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Review Article

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Using Artificial Intelligence in the Comprehensive Management of Spinal Cord Injury

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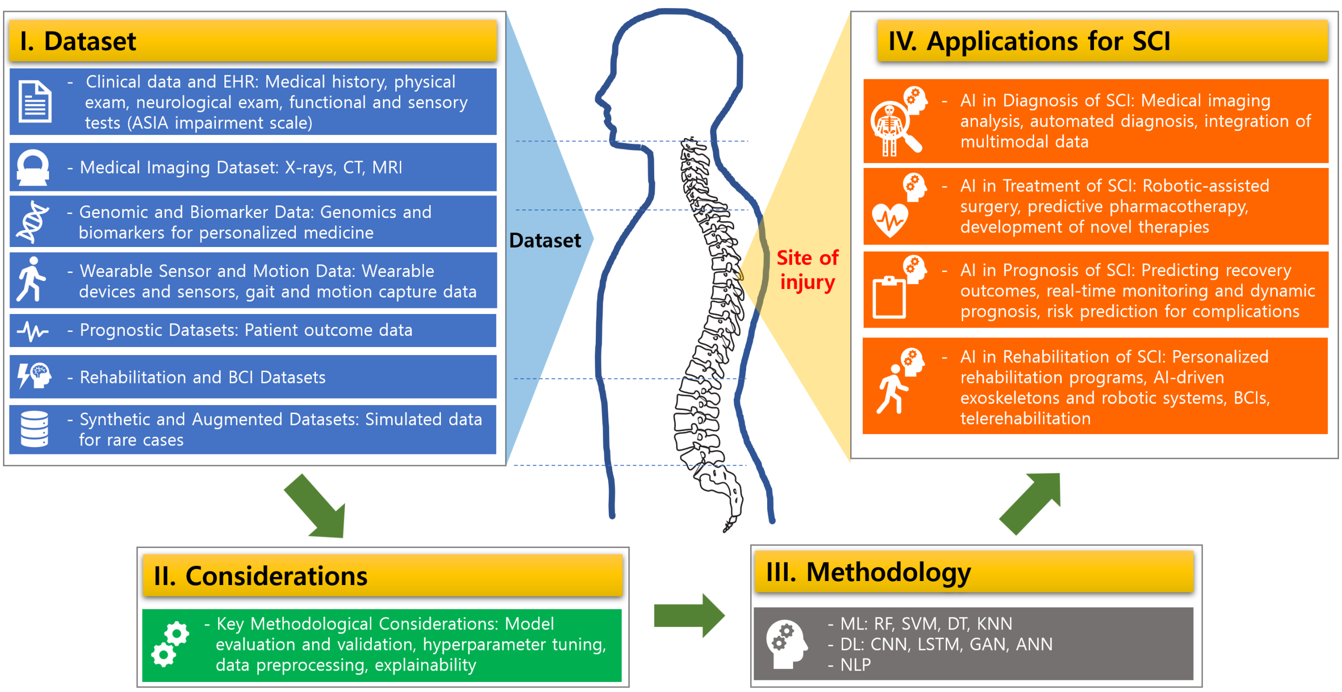
ABSTRACT

Spinal cord injury (SCI) frequently results in persistent motor, sensory, or autonomic dysfunction, and the outcomes are largely determined by the location and severity of the injury. Despite significant technological progress, the intricate nature of the spinal cord anatomy and the difficulties associated with neuroregeneration make full recovery from SCI uncommon. This review explores the potential of artificial intelligence (AI), with a particular focus on machine learning, to enhance patient outcomes in SCI management. The application of AI, specifically machine learning, has revolutionized the diagnosis, treatment, prognosis, and rehabilitation of patients with SCI. By leveraging large datasets and identifying complex patterns, AI contributes to improved diagnostic accuracy, optimizes surgical procedures, and enables the personalization of therapeutic interventions. AI-driven prognostic models provide accurate predictions of recovery, facilitating improved planning and resource allocation. Additionally, AI-powered rehabilitation systems, including robotic devices and brain-computer interfaces, increase the effectiveness and accessibility of therapy. However, realizing the full potential of AI in SCI care requires ongoing research, interdisciplinary collaboration, and the development of comprehensive datasets. As AI continues to evolve, it is expected to play an increasingly vital role in enhancing the outcomes of patients with SCI.

