thus far outpaced most regulatory bodies, adding another layer of unclarity of how sensitive patient data is being distributed. There remains a need for large-scale global initiatives that help standardize the laws governing patient data distribution in healthcare-related AI systems.

Limitations to Data in Healthcare

Although healthcare data is rapidly growing and becoming more accessible, it still lags the massive scale of big data available outside the healthcare industry. Accuracy is essential for big data analytics. There have been some limitations due to issues with data collection. For example, personal records may contain typing errors or abbreviations. Medical data input placed by a medical assistant may contain errors or misspellings that alter meaning. There may also be an underrepresentation of groups in health care data due to issues such as literacy and language barriers, resulting in data sets that may not be representative.

 https://doi.org/10.2147/JPR.S529465

There are many economic challenges in collecting big data as well. Smaller healthcare enterprises are poorly equipped to modernize data collection systems. Most healthcare organizations are highly fragmented, preventing universal data collection. Security and privacy issues pose another. Finally, bureaucratic limitations, heavy regulation, and security concerns limit data aggregation and availability.

Legal Challenges to AI Use

Copyright Infringement. With the rapid evolution of AI in medicine, we must understand the current copyright laws in place to protect both creators and their creations. In the United States, copyright law grants the creator ownership of the work. Copyright protection supports the original works of authorship fixed in a tangible medium of expression.[71] One of the exceptions to copyright protection is fair use, which allows a creation to be used without notifying or getting permission from the author for criticism, commentary, news reporting, teaching, scholarship, or research purposes.[72] The Copyright Act of 1976 gives ownership to the natural person or persons who created the work unless created within the scope of work or person(s) or as "work made for hire". This is defined as "a work specially ordered or commissioned for use as a contribution to a collective work, as part of a motion picture or other audiovisual work, as a translation, as a supplementary work, as a compilation, as an instructional text, as a test, as answer material for a test, or as an atlas".[73] It is essential to know that there is a significant exception to this general rule found in Section 201 (b) of the Copyright Act. This states "in the case of a work made for hire, the employer or other person for whom the work was prepared is considered the author for purposes of this title, and, unless the parties have expressly agreed otherwise in a written instrument signed by them, owns all the rights comprised in the copyright". To summarize, the employer owns the copyright of a creation that is AI generated content made at work or under "work made for hire". This leads to the question of who owns AI-generated content when an AI system autonomously generates it without direct human input. Some jurisdictions may consider the AI system developer as the owner, while others may consider the AI system itself or the user of the AI system the owner.[74] There have been several cases in the United States where AI systems were used as joint authors of a work under US law. One case in the Southern District of New York declared that only a natural person can be the inventor.[74] We must also consider copyright protection of original work. This depends on various factors, including the degree of human involvement in the creation process. In March of 2023, a notice of proposed rulemaking was published that allowed works containing AI-generated material to be eligible for registration under specific circumstances.[74] The United States Copyright Office has declared that a human author must produce copyright material. Therefore, any material created by AI is, by definition, uncopyrightable because it does not require human creativity.[75]

Because AI models require the consumption of large quantities of data, copyright infringement issues come to the forefront when training large systems with inputs that the AI developer does not directly own. This has been well publicized in the case of Meta allegedly downloading over 80 terabytes of copyrighted materials such as books and textbooks, to train their LLaMa AI.[76] Employees even had extensive discussion questioning whether this was legal.

As medical implementations of AI move forward, these types of concerns regarding the underlying datasets that power models will quickly become relevant. There are certainly arguments to be made that transparency as to the entirety of inputted works and their provenance will instill greater confidence in utilizing AI models within healthcare. Furthermore, they will allow outsiders to assess flaws with the underlying knowledge set or risk for bias.

Lack of Oversight

Oversight in AI Use in Pain Medicine. Artificial intelligence (AI) has been rapidly integrated into various fields of medicine, including pain management, promising significant advancements in diagnostics, treatment personalization, and patient monitoring. However, the pace of AI development and implementation has often outstripped the ability of regulatory frameworks to keep up, resulting in limited oversight. This gap poses potential risks, including biases in AI algorithms, privacy concerns, and the unintended consequences of AI-driven decisions on patient care.

Current oversight mechanisms for AI in pain medicine primarily revolve around existing medical device regulations and healthcare data privacy laws. In the United States, the Food and Drug Administration (FDA) has started to develop frameworks specifically for AI and machine learning (ML) in healthcare. The FDA's Digital Health Innovation Action Plan outlines the agency's approach to fostering innovation while ensuring patient safety.[77] This includes a proposed regulatory framework for AI/ML-based Software as a Medical Device (SaMD), emphasizing the need for continuous learning and adaptation of AI systems while maintaining rigorous safety and effectiveness standards.[77] However, the oversight remains fragmented and often reactive rather than proactive. The approval process for AI tools is not always transparent, and there is a lack of standardized methods for evaluating AI's performance in real-world clinical settings.[77] Moreover, many AI applications in pain medicine are not strictly regulated as medical devices, such as decision support tools or predictive analytics platforms, which can fall through the regulatory cracks.[78]

Future Regulatory Issues in AI Use in Pain Medicine. Integrating AI into pain medicine holds immense promise but also presents significant challenges. Limited oversight, rapid expansion, and potential unintended consequences highlight the urgent need for robust regulatory frameworks that can keep pace with technological advancements. By addressing critical issues proactively, the medical community can harness the benefits of AI while safeguarding patient safety and equity. One major challenge is the establishment of comprehensive guidelines for AI development, validation, and deployment. This includes creating standardized evaluation metrics that reflect real-world clinical outcomes and integrating continuous post-market surveillance to monitor AI performance over time.[79] Another significant regulatory issue is addressing biases in AI algorithms. Training on biased data may perpetuate healthcare disparities. Therefore, regulations must require transparency in AI training data and enforce bias mitigation and fairness standards. Additionally, there is a need for clear accountability structures to address adverse outcomes resulting from AI-driven decisions.[80] Data privacy and security also remain paramount. With AI systems often requiring vast amounts of patient data, robust data protection regulations must be enforced to safeguard sensitive information and maintain patient consent and autonomy.[26]

