# A Comprehensive Review of Electromyography in Rehabilitation: Detecting Interrupted Wrist and Hand Movements with a Robotic Arm Approach

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#### **Abstract**

Electromyography (EMG) is a diagnostic technique that measures the electrical activity generated by skeletal muscles. Utilizing electrodes placed either on the skin (surface EMG) or inserted directly into the muscle (intramuscular EMG), it detects electrical signals produced during muscle contractions. EMG is widely employed in clinical and research settings to assess muscle function, diagnose neuromuscular disorders, and guide rehabilitation therapy. Over the years, EMG has evolved from a basic measurement tool into an essential technology within clinical and research environments, propelled by advances in recording techniques and digital innovations. The integration of wearable technology and artificial intelligence (AI) has significantly expanded its applications, particularly in rehabilitation and sports science. By capturing muscle electrical activity through surface or intramuscular electrodes, EMG benefits from enhanced signal processing that improves accuracy and data analysis. Despite challenges such as signal interference and the complexities of movement patterns—especially in wrist and hand rehabilitation—EMG combined with robotic systems offers real-time feedback for precise and personalized therapy. However, obstacles like cost, complexity, and variability among patients still remain. Future advancements aim to make EMG more accessible and to integrate AI for tailored rehabilitation strategies, alongside improvements in sensors and wireless communication to enhance reliability and performance. This review explores various facets of EMG, from its fundamental principles to its application in detecting disrupted wrist and hand movements through robotic approaches. It provides a comprehensive analysis of EMG's historical and technological evolution, recent innovations like AI and wearable devices, and its extensive applications in rehabilitation and sports science. Detailed case studies illustrate its effectiveness in areas such as stroke recovery and spinal cord injury rehabilitation. Additionally, the review addresses challenges like technical limitations and patient variability while emphasizing the integration of EMG with robotic systems for personalized therapy. It also discusses the significance of real-time feedback, future enhancements in AI and sensor technology, and the pressing need for more affordable, user-friendly solutions to improve therapeutic outcomes.

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Keywords: Electromyography (EMG), neuromuscular disorders, rehabilitation therapy, Artificial Intelligence (AI), wearable technology, robotic systems

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# **1. Introduction**

Electromyography (EMG) is a medical diagnostic procedure that measures and records the electrical

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activity of muscles [\[1\]](#page-17-0). It is used to assess the health of muscles and the nerve cells that control them, known as motor neurons. Motor neurons transmit electrical signals from the brain to the muscles, causing them to contract [\[2\]](#page-17-1). EMG is a versatile and valuable tool for understanding muscle function, diagnosing disorders, guiding rehabilitation, real-time muscle monitoring and improving ergonomic practices. Its applications span across multiple fields, offering insights into both normal and abnormal muscle activity [\[3\]](#page-17-2)[\[4\]](#page-17-3). EMG is essential for diagnosing neuromuscular disorders by measuring muscle electrical activity. It helps in guiding treatment, monitoring disease progression, and planning surgeries [\[5\]](#page-17-4). EMG is widely used in neurology for conditions like Amyotrophic Lateral Sclerosis (ALS), in rehabilitation for muscle recovery, and in sports medicine for performance analysis  $[6]$ . It also plays a role in ergonomics for workplace assessments and in research for developing advanced prosthetics and studying motor control [[\[7\]](#page-18-1)[\[8\]](#page-18-2)[\[9\]](#page-18-3). EMG enhances motor learning and coordination by guiding muscle activity and adapting robotic therapy. It aids in diagnosing and monitoring neuromuscular conditions, preventing reinjury through correct exercise techniques. Additionally, EMG supports research and development of innovative therapies and evidence-based practices [\[10\]](#page-18-4). This systematic review of 142 papers on EMG and its applications for wrist and hand robotics reveals a wide distribution of sources across multiple publishing platforms. The IEEE, covering both journal and conference papers (17 conference and 21 journal), contributed the most, with 26.76% of the total papers. MDPI followed, accounting for 21.13%, while Springer and Elsevier contributed 14.79% and 10.56%, respectively. A significant portion of the reviewed papers (87.32%) were published after 2020, indicating an increasing focus on the field in recent years. Notably, 42.25% of the papers (60 in total) were published since 2023, with 43 papers from 2023 alone and 17 from 2024. This analysis underscores the shift towards more recent publications and the diverse contributions from various platforms, in accordance with the PRISMA guidelines for transparent and comprehensive reporting (Fig 1).

The objectives of this review paper are outlined as follows:

- 1. Historical and Technological Context along with Current Innovations: The review effectively outlines the evolution of Electromyography (EMG) from its origins to its current applications, providing a comprehensive historical and technological perspective. It highlights recent advancements in EMG technology, such as wearable devices and AI integration, showcasing how these innovations enhance its application in rehabilitation and sports science.
- 2. Comprehensive Applications and Detailed Case Studies: The review covers a broad range of applications for EMG and robotic arms, including stroke rehabilitation, post-surgical recovery,

spinal cord injury rehabilitation, sports performance, chronic pain management, and pediatric development. Specific case studies illustrate practical achievements and successes in using EMG and robotic technologies, offering real-world examples of their effectiveness and benefits.