Keywords: Spinal cord injury; Artificial intelligence; Diagnosis; Treatment; Prognosis; Rehabilitation

GRAPHICAL ABSTRACT



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Informed Consent
This study does not involve the collection of any patient-specific information.

Ethics Approval
This study does not involve the collection of patient-specific data or personally identifiable information.

INTRODUCTION

Spinal cord injury (SCI) has a global incidence of approximately 10 to 80 cases per million people each year, often resulting in permanent motor, sensory, or autonomic dysfunctions that depend on the injury's location and severity.[13,19] Despite advancements in medical technology, the complexity of spinal cord anatomy and the challenge of neuroregeneration mean that full recovery after SCI remains rare.[13,40] In recent years, artificial intelligence (AI) has emerged as a powerful tool in medical research, capable of transforming diagnostics, treatment, prognosis, and rehabilitation.[39,43] Specifically, deep learning (DL), a subset of machine learning (ML), has shown remarkable success in recognizing patterns in large datasets and has been applied across various healthcare domains, including spinal cord injuries.[28] The integration of AI, powered by ML models, promises a new era in SCI management by enhancing human expertise, predicting outcomes, and personalizing treatments in a preclinical SCI model.[33] This review explores the role of AI technology using ML in the diagnosis, treatment, prognosis, and rehabilitation of SCI, aiming to highlight its transformative potential in improving patient outcomes (**FIGURE 1**).

AI IN DIAGNOSIS OF SCI

Accurate and timely diagnosis of spinal cord injuries is essential for preventing further damage and improving patient outcomes.[42] While traditional diagnostic methods such as X-rays, computed tomography (CT) scans, and magnetic resonance imaging (MRI) are

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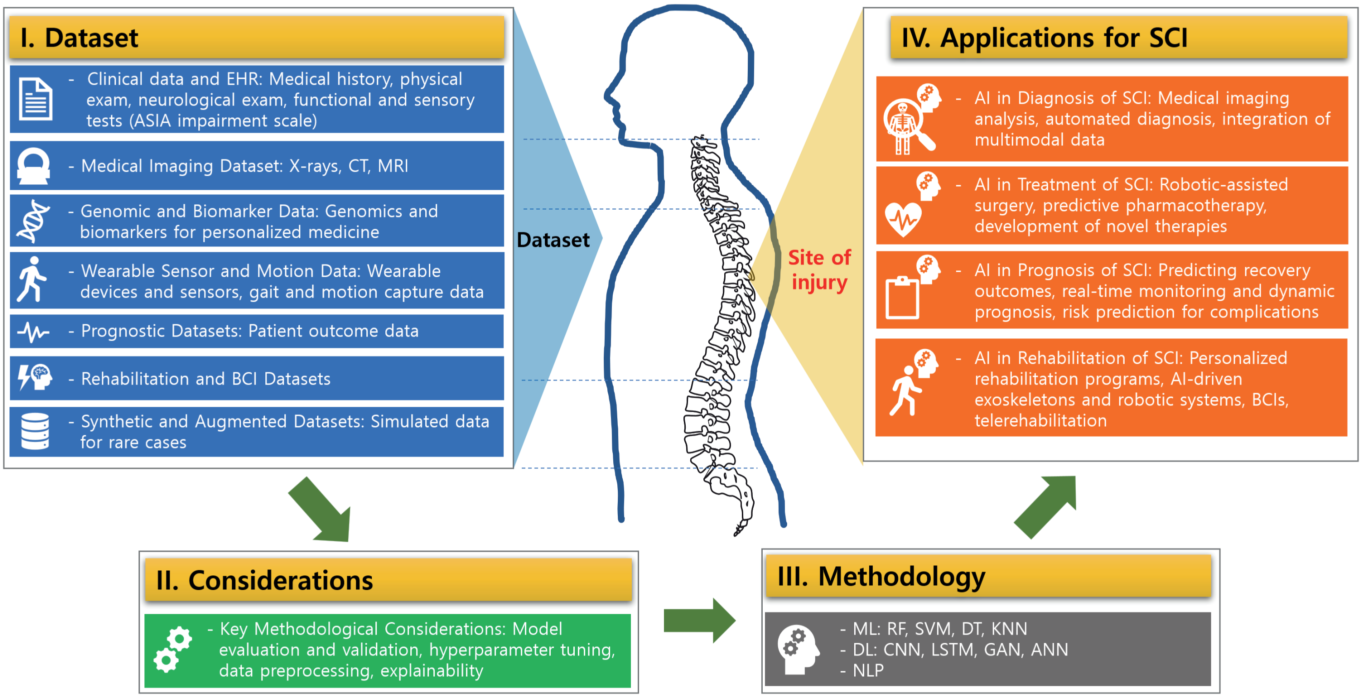