AI can significantly enhance diagnostic accuracy, treatment personalization, and patient outcomes. However, errors or biases in AI algorithms can lead to incorrect diagnoses or inappropriate treatment recommendations, potentially causing harm to patients. Additionally, If the pace of innovation outstrips the development of regulatory and oversight mechanisms, treatment gaps could jeopardize patient safety and trust.[81,82] Moreover, integrating AI can alter the doctor-patient relationship, as patients may feel alienated by the increasing reliance on technology over human judgment. This could affect patient satisfaction and adherence to treatment plans. Regulatory bodies must, therefore, adapt to the fast-evolving landscape by implementing agile and iterative regulatory processes. This may include environments where AI tools can be tested in real-world settings under regulatory supervision, enabling quicker identification and mitigation of risks.[83]

Rapid Expansion

The last few years have seen an unprecedented growth and expansion of AI systems which has significantly outpaced most modes of regulatory oversight.[83] Regulation and supervision of AI remains challenging for lawmakers and governing bodies. AI's dynamic nature not only makes it highly sought after, but it also makes it difficult to regulate. Regulatory frameworks must incorporate mechanisms to identify and address potential consequences, ensuring that AI enhances rather than detracts from the quality of care. The constantly evolving nature of AI creates an obvious predicament for regulatory bodies such as the Food and Drug Administration (FDA). In a statement, former FDA Commissioner Robert Califf indicated that they would need another "doubling of size" if they were tasked to provide regulatory oversight for AI systems.[84] Consequently, Califf and other lawmakers have proposed involving public-private entities such as universities as the authority to oversee this technology. However, the concern with this proposed model is that what works for a rural university may not be the ideal AI system for an urban university. Henceforth, we are left with a technology that continues to expand rapidly and outpace the development of regulatory methods applied to other traditional healthcare technologies within our institutions.

Ensuring Benefits Outweigh Harms in Using AI in Healthcare

Integrating Artificial Intelligence (AI) into healthcare and medicine offers immense potential benefits. However, to ensure these benefits outweigh potential drawbacks, a multifaceted approach is essential, addressing various ethical, technical, and regulatory considerations.[85]

 https://doi.org/10.2147/JPR.S529465

Establishing Ethical Guidelines and Regulatory Frameworks

As a top priority, establishing clear ethical guidelines and regulatory frameworks is crucial to govern the development, deployment, and use of AI technologies in healthcare.[86] These guidelines should prioritize patient safety and privacy while ensuring transparency, fairness, and accountability in AI-driven decision-making processes and applications.[86] Ethical guidelines must address issues such as informed consent, where patients should know that AI is being used in their care and understand the implications.[87]

Ensuring Explainability and Transparency

It is vitally important that AI models are explainable and transparent in their decision-making processes and the data they use. This will increase trust and facilitate collaboration between machines and humans. Doctors and healthcare workers must understand how AI arrives at its conclusions to ensure the correct datasets are used. Faulty data can lead to incorrect outcomes, and a lack of transparency would prevent the identification and prevention of such outcomes. Data governance and monitoring are crucial to avoid harm from AI applications.[88] Ensuring patient data is confidential and safe should be a top priority, and the highest quality data must be used in AI models to genuinely contribute to healthcare professionals' work without increasing potential harm.

Access and Expertise

Access to AI resources should be closely monitored and restricted to qualified individuals with proper medical knowledge.[89] High quality data must be fed to AI systems and healthcare professionals should be adequately trained to use AI tools. Without the necessary expertise, the use of AI resources and the data they generate could compromise the overall reliability of AI-powered tools in medicine. Additionally, AI systems should have safeguards to prevent data biases that could lead to erroneous decision-making.[89] Distortion of a patient's healthcare plan due to recommendations based on faulty data could be detrimental. Future education should include AI into medical training programs and provide ongoing professional development opportunities.[90]

Interdisciplinary Collaboration

Interdisciplinary collaboration is critical for realizing the full potential of AI in medicine. By bringing together healthcare professionals, AI researchers, ethicists, and policymakers, potential risks and challenges associated with AI in healthcare can be identified and addressed while maximizing its benefits. Such collaboration can foster innovation, facilitate knowledge exchange, and ensure AI technologies are developed and deployed in ways that align with the values and goals of healthcare delivery. Collaborative efforts can also lead to developing standards and best practices for AI in healthcare, ensuring consistency and reliability across different applications and institutions.

Continuous Monitoring and Evaluation

Establishing a continuous monitoring system for AI algorithms and their outcomes is crucial for maintaining confidence and trust in AI systems and protecting patients from harm.[91] This governance system ensures the promise of improving patient outcomes and quality of life by continuously monitoring and evaluating AI technologies. Monitoring should include regular audits of AI systems to ensure they remain compliant with ethical standards and regulatory requirements. Feedback loops will allow healthcare professionals and patients to report issues and suggest improvements. Real-time monitoring systems can also be employed to detect and mitigate any adverse effects promptly.[91]

The potential of AI technology in medicine is vast. It is a tool that can assist in every healthcare niche. Still, we must ensure it is applied as intended: to help human beings, regardless of social, economic, racial, or other differences. By carefully considering ethical guidelines, transparency, interdisciplinary collaboration, and continuous monitoring, AI can significantly contribute to advancing healthcare and medicine.