- 3. Challenges and Limitations with Future Directions: It addresses the technical challenges, patient-specific factors, and cost issues associated with EMG and robotic systems, providing a balanced view of limitations. The review provides insight into future technological advancements, such as improvements in AI, data analytics, and sensor technology, suggesting ways to overcome current challenges and enhance rehabilitation practices.
- 4. Integration of Technologies -Focus on Personalization and Discussion of Real-Time Feedback: The review emphasizes the advantages of integrating EMG with robotic systems, such as improved precision, real-time feedback, and personalized therapy. It highlights the importance of tailoring rehabilitation programs to individual needs through data analytics and AI. Additionally, it discusses how real-time feedback from these systems enables dynamic and effective therapeutic adjustments.
- 5. Consideration of Future Improvements: It outlines potential improvements in user interfaces, cost reduction, and integration with traditional therapies, offering a forward-looking perspective on enhancing the accessibility and effectiveness of these technologies.

The authors highlight the review's importance in detailing EMG's evolution and current innovations, showcasing its broad applications and practical case studies. It addresses challenges and future advancements, emphasizing the benefits of integrating EMG with robotics for personalized, real-time therapeutic adjustments and suggesting improvements for accessibility and effectiveness. The paper is structured as follows: Section 2 provides a comprehensive background on Electromyography (EMG), starting with the basic principles and distinguishing between Surface EMG (sEMG) and Intramuscular EMG. Section 3 focuses on the application of EMG in rehabilitation, discussing the role of EMG in movement detection, the challenges associated with detecting interrupted movements, and the importance of accurate detection for wrist and hand rehabilitation. Section 4 offers an overview of robotic arm systems and explores how EMG can be integrated with robotic arms to enhance rehabilitation processes. In Section 5, the review delves into





**Figure 1.** The review paper analysis

the mechanisms of movement interruption, EMG techniques for detecting these interruptions, and the role of robotic arms in improving detection accuracy. Section 6 presents detailed case studies and practical applications of EMG and robotic technologies in various rehabilitation contexts. Finally, Section 7 addresses technological advancements and future directions, including current challenges, limitations, and potential improvements to enhance the effectiveness and accessibility of EMG and robotic technologies. The review concludes by summarizing the key findings and emphasizing the significance of ongoing research and development in the field.

# **2. Background on Electromyography (EMG)**

The history of EMG as it shows in Figure 2, It was first developed in the early 20th century and has since become a critical tool in both clinical and research settings [\[11\]](#page-18-5).

As shown in Figure 2, in the early 1900s, EMG was introduced, with initial studies establishing the basics of measuring muscle electrical activity [\[12\]](#page-18-6). The 1930s and 1940s marked the development of early recording techniques and equipment, laying the groundwork for more advanced applications [\[13\]](#page-18-7). The 1950s and 1960s brought significant improvements with the advent of more sophisticated amplifiers and surface electrodes, which made EMG more practical for clinical diagnostics and research. During the 1970s and 1980s, advancements in signal processing and

digital technology greatly enhanced the accuracy and reliability of EMG, expanding its use in various fields [\[14\]](#page-18-8). The 1990s and 2000s saw the development of portable and wearable EMG devices, integrating with robotics and assistive technologies to support rehabilitation and functional assessment [\[15\]](#page-18-9). In recent years, from the 2010s to the present, EMG has advanced with the integration of wearable technology and artificial intelligence, leading to improved applications in rehabilitation, ergonomics, and sports science, and fostering innovations in personalized medicine and advanced therapeutic techniques [\[16\]](#page-18-10).

# 2.1. Electromyography (EMG) Basic Principle

The fundamental principle behind EMG involves detecting and recording the electrical impulses generated by motor neurons as they stimulate muscle fibers Electromyography (EMG) measures the electrical activity produced by muscle contractions [\[17\]](#page-18-11). The main block diagram of EMG is shown in Figure (3).

As shown in Figure (3), the main block diagram of EMG consists of four key parts: Electrical Impulses, Signal Detection, Signal Amplification/Processing, and Data Analysis. In the Electrical Impulses section, when a muscle contracts, motor neurons send electrical signals (action potentials) to muscle fibers, causing them to contract and produce movement. The next step, Signal Detection, involves placing electrodes on the skin (surface EMG) or inserting them into the muscle tissue



·Fundamental principles of electromy ography are established. ·Early researchers, including H. L. Hodes and E. G. G. B. Henley, began studying muscle electrical activity.

# **1900s**

•1950s: Introduction of sophisticated amplifiers and electrodes: EMG gains wider use in clinical diagnostics and research.

1960s: Development of surface EMG electrodes enables noninvasive muscle activity monitoring, broadening clinical and research applications

1950s-1960s

 $\cdot$ 1990s: Integration with computer technology and software enables detailed, realtime EMG signal analysis; development of portable and wearable EMG devices begins 2000s: Increased use of EMG with robotics and assistive technologies for rehabilitation and functional assessment.

# 1990s-2000s



# 1930s-1940s

-1930s: Initial EMG recordings with rudimentary equipment; used for research.  $\cdot$ 1940s: Early amplifiers and recording devices improve EMG quality and usability



·1970s: Advances in signal processing and digital technology enhance EMG data analysis, improving accuracy and reliability. .1980s: EMG becomes standard in neuromuscular diagnostics, with applications in rehabilitation and sports science.

1970s-1980s

#### 2010s-present

·2010s: Advancements in wearable technology and realtime data analysis expand EMG applications in rehabilitation, ergonomics, and sports science. 2020s: Research improves EMG accuracy, integrates EMG with machine learning and AI, and explores new applications in personalized medicine and advanced rehabilitation therapies