FIGURE 1. The role and methodology of AI technology, utilizing deep learning, in the diagnosis, treatment, prognosis, and rehabilitation of SCI.
EHR: electronic health record, ASIA: American Spinal Injury Association, CT: computed tomography, MRI: magnetic resonance imaging, BCI: brain-computer interface, AI: artificial intelligence, SCI: spinal cord injury, ML: machine learning, RF: random forest, SVM: support vector machine, DT: decision tree, KNN: K-nearest neighbors, DL: deep learning, CNN: convolutional neural network, LSTM: long short-term memory, GAN: generative adversarial network, ANN: artificial neural network, NLP: natural language processing.

indispensable in assessing SCI, they are limited by the subjective interpretation of clinicians and the difficulty of detecting subtle or early-stage injuries.[25)] DL, particularly convolutional neural networks (CNNs), has been increasingly applied to the field of medical imaging, where it demonstrates superior performance in recognizing complex patterns and anatomical features.[1)] CNNs have been successfully used to analyze medical images such as MRIs and CT scans in the context of SCI, identifying abnormalities with greater accuracy than traditional methods.[2,11)] For example, a DL-based model by Artha Wiguna et al.[2)] demonstrated the ability to determine the cervical cord injury severity through axial and sagittal MRI segmentation and classification. AI models are also capable of identifying subtle lesions or fiber tract disruptions that are often difficult for human radiologists to detect.[11)] Furthermore, AI-driven systems can integrate multimodal data, such as clinical notes, patient history, and genetic profiles, to provide a more comprehensive and individualized diagnosis of SCI.[10)] This multimodal approach improves diagnostic accuracy and provides a more personalized treatment plan.

AI-powered diagnostic systems not only offer faster image analysis, reducing delays in patient care but also reduce human errors associated with fatigue and cognitive biases.[2,11)] Moreover, advanced AI algorithms can predict secondary complications such as edema, hemorrhage, and spinal cord swelling, providing clinicians with the information necessary for early intervention.[32)]

In case of use of electromyography (EMG), a classification system for traumatic SCI (TSCI) was developed using a CNN that automatically extracts features in a nonhuman primate model.[26)] Masood et al. collected intramuscular EMG data from agonist and antagonist tail

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muscle pairs both before and after SCI in five Macaca fascicularis monkeys.[26] Their results demonstrated that CNN is a promising tool for classifying TSCI, achieving F-measures of 89.8% and 96.9% for the left and right muscles, respectively.

The application of AI in SCI diagnosis represents a significant step forward in precision medicine, where individualized care becomes the norm.