Discussion

The Expert Consensus Guidelines were created from our expert panel using the information obtained in our literature review (Table 4). They are designed to evolve with the rising popularity of Artificial Intelligence (AI) and subsequent rapid growth. Because artificial intelligence in pain medicine is relatively new, and due to a lack of adequate randomized control trials, these guidelines are based on expert consensus rather than current evidence. With the tools provided in this article, we hope that more AI studies and trials will be performed to improve pain management. The scope of AI in healthcare is broad and far-reaching and will eventually encompass all aspects of patient care, including charting, diagnosing, and managing treatment. Healthcare practitioners need to have a basic understanding of AI and Machine

Table 4 Best Practice Guidelines: Expert Consensus Statements

Development & Implementation		
1	Clinicians must be able to understand high level AI fundamentals so they can better understand the capabilities and limitations of such systems and leverage them appropriately in their practice.	A deeper understanding of AI fundamentals will allow clinicians to assess and select appropriate tools and gain a better understanding of how the data they generate influences these models. This understanding may translate into better design of clinician-facing workflows to facilitate higher quality data input.
Clinical Use		
2	Clinician-facing AI programs should always be designed with clinician input.	The power of AI lies in its ability to enhance and supplement clinician workflow. The best way to achieve this goal is by integration of experienced clinicians during the development of these applications.
3	AI used in pain medicine should judiciously employ data to enhance the ability of the pain clinician, APPs, and clinical staff to provide efficient and safe care.	The increase of technologies used in medicine today including EMR, PACS, wearables, and other digital tools, can result in overburdening of the clinician with overwhelming amounts of data to review. AI should be utilized to analyze and streamline the output of large data for clinicians. It is imperative that any application or device that utilizes AI consider the potential burden on the clinician, and ensure that it enhances, rather than hinders, his or her ability to provide efficient and safe care.
Data Management		
4	AI programs should be HIPPA compliant and have adequate safeguards in place to prevent breach of patient privacy.	Robust legal frameworks must clearly define accountability for adverse outcomes resulting from AI-driven decisions, ensuring fair allocation of responsibility among clinicians, developers, and manufacturers. Any application that utilizes AI must have proper safeguards in place to ensure the safety of patients' sensitive healthcare data. Model training should not permit retention of protected health data that could be exposed by subsequent queries.
5	Data collection and storage should be standardized to be able to be used across platforms	AI is dependent on having access to large amounts of data to build underlying models and maintain learning. It is important that the data is created and stored in a uniform manner that permits merging at a higher level, potentially using deidentified multicenter data.
Quality Assurance, Regulatory Compliance & Transparency		
6	While AI models can be complex, there should be efforts towards developing explainable AI models or at the minimum, describing the architecture of the models in detail sufficient to provide transparency to users.	There is a growing interest in understanding how AI models function. Explainable AI is a budding field and may not be applicable to more complex models. Providing transparency into the architecture and structure of AI models provides important insights that can be used to ensure there are no fundamental flaws that could affect output or make a model inappropriate for a particular patient population. Additionally, publishing architecture and methodology used to create models ensures that clinicians are not misled by tech that only claims to be AI.

(*Continued*)

Table 4 (Continued).

7	The use of AI in clinical practice, study design, or validation must be transparently disclosed in a compliant manner.	Any use of AI tools to assist with clinical decision-making, research design, or data validation must be clearly disclosed to ensure transparency, ethical practice, and compliance with institutional and regulatory standards. Proper acknowledgment ensures trust, reproducibility, and accountability while preventing misrepresentation of work and outcomes. Guidelines for disclosure should be standardized across publications and clinical settings
8	Evaluation metrics should be available for all AI models to allow for comparison and help determine confidence in the results.	AI models can vary in performance. For clinicians to determine confidence in the output of AI solutions, evaluation metrics including accuracy, precision and Area Under the ROC Curve (AUC) should be publicly accessible.
9	Large Language Models (LLM) such as ChatGPT may be used to guide and provide tools for assisting study design but should not be overly relied upon to author entire scientific papers or result in refurbished works. The extent and nature of its use should be appropriately disclosed.	Large Language models are useful when creating narratives and therefore are very attractive when writing scientific papers. However, they only have access to data they are given and may not always be up to date on the latest literature. Additionally, large language models are prone to hallucinations and fabrication of data. Over-reliance on large language models in writing scientific papers can lead to incorrect interpretation of data, and it becomes increasingly hard to understand what "good science" is and what is "bad science". It can also result in serious issues with plagiarism of others' works.
Patient Engagement		
10	Clinicians must be able to utilize AI to their advantage, increasing their marketability and personal brand.	AI can be used to enhance marketing capabilities and education for the busy clinician. For example, AI can improve marketing for pain clinicians. It can assist with generating original content that can be put out on social media and blog posts. This can allow patient discussion in the office regarding the latest procedures that may be beneficial for their pain.
11	Best practices for the use of AI in pain medicine must evolve with the rapid advancements in AI technology and be regularly reevaluated.	AI technology is advancing at an unprecedented pace, with new tools, applications, and capabilities emerging continuously. It is essential that guidelines, best practices, and ethical standards surrounding AI in pain medicine are regularly reviewed and updated. This ensures clinicians are using the most current, validated, and safe technologies while adapting to changes in AI capabilities and limitations. Ongoing education and collaboration will be critical to maintaining effective and responsible AI integration.
Ethical consideration		
12	AI models should be implemented in ethical and equitable ways.	The implementation of AI in pain medicine must align with ethical principles, emphasizing transparency, informed consent, and patient autonomy. Developers and clinicians should proactively address biases in AI models by incorporating diverse datasets and performing regular audits to ensure equitable outcomes for all populations. AI must complement human judgment to enhance compassionate, personalized care and prevent over-reliance that could erode empathy and trust.

(*Continued*)

Table 4 (Continued).