AI IN TREATMENT OF SCI

AI's potential in the treatment of spinal cord injuries is centered on its ability to process and analyze vast amounts of patient-specific data, leading to optimized, personalized treatment strategies.[14] DL models, which excel at recognizing patterns in complex datasets, are used to predict the best surgical approaches, optimize pharmacological regimens, and guide experimental therapies such as neural regeneration and stem cell transplantation.[12] Petillo et al.[33] proposed a DL-based approach to quantify microglial activation in a preclinical SCI model following treatment with drug-loaded nanovectors. Microglia, the immune surveillance cells of the central nervous system, represent promising therapeutic targets for both SCI and neurodegenerative diseases.[33] Nanovectors are considered the most effective means of delivering drugs and modulating microglial inflammation. In this context, a DL-based method was developed to quantify microglial activation following drug-loaded nanovector treatment in preclinical SCI models, where microglia were segmented and classified based on their morphological features. The study demonstrates the potential of nanovectors to both analyze microglial activation in diverse neuropathologies and modulate microglial function in SCI and other neurological disorders.[33]

Furthermore, AI has been integrated into robotic-assisted surgery platforms, which allow for greater precision and reduce the risk of human error during complex spinal surgeries.[34] In a 2021 study, Rasouli et al. demonstrated that AI offers significant advancements in multiple areas of spine care, such as improving preoperative evaluations, refining patient selection processes, and predicting outcomes.[34] It also plays a role in enhancing the quality and consistency of spine research, supporting perioperative surgical processes and optimizing data tracking, as well as improving performance during surgeries. This narrative review aims to concisely explore, analyze, and discuss the latest trends and applications of AI and ML in both conventional and robotic-assisted spine surgery.[34] And DL models can also simulate surgical outcomes based on preoperative imaging, helping surgeons plan safer, more effective procedures.

In pharmacotherapy, AI is being used to predict patient responses to various drug treatments, allowing for personalized medication plans aimed at minimizing side effects and maximizing therapeutic efficacy.[3] However, studies are still ongoing, such as using DL algorithms to predict the effectiveness of medications after SCI to prevent secondary damage, and showing that personalized dosing can significantly improve outcomes.

While AI has proven to be useful in diagnosis, rehabilitation, and prognosis, with some technologies already being implemented in clinical settings, its role in treating SCI, particularly during the acute phase, is still limited. Current research primarily focuses on innovative and emerging approaches that have yet to become part of standard clinical practice. Currently, most AI applications are concentrated on predicting patient outcomes

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and analyzing diagnostic images rather than being used directly for treatment. Additionally, applying AI to acute-phase treatment faces significant practical and ethical challenges that must be addressed for broader adoption.

Nevertheless, AI models could also help develop novel treatments, such as stem cell and gene therapies, by predicting cell survival, integration, and the likelihood of functional recovery.[3)] DL models have also been used to model neural regeneration, helping researchers design more effective interventions.[30)] Going forward, AI-based research will be essential to advancing these cutting-edge treatments that hold great promise for restoring lost function in SCI patients.

AI IN PROGNOSIS OF SCI

Prognosis after a SCI is challenging due to the complexity and variability of recovery pathways.[35)] Traditional methods for predicting outcomes, such as the American Spinal Injury Association Impairment Scale (AIS), provide a general overview but fail to account for the many factors influencing recovery.[2,7,41)]

The strengths of conventional prognosis methods for SCI lie in their simplicity, reliability, and clinical interpretability. These methods are based on medical knowledge and experience, utilizing well-established criteria like the AIS and clinical assessments to guide predictions.

AI offers a more sophisticated method for predicting SCI prognosis by analyzing large datasets that include demographic information, injury characteristics, comorbidities, and treatment responses.[10,15)] Håkansson et al.[15)] observed a trend toward utilizing routinely collected data such as the International Standards for Spinal Neurological Classification, imaging, and demographics to predict functional outcomes derived from the Spinal Independence Measure III and Functional Independence Measure scores, which focus on motor abilities. And studies using AI were characterized by implementations using conventional ML architectures such as linear regression and tree-based approaches.[15)]