13	AI models should be tested to work with heterogeneous populations and include constructs for bias prevention and equitable use.	The ability to generalize scientific results to the greater population validates results and ensures they are accurate and safe to most patients. Scientific studies utilizing AI must be tested to ensure they are reproducible in the population and not only beneficial to a select few. These should include, yet not necessarily be limited to, diversity of gender, race and ethnicity, physical and mental disability status, and socioeconomic status. Care to avoid bias against all and any marginalized populations should be taken. Bias is a legitimate concern with AI models.

Learning (ML) to ensure they are used to benefit patients first. AI has shown it has the potential to improve treatment, increase efficiency, and reduce complications in the healthcare setting. Although some ML models seem to be superior to physicians in image interpretation, scaling these models for daily use is highly complex. As AI continues to expand into healthcare, it becomes more important to have strict guidelines and regulations for clinicians and AI creators to follow. This Neuron Project provides these essential guidelines and is designed to be dynamic and allow for future periodic updates.

Many concerns about AI need to be addressed before they can be used to treat patients: current ML models are still prone to hallucinations and errors, the large amount of data required to train models properly is difficult to regulate and vulnerable to cyber-attack, and lack of proper legislative oversight of this data leaves patients vulnerable. We must establish clear ethical guidelines on safely using patient data with AI models. It is equally important to ensure that all AI models are easily explainable and transparent to clinicians who may not have a technical background, and that they can closely monitor the models. Interdisciplinary collaboration between specialties, AI researchers, ethicists, and policy-makers will help ensure AI continues to move forward in a positive direction.

The potential harms of AI discussed are not exhaustive, as unforeseen consequences can always arise. Clinician involvement in creating and implementing AI will always be necessary until these can be avoided. Until AI surpasses human capability, the ultimate responsibility of patient care falls upon healthcare providers.

As artificial intelligence (AI) technology rapidly evolves, its integration into pain medicine is still emerging in machine learning algorithms and predictive analytics amongst many others that could revolutionize the way pain conditions are diagnosed, treated, and managed. Using AI-based interventions to improve pain recognition, prediction, and self-management is effective.[92] Additionally, the utilization of AI patient education platforms can empower patients to actively participate in their pain treatment by understanding their pain and making informed decisions.[93] AI should improve health care access and delivery resulting in an improved experience for clinicians and patients.

Clinician oversight is crucial in ensuring AI technology's safe and effective implementation in pain medicine due to the complexity of pain conditions and the variability of patient treatment responses. Pain is a multifactorial and subjective experience that can influence the psychological state, social environment, and individual differences in pain perception. Finally, clinicians are essential to maintaining patients' trust in the healthcare system. Clinicians help bridge the gap between AI technology and patient care, providing reassurance and confidence in the effective treatment of chronic pain patients.

In conclusion, while AI technologies have the potential to revolutionize the field and improve patient outcomes, the expertise and judgment of clinicians are irreplaceable in ensuring the safe, effective, and ethical use of AI. By working collaboratively with AI systems, clinicians can harness the power of technology to deliver personalized, evidence-based care that meets each patient's unique needs.

Disclosure

Dr Usman Latif reports personal fees, advisory board, equity, and/or research grants from Abbott, Brixton Biosciences, Glucotrack, InFormed Consent, Nalu, Nevro, Saluda, Spinal Simplicity, SPR, Stryker, Vertex Pharmaceuticals, Vertos, Vivex Biologics, WISE, Mainstay Medical. Dr Timothy Deer reports personal fees for consulting, advisory board, research and/or stock options from Abbott, SpineThera, Saluda Medical, Cornerloc, Boston Scientific, Pain Teq, Spinal Simplicity, Biotronik, Aurora, Nervonik, SPR Therapeutics, outside the submitted work; In addition, Dr Timothy Deer has a patent pending to Abbott. Dr Hemant Kalia is a consultant for Abbott, Nalu, Curonix, SPR, and Nervonik, during the conduct of the study. Dr Maged Guirguis is a consultant for Avanos Medical, Saluda medical, Boston Scientific, Averitas Pharm., Vivex Biologics, and Pacira Pharm, outside the submitted work. Dr Mark Bicket reports grants from NIH, PCORI, CDC, FDA, Michigan Department of Health and Human Services/SAMHSA, and Blue Cross Blue Shield of Michigan, outside the submitted work. Dr Nasir Khatri reports grants and/or personal fees from Nevro, Abbott, SPR Therapeutics, Spinal Simplicity, WISE, Srl, Saluda Medical, Nalu Medical, Brixton Biomed, outside the submitted work. Dr David Lee is a consultant for Abbott, Boston Scientific, Mainstay Medical, Intracept, Johnson & Johnson, and Biotronik, outside the submitted work. Dr Derron Wilson is a consultant for Abbott, Saluda Medical, Boston Scientific, outside the submitted work. Dr Kenneth Chapman reports research funding from Abbott, during the conduct of the study. Dr Chau Vu is a consultant for Saluda Medical and Painteq, outside the submitted work. Dr. Patrick Buchanan is a consultant for Saluda Medical, Mainstay Medical, and Painteq, outside the submitted work. Dr Erika Petersen reports research support from Mainstay, Medtronic, Nalu, Neuros Medical, Nevro Corp, ReNeuron, SPR, Surgical Information Systems, and Saluda, as well as personal fees from Abbott Neuromodulation, Biotronik, Medtronic Neuromodulation, Nalu, Neuros Medical, Nevro, Presidio Medical, Saluda, and Vertos. She holds stock and/or options from USPain, SynerFuse, and neuro42. Dr Michael Schatman is a senior medical advisor for Apurano Pharma, outside the submitted work. Dr Alaa Abd-Elsayed is a consultant for Medtronic, Curonix, Avanos and Averitas. Dr Dawood Sayed reports options from PainTeq, Mainstay, personal fees from Abbott and Saluda, outside the submitted work. The authors report no other conflicts of interest in this work.