From the perspective of collecting real-time data, DL models are also being applied to real-time data from wearable devices and sensors that monitor a patient's physiological state, providing continuous updates on their recovery status.[36)] This real-time data allows for dynamic prognostic models that adjust predictions based on the patient's current condition, enabling more precise treatment decisions.[36)] For example, a study by Ahammad et al.[1)] presented a DL framework to help diagnose SCI features based on segmentation process, and applied a novel CNN-deep segmentation-based boosting classifier to sensor SCI image data. In this study, SCI data with various shapes and orientations were collected using real-time wearable sensors, and the experimental results show that the current CNN-deep segmentation-based boosting classifier has higher computational SCI disorder prediction than the conventional CNN-based classifier.[1)] AI-based prognostic tools are invaluable in clinical settings, helping to guide decisions regarding rehabilitation intensity, the need for assistive devices, and long-term care planning in **TABLE 1**.[16,32,37,38)] A study by Okimatsu et al.[32)] demonstrated that DL-based radiomics utilizing MRI performed within 24 hours of acute cervical SCI can effectively assess neurological prognosis. This approach may serve as a novel imaging biomarker for SCI patients, enhancing the quality of patient care and improving predictions regarding future independence in activities of daily living and quality of life (QOL).

And Tamburella et al.[38] highlighted the importance of predicting neurorehabilitation outcomes following SCI for optimizing healthcare resource allocation and enhancing prognosis and rehabilitation strategies. In their study, artificial neural networks have emerged as a valuable alternative to traditional statistical methods, offering a more effective means of identifying complex prognostic factors in SCI patients (**TABLE 1**). And Shimizu et al. developed a ML model to predict neurological outcomes in patients with cervical SCI (CSCI).[37] A retrospective analysis was conducted on 135 CSCI patients who underwent surgery within 24 hours of injury. As a result, important predictors were categorized by AIS grade at admission, intramedullary hemorrhage, longitudinal extent of intramedullary T2 hyperintensity, and HbA1c (CatBoost: accuracy, 0.800) in **TABLE 2**. However, by improving the accuracy of prognosis for various prognostic factors with different AI models and researches in more diverse fields. Additionally, conventional outcome prediction approaches provide a level of transparency that AI-driven models sometimes lack, allowing clinicians

TABLE 1. Artificial intelligence in outcome prediction applications for spinal cord injury

Authors	Year	Input factors	Subjects (n)	AI Methods	Results
Tamburella et al.[38]	2024	SCIM at admission, age, level of lesion, ASIA score, and presence of pressure sores at admission, etc.	1,256	ARIANNA and LR	Key predictions: age, injury level, and initial SCIM scores (correlation with actual outcome: R=0.75 and 0.73, respectively)
Shimizu et al.[37]	2023	34 variables (demographic variables, laboratory variables, surgical factors, neurological status, and radiological findings).	135	gradient boosting tree-based classification models (Light GBM, XGBoost, CatBoost)	Feature importance: AIS grade at admission, intramedullary hemorrhage, longitudinal extent of intramedullary T2 hyperintensity, and HbA1c (CatBoost: accuracy, 0.800)
Okimatsu et al.[32]	2022	AIS probabilities, age and initial AIS at admission	215	RF	Feature importance of age and the initial AIS were 0.1311 and 0.297 (accuracy, precision, recall and F1 score: 0.714, 0.590, 0.565 and 0.567, respectively.
Inoue et al.[16]	2020	44 basic variables (demographics, neurological status, mechanisms of injury, treatment strategies, radiographic information, and concomitant degenerative spine disease)	165	XGBoost, LR, and DT	BASIC score of 4, followed by AIS B, SIR on T2WI, and a BASIC score of 3 for neurological improvements (accuracy: XGBoost, 81.1%; LR, 80.6%; DT, 78.8% and AUC: LR, 0.877; XGBoost, 0.867; DT, 0.753)

SCIM: spinal cord independence measure, ASIA: American spinal injury association, LR: linear regression, SIR: signal intensity ratio, ARIANNA: artificial intelligent assistant for neural network analysis, Light GBM: light gradient boosted machine, XGBoost: extreme gradient boosting, CatBoost: category boosting, AIS: American spinal injury association impairment scale, RF: random forest, DT: decision tree, AUC: area under the receiver operating characteristic curve.

TABLE 2. AI in rehabilitation applications for SCI

Authors	Year	Aim	Subjects (n)	AI Methods	Results
Yoo et al.[45]	2024	Deep learning-based prediction for gait recovery after SCI upon discharge from an acute rehabilitation facility	405	RNN, LR, Ridge, and Lasso methods were compared for FAC-DC prediction in terms of the RMSE.	In RNN variable importance, ankle dorsiflexors, right knee extensors, left long toe extensors, and neurological level of injury were ranked among the top five across the board in all the patient groups (RMSE for RNN, LR, Ridge, and Lasso: 0.3738, 2.2831, 1.3161, and 1.0246 for all the participants).
Yoo et al.[44]	2024	Gait recovery prediction after SCI at discharge from an acute rehabilitation facility using various ML algorithms	353	LR analysis, RF, DT, and SVM were used to predict the FAC-DC	The initial FAC was found to be the most influential factor in all groups (RMSE of RF and the DT: 1.09 and 1.24 for all participants, 1.20 and 1.06 for those with trauma, and 1.12 and 1.03 for those with non-trauma, respectively).
Lee et al.[22]	2023	Developing AI-based real-time motion feedback system for patients with SCI during rehabilitation	9	The AI-based motion analysis program for the upper extremity exercises (MediaPipe, Google Inc., Mountain View, CA, USA).	EG=4 and the CG=5 and participated in 1-hour sessions 3 times a week for 8 weeks, which confirmed the effect of muscle strengthening in chest press, shoulder press, and arm curl.
Jacob et al.[18]	2021	Designing AI-based smart lightweight exoskeleton system to provide rehabilitation and support for paralyzed patients (SCI)	N/A	AI-powered real-time navigation with intelligent decision making (ANN approach of global Bayesian with detector in closure loop)	Precise control of the exoskeleton integrates multiple sensory hardware to detect various parameters including distance, obstacle avoidance, orientation, tilt, velocity, and acceleration using simultaneous localization and mapping.

AI: artificial intelligence, SCI: spinal cord injury, RNN: recurrent neural network, LR: linear regression, FAC-DC: functional ambulation category at the time of discharge, RMSE: root-mean-squared error, RF: random forest, DT: decision tree, SVM: support vector machine, EG: experimental group, CG: control group, N/A: not applicable, ANN: artificial neural network.

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to understand exactly how predictions are generated and enabling them to make decisions based on their medical judgment. The straightforward nature of these methods makes them ideal for environments where access to high-tech solutions or large datasets may be limited. However, AI can also help manage SCI patient expectations and optimize resource allocation within healthcare systems by actively complementing methods such as explainable artificial intelligence (XAI).[21,22]

AI IN REHABILITATION OF SCI

Rehabilitation is a crucial aspect of recovery for SCI patients, focusing on maximizing functional independence and QOL, in contrast to distinguish acute-phase interventions such as surgery and pharmacological strategies.[4,27] Traditional rehabilitation protocols are often labor-intensive and require highly individualized approaches based on the patient's unique impairments and progress.[6,29] AI-driven platforms, particularly those powered by DL, are transforming the field of rehabilitation by automating parts of the process and providing real-time feedback for both patients and clinicians in **TABLE 2**.[18,24,45] For example, from the perspective of guiding rehabilitation strategy, intelligent rehabilitation systems can use ML algorithms to personalize therapy plans based on a patient's progress, continuously adjusting the difficulty and focus of exercises.[44] The development of a decision support system based on predictive factors can assist clinicians in planning personalized rehabilitation programs. A study by Lee et al.[24] showed that an AI-driven rehabilitation system improved patient outcomes by adapting its support based on the patient's real-time performance (**TABLE 2**).