References

1. Amisha MP, Pathania M, Rathaur VK, Rathaur V. Overview of artificial intelligence in medicine. *J Family Med Prim Care*. 2019;8(7):2328–2331. PMID: 31463251; PMCID: PMC6691444. doi:10.4103/jfmpc.jfmpc_440_19
2. Kaul V, Enslin S, Gross SA. History of artificial intelligence in medicine. *Gastrointest Endosc*. 2020;92(4):807–812. PMID: 32565184. doi:10.1016/j.gie.2020.06.040
3. Arora S, Jariwala SP, Balsari S. Artificial intelligence in medicine: a primer and recommendation. *J Hosp Med*. 2024;19(12):1197–1200. PMID: 38639172. doi:10.1002/jhm.13371
4. Jiang F, Jiang Y, Zhi H, et al. Artificial intelligence in healthcare: past, present and future. *Stroke Vasc Neurol*. 2017;2(4):230–243. PMID: 29507784; PMCID: PMC5829945. doi:10.1136/svn-2017-000101
5. Stoltzfus JC. Logistic regression: a brief primer. *Acad Emerg Med*. 2011;18(10):1099–1104. PMID: 21996075. doi:10.1111/j.1553-2712.2011.01185.x
6. Scott IA. Demystifying machine learning: a primer for physicians. *Intern Med J*. 2021;51(9):1388–1400. doi:10.1111/imj.15200 PMID: 33462882.
7. Wolterink JM, Mukhopadhyay A, Leiner T, Vogl TJ, Bucher AM, Išgum I. Generative adversarial networks: a primer for radiologists. *Radiographics*. 2021;41(3):840–857. PMID: 33891522. doi:10.1148/rg.2021200151
8. Thirunavukarasu AJ, Ting DSJ, Elangovan K, Gutierrez L, Tan TF, Ting DSW. Large language models in medicine. *Nat Med*. 2023;29(8):1930–1940. PMID: 37460753. doi:10.1038/s41591-023-02448-8
9. Pacurari AC, Bhattarai S, Muhammad A, et al. Diagnostic accuracy of machine learning ai architectures in detection and classification of lung cancer: a systematic review. *Diagnostics*. 2023;13(13):2145. PMID: 37443539; PMCID: PMC10340581. doi:10.3390/diagnostics13132145
10. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24–29. PMID: 30617335. doi:10.1038/s41591-018-0316-z.
11. Yang JH, Goodman ED, Dawes AJ, et al. Using AI and computer vision to analyze technical proficiency in robotic surgery. *Surg Endosc*. 2023;37(4):3010–3017. PMID: 36536082. doi:10.1007/s00464-022-09781-y
12. Tiwari PC, Pal R, Chaudhary MJ, Nath R. Artificial intelligence revolutionizing drug development: exploring opportunities and challenges. *Drug Dev Res*. 2023;84(8):1652–1663. PMID: 37712494. doi:10.1002/ddr.22115
13. Johnson KB, Wei WQ, Weeraratne D, et al. Precision medicine, AI, and the future of personalized health care. *Clin Transl Sci*. 2021;14(1):86–93. PMID: 32961010; PMCID: PMC7877825. doi:10.1111/cts.12884
14. Lee JM. Strategies for integrating ChatGPT and generative AI into clinical studies. *Blood Res*. 2024;59(1):45. doi:10.1007/s44313-024-00045-3 Erratum in: Blood Res. 2025 Jan 21;60(1):6. PMID: 39718704; PMCID: PMC11668709. doi: 10.1007/s44313-025-00058-6
15. Exec. Order No. 14110, 3 C.F.R. Vol. 88, No. 210. 2023. Available from: https://www.federalregister.gov/d/2023-24283. Accessed July 29, 2025.
16. Exec. Order No. 14179, 3 C.F.R. Vol 90, No. 20. 2025.

17. The White House. 2022. "Blueprint for an AI Bill of Rights: making Automated Systems Work for the American People. Available from: https://www.whitehouse.gov/ostp/ai-bill-of-rights/. Accessed July 29, 2025.
18. Artificial Intelligence/Machine Learning (AI/ML)-Based Software as a Medical Device (SaMD) Action Plan. Center for Devices and Radiological Health, FDA.gov (2021). Available from: https://www.fda.gov/media/145022/download. Accessed July 29, 2025.
19. "U.S. Department of Health and Human Services. Strategic Plan for the Use of Artificial Intelligence in Health, Human Services, and Public Health. Available from: https://www.healthit.gov/sites/default/files/2025-01/HHS%20AI%20Strategic%20Plan_Overview_FINAL_508.pdf. Accessed July 29, 2025.
20. Adams MCB, Nelson AM, Narouze S. Daring discourse: artificial intelligence in pain medicine, opportunities and challenges. *Reg Anesth Pain Med*. 2023;48(9):439–442. PMID: 37169486; PMCID: PMC10525018. doi:10.1136/rapm-2023-104526
21. Sankaran R, Kumar A, Parasuram H. Role of Artificial Intelligence and Machine Learning in the prediction of the pain: a scoping systematic review. *Proc Inst Mech Eng H*. 2022;236(10):1478–1491. PMID: 36148916. doi:10.1177/09544119221122012
22. Sarzi-Puttini P, Giorgi V. The potential and challenges of artificial intelligence and machine learning in the study of pain. *Clin Exp Rheumatol*. 2023;41(6):1214–1215. PMID: 37140685. doi:10.55563/clinexprheumatol/d3n8dc
23. "Artificial Intelligence (AI) in Healthcare Market Growth, Drivers, and Opportunities. MarketsandMarkets, December 2024. Available from: https://www.marketsandmarkets.com/Market-Reports/artificial-intelligence-healthcare-market-54679303.html. Accessed July 29, 2025.
24. Ai in healthcare market size, share & growth report, 2030. AI In Healthcare Market Size, Share & Growth Report, 2030. Available from: https://www.grandviewresearch.com/industry-analysis/artificial-intelligence-ai-healthcare-market. Accessed July 29, 2025.
25. Artificial Intelligence in healthcare market size, report 2034. Precedence Research. Available from: https://www.precedenceresearch.com/artificial-intelligence-in-healthcare-market. Accessed July 29, 2025.
26. Obermeyer Z, Emanuel EJ. Predicting the future - big data, machine learning, and clinical medicine. *N Engl J Med*. 2016;375(13):1216–1219. PMID: 27682033; PMCID: PMC5070532. doi:10.1056/NEJMp1606181
27. Chen MM, Terzic A, Becker AS, et al. Artificial intelligence in oncologic imaging. *Eur J Radiol Open*. 2022;9:100441. PMID: 36193451; PMCID: PMC9525817. doi:10.1016/j.ejro.2022.100441
28. Choy G, Khalilzadeh O, Michalski M, et al. Current applications and future impact of machine learning in radiology. *Radiology*. 2018;288(2):318–328. PMID: 29944078; PMCID: PMC6542626. doi:10.1148/radiol.2018171820
29. Char DS, Shah NH, Magnus D. Implementing machine learning in health care - addressing ethical challenges. *N Engl J Med*. 2018;378(11):981–983. PMID: 29539284; PMCID: PMC5962261. doi:10.1056/NEJMp1714229
30. Hall WJ, Chapman MV, Lee KM, et al. Implicit racial/ethnic bias among health care professionals and its influence on health care outcomes: a systematic review. *Am J Public Health*. 2015;105(12):e60–76. PMID: 26469668; PMCID: PMC4638275. doi:10.2105/AJPH.2015.302903
31. Rajkomar A, Hardt M, Howell MD, Corrado G, Chin MH. Ensuring fairness in machine learning to advance health equity. *Ann Intern Med*. 2018;169(12):866–872. PMID: 30508424; PMCID: PMC6594166. doi:10.7326/M18-1990
32. Chen M, Hao Y, Hwang K, Wang L, Wang L. Disease prediction by machine learning over big data from healthcare communities. *IEEE Access*. 2017;5:8869–8879. doi:10.1109/ACCESS.2017.2694446
33. Lee JG, Jun S, Cho YW, et al. Deep learning in medical imaging: general overview. *Korean J Radiol*. 2017;18(4):570–584. PMID: 28670152; PMCID: PMC5447633. doi:10.3348/kjr.2017.18.4.570
34. Aczon M, Ledbetter D, Ho L, et al. Dynamic mortality risk predictions in pediatric critical care using recurrent neural networks. *arXiv preprint*. 2017;2017:1.arXiv:1701.06675.
35. Shamout F, Zhu T, Clifton DA. Machine learning for clinical outcome prediction. *IEEE Rev Biomed Eng*. 2021;14:116–126. PMID: 32746368. doi:10.1109/RBME.2020.3007816
36. Shai Shalev-Shwartz SB-D. *Understanding Machine Learning: From Theory to Algorithms*. New York: Cambridge University Press; 2014:1–6.
37. Sdrulla AD, Guan Y, Raja SN. Spinal cord stimulation: clinical efficacy and potential mechanisms. *Pain Pract*. 2018;18(8):1048–1067. PMID: 29526043; PMCID: PMC6391880. doi:10.1111/papr.12692
38. Browd SR, Park C, Donoho DA. Potential applications of artificial intelligence and machine learning in spine surgery across the continuum of care. *Int J Spine Surg*. 2023;17(S1):S26–S33. PMID: 37291063; PMCID: PMC10318910. doi:10.14444/8507
39. Verhey JT, Haglin JM, Verhey EM, Hartigan DE. Virtual, augmented, and mixed reality applications in orthopedic surgery. *Int J Med Robot*. 2020;16(2):e2067. PMID: 31867864. doi:10.1002/rcs.2067
40. Pritzlaff SG, Goree JH, Hagedorn JM, et al. Pain education and knowledge (PEAK) consensus guidelines for neuromodulation: a proposal for standardization in fellowship and training programs. *J Pain Res*. 2023;16:3101–3117. PMID: 37727682; PMCID: PMC10505612. doi:10.2147/JPR.S424589
41. McCloskey K, Turlip R, Ahmad HS, Ghenbot YG, Chauhan D, Yoon JW. Virtual and augmented reality in spine surgery: a systematic review. *World Neurosurg*. 2023;173:96–107. PMID: 36812986. doi:10.1016/j.wneu.2023.02.068
42. Wang H, Wang F, Leong AP, Xu L, Chen X, Wang Q. Precision insertion of percutaneous sacroiliac screws using a novel augmented reality-based navigation system: a pilot study. *Int Orthop*. 2016;40(9):1941–1947.PMID: 26572882. doi:10.1007/s00264-015-3028-8
43. Hopkins BS, Mazmudar A, Driscoll C, et al. Using artificial intelligence (AI) to predict postoperative surgical site infection: a retrospective cohort of 4046 posterior spinal fusions. *Clin Neurol Neurosurg*. 2020;192:105718. PMID: 32065943. doi:10.1016/j.clineuro.2020.105718
44. Nich C, Behr J, Crenn V, Normand N, Mouchère H, d'Assignies G. Applications of artificial intelligence and machine learning for the hip and knee surgeon: current state and implications for the future. *Int Orthop*. 2022;46(5):937–944. PMID: 35171335. doi:10.1007/s00264-022-05346-9
45. Fong KM, Au SY, Lee MKY. Artificial intelligence-assisted frame rate augmentation in fluoroscopy. *J Cardiovasc Med*. 2022;23(1):e8–e10. PMID: 34346905. doi:10.2459/JCM.0000000000001190
46. Bang JY, Hough M, Hawes RH, Varadarajulu S. Use of artificial intelligence to reduce radiation exposure at fluoroscopy-guided endoscopic procedures. *Am J Gastroenterol*. 2020;115(4):555–561. PMID: 32195731. doi:10.14309/ajg.0000000000000565
47. Auloge P, Cazzato RL, Ramamurthy N, et al. Augmented reality and artificial intelligence-based navigation during percutaneous vertebroplasty: a pilot randomised clinical trial. *Eur Spine J*. 2020;29(7):1580–1589. PMID: 31270676. doi:10.1007/s00586-019-06054-6
48. Nassif AB, Talib MA, Nasir Q, Afadar Y, Elgendy O. Breast cancer detection using artificial intelligence techniques: a systematic literature review. *Artif Intell Med*. 2022;127:102276. PMID: 35430037. doi:10.1016/j.artmed.2022.102276