AI also facilitates telerehabilitation, allowing patients to engage in therapy from home while still receiving guidance from healthcare providers.[23,31] Motion analysis algorithms can monitor patient movements and provide feedback on their performance, ensuring that they are performing exercises correctly even in a remote setting.[31]

In addition to traditional physical rehabilitation, AI has been integrated into brain-computer interface (BCI) systems, enabling patients with severe SCI to control prosthetic devices or robotic limbs using their neural signals.[8,17] BCIs powered by DL algorithms have demonstrated the ability to decode complex neural signals and translate them into commands for controlling external devices, significantly improving functionality and independence for patients with high-level injuries.[5] However, a significant gap in the current landscape of BCI technology, particularly concerning its applications for human bodies. While BCIs hold immense potential for individuals with SCI, the slow pace of research and clinical applications raises several concerns. By prioritizing research, ethical considerations, and interdisciplinary collaboration, we can unlock the potential of BCIs to empower SCI patients, enhance their motor skills, and ultimately transform their QOL.

DISCUSSION

Limitations and risks of AI in clinical settings

The integration of AI in clinical environments, particularly for managing complex conditions in SCI, necessitates a thorough understanding of its limitations and risks. One of the most significant challenges is data bias, where AI models may be trained on datasets that do not adequately represent the diversity of patient populations.[9] This can lead to skewed predictions and misdiagnoses, particularly for underrepresented groups. Additionally, the lack of algorithmic transparency in many AI models, especially ML systems, poses a problem for clinical decision-making, as healthcare professionals may not fully understand how conclusions are reached.[9] The black box nature can make it difficult to validate AI-driven recommendations, potentially leading to a lack of trust among clinicians. These models often involve complex layers of computation that are not easily interpretable by humans, making it difficult for clinicians to grasp how specific predictions or recommendations are made. This lack of transparency can hinder the validation of AI-driven decisions, as healthcare providers may struggle to verify the reasoning behind the AI's output. XAI aims to address this by creating models that are more interpretable, offering clear insights into the decision-making process.[21,22] Moreover, XAI techniques can provide explanations or visualizations that make the model's behavior understandable, increasing the likelihood of clinical acceptance and trust in its applications for SCI.

Ethical and legal issues in AI-driven healthcare

The use of AI in healthcare, particularly in the management of SCI, also brings forth several ethical and legal issues that must be addressed to ensure patient safety and trust.[20] Data privacy is a primary concern, as the effective use of AI often requires access to large amounts of patient information, increasing the risk of unauthorized data access and breaches. Transparency in AI decision-making is equally vital because patients and healthcare providers need clear explanations of how AI algorithms make their predictions or recommendations in order to make informed decisions about care.[9] Additionally, accountability is a critical issue when an AI model provides an inaccurate diagnosis or prognosis. It is often unclear who is responsible for the software developer, the healthcare provider, or the entity utilizing the technology.[20] Establishing clear guidelines and regulations for the use of AI in healthcare is necessary to address these challenges, protect patients, and ensure that the benefits of AI are realized without compromising ethical standards.

CONCLUSION

The use of AI technology, specifically ML, in the management of spinal cord injuries represents a paradigm shift in the diagnosis, treatment, prognosis, and rehabilitation of SCI patients. By leveraging large datasets, recognizing complex patterns, and providing individualized recommendations, AI has the potential to revolutionize how SCI is managed. DL models are improving diagnostic accuracy by identifying subtle changes in imaging data that may go unnoticed by human clinicians. In treatment, AI is being explored to enhance surgical procedures, support the creation of new therapeutic approaches, and tailor pharmacological interventions to individual patient needs, although its widespread clinical application remains limited. Prognostic models powered by AI are providing more accurate predictions of recovery, enabling better planning and resource allocation. Finally, AI-driven rehabilitation systems are making therapy more accessible and effective, particularly through the use of robotic devices and BCIs. However, realizing the full potential of AI in SCI care requires ongoing research, collaboration between clinicians and data scientists, and the development of robust datasets to train these models. As AI continues to evolve, it is poised to play an increasingly integral role in improving the lives of patients living with spinal cord injuries.

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