49. Yousif M, van Diest PJ, Laurinavicius A, et al. Artificial intelligence applied to breast pathology. *Virchows Arch*. 2022;480(1):191–209. PMID: 34791536. doi:10.1007/s00428-021-03213-3
50. Garbin C, Marques N, Marques O. Machine learning for predicting opioid use disorder from healthcare data: a systematic review. *Comput Methods Programs Biomed*. 2023;236:107573. PMID: 37148670. doi:10.1016/j.cmpb.2023.107573
51. Anthony CA, Rojas EO, Keffala V, et al. Acceptance and commitment therapy delivered via a mobile phone messaging robot to decrease postoperative opioid use in patients with orthopedic trauma: randomized controlled trial. *J Med Internet Res*. 2020;22(7):e17750. PMID: 32723723; PMCID: PMC7458063. doi:10.2196/17750
52. Hasan MM, Young GJ, Shi J, et al. A machine learning based two-stage clinical decision support system for predicting patients' discontinuation from opioid use disorder treatment: retrospective observational study. *BMC Med Inform Decis Mak*. 2021;21(1):331. PMID: 34836524; PMCID: PMC8620531. doi:10.1186/s12911-021-01692-7
53. Dhowan B, Lim J, MacLean MD, et al. Simple minimally-invasive automatic antidote delivery device (A2D2) towards closed-loop reversal of opioid overdose. *J Control Release*. 2019;306:130–137. PMID: 31158402; PMCID: PMC6629496. doi:10.1016/j.jconrel.2019.05.041
54. Hagedorn JM, George TK, Aiyer R, Schmidt K, Halamka J, D'Souza RS. Artificial intelligence and pain medicine: an introduction. *J Pain Res*. 2024;17:509–518. PMID: 38328019; PMCID: PMC10848920. doi:10.2147/JPR.S429594
55. Matsuda Y, Beppu T, Arima K. Crystallization and positional specificity of hydroperoxidation of Fusarium lipoxygenase. *Biochim Biophys Acta*. 1978;530(3):439–450. PMID: 100142. doi:10.1016/0005-2760(78)90164-9
56. Ghim JL, Ahn S. Transforming clinical trials: the emerging roles of large language models. *Transl Clin Pharmacol*. 2023;31(3):131–138. PMID: 37810626; PMCID: PMC10551746. doi:10.12793/tcp.2023.31.e16
57. Guckenberger M, Andratschke N, Ahmadsei M, et al. Potential of ChatGPT in facilitating research in radiation oncology? *Radiother Oncol*. 2023;188:109894. PMID: 37659658. doi:10.1016/j.radonc.2023.109894
58. Lenert LA, Lane S, Wehbe R. Could an artificial intelligence approach to prior authorization be more human? *J Am Med Inf Assoc*. 2023;30 (5):989–994. doi:10.1093/jamia/ocad016
59. Matulis JC, McCoy R. Patient-centered appointment scheduling: a call for autonomy, continuity, and creativity. *J Gen Intern Med*. 2021;36 (2):511–514. PMID: 32885369; PMCID: PMC7471539. doi:10.1007/s11606-020-06058-9
60. Chakraborty C, Bhattacharya M, Lee SS. Artificial intelligence enabled ChatGPT and large language models in drug target discovery, drug discovery, and development. *Mol Ther Nucleic Acids*. 2023;33:866–868. PMID: 37680991; PMCID: PMC10481150. doi:10.1016/j.omtn.2023.08.009
61. Ross C, Swetlitz I. IBM's Watson supercomputer recommended 'unsafe and incorrect' cancer treatments, internal documents show. Stat News. 2018. Available from: https://www.statnews.com/2018/07/25/ibm-watson-recommended-unsafeincorrect-treatments/. Accessed May 25, 2024.
62. Alkaissi H, McFarlane SI. Artificial hallucinations in ChatGPT: implications in scientific writing. *Cureus*. 2023;15(2):e35179. doi:10.7759/cureus.35179
63. Wu Q, Jin Z, Wang P. The relationship between the physician-patient relationship, physician empathy, and patient trust. *J Gen Intern Med*. 2022;37 (6):1388–1393. PMID: 34405348; PMCID: PMC9086002. doi:10.1007/s11606-021-07008-9
64. Healthcare Engineering JO. Retracted: study on automatic multi-classification of spine based on deep learning and postoperative infection screening. *J Healthc Eng*. 2023;2023:9861723. doi:10.1155/2023/9861723.
65. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nat. *Med*. 2019;25(1):44–56. doi:10.1038/s41591-018-0300-7
66. Khan B, Fatima H, Qureshi A, et al. Drawbacks of artificial intelligence and their potential solutions in the healthcare sector. *Biomed Mater Devices*. 2023;8:1–8. PMID: 36785697; PMCID: PMC9908503. doi:10.1007/s44174-023-00063-2
67. Norori N, Hu Q, Aellen FM, Faraci FD, Tzovara A. Addressing bias in big data and AI for health care: a call for open science. *Patterns*. 2021;2 (10):100347. PMID: 34693373; PMCID: PMC8515002. doi:10.1016/j.patter.2021.100347
68. Dziedzic A, Issa J, Chaurasia A, Tanasiewicz M. Artificial intelligence and health-related data: the patient's best interest and data ownership dilemma. *Proc Inst Mech Eng H*. 2024;238(10):1023–1028. PMID: 39275850. doi:10.1177/09544119241279630
69. Healthcare Data Breach statistics: the HIPAA Journal. 2020. Available from: https://www.hipaajournal.com/hipaa-privacy-rule/. Accessed May 25, 2024.
70. Koczkodaj WW, Masiak J, Mazurek M, Strzałka D, Zabrodskii PF. Massive health record breaches evidenced by the office for civil rights data. *Iran J Public Health*. 2019;48(2):278–288. PMID: 31205882; PMCID: PMC6556182.
71. U.S. code § 102 – subject matter of copyright: in general. Legal Information Institute. Cornell Law School. Available from: http://www.law.cornell.edu/uscode/text/17/102. Accessed May 25, 2024.
72. U.S code § 107 – limitations on exclusive rights: fair use. Legal Information Institute. Cornell Law School. Available from: http://www.law.cornell.edu/uscode/text/17/107. Accessed May 25, 2024.
73. U.S. Code § 101 – definitions(n.d.). Legal Information Institute. Cornell Law School.Available from: https://www.law.cornell.edu/uscode/text/17/101. Accessed May 25, 2024.
74. Zhuk A. Navigating the legal landscape of AI copyright: a comparative analysis of EU, US, and Chinese approaches. AI Ethics 4, 1299–1306 (2024). doi:10.1007/s43681-023-00299-0
75. Copyright Registration Guidance: works Containing Material Generated by Artificial Intelligence. 2023. Available from: https://www.copyright.gov/ai/ai_policy_guidance.pdf. Accessed May 25, 2024.
76. Litchfield T. Court documents show not only did meta torrent terabytes of pirated books to train AI models, employees wouldn't stop emailing each other about it: "torrenting from a corporate laptop doesn't feel right. pcgamer. February 7, 2025. Available from: https://www.pcgamer.com/gaming-industry/court-documents-show-not-only-did-meta-torrent-terabytes-of-pirated-books-to-train-ai-models-employees-wouldnt-stop-emailing-each-other-about-it-torrenting-from-a-corporate-laptop-doesnt-feel-right/. Accessed May 25, 2024.
77. FDA Digital Health Innovation Action Plan. U.S. Food and Drug Administration. Available from: https://www.fda.gov/media/106331/download. Accessed May 25, 2024.
78. FDA Proposed Regulatory Framework for Modifications to AI/ML-Based SaMD. U.S. Food and Drug Administration. Available from: https://www.fda.gov/media/122535/download. Accessed May 25, 2024.

79. JASON Report on Artificial Intelligence for Health and Health Care. JASON Advisory Group. Available from: https://www.healthit.gov/sites/default/files/jsr-17-task-002_aiforhealthandhealthcare12122017.pdf. Accessed May 25, 2024.
80. European Commission: directorate-General for Communications Networks, Content and Technology, Ethics guidelines for trustworthy AI, Publications Office, 2019, Available from: https://data.europa.eu/doi/10.2759/346720. Accessed July 29, 2025.
81. General Data Protection Regulation (GDPR). Intersoft Consulting. Available from: https://gdpr-info.eu/. Accessed May 25, 2024.
82. Topol E. *Deep Medicine: How Artificial Intelligence Can Make Healthcare Human Again*. Basic Books; 2019.
83. Meskó B, Topol EJ. The imperative for regulatory oversight of large language models (or generative AI) in healthcare. *NPJ Digit Med*. 2023;6 (1):120. PMID: 37414860; PMCID: PMC10326069. doi:10.1038/s41746-023-00873-0
84. Califf R. 2024. Remarks by dr. Califf to the Coalition for Health Ai (chai). U.S. Food and Drug Administration. Available from: https://www.fda.gov/news-events/speeches-fda-officials/remarks-fda-commissioner-robert-m-califf-coalition-health-ai-chai-03052024. Accessed July 29, 2025.
85. European Union Agency for Fundamental Rights. Artificial Intelligence, Big Data and Fundamental Rights. FRA Focus; 2018.
86. Mittelstadt BD, Allo P, Taddeo M, Wachter S, Floridi L. The ethics of algorithms: mapping the debate. *Big Data and Society*. 2016;3(2). doi:10.1177/2053951716679679
87. Institute of Electrical and Electronics Engineers (IEEE). *Ethically Aligned Design: A Vision for Prioritizing Human Well-Being with Autonomous and Intelligent Systems*. IEEE; 2019.
88. European Commission. Guidelines on Ethics in Artificial Intelligence. EC; 2019.
89. Nuffield Council on Bioethics. Artificial Intelligence (AI) in Healthcare and Research. Nuffield Council; 2018.
90. World Health Organization. Artificial Intelligence for Health. WHO; 2021.
91. World Health Organization. WHO Global Strategy on Digital Health 2020–2025. WHO; 2020.
92. Zhang M, Zhu L, Lin SY, et al. Using artificial intelligence to improve pain assessment and pain management: a scoping review. *J Am Med Inform Assoc*. 2023;30(3):570–587. PMID: 36458955; PMCID: PMC9933069. doi:10.1093/jamia/ocac231
93. Robinson CL, D'Souza RS, Yazdi C, et al. Reviewing the potential role of artificial intelligence in delivering personalized and interactive pain medicine education for chronic pain patients. *J Pain Res*. 2024;17:923–929. PMID: 38464902; PMCID: PMC10924768. doi:10.2147/JPR.S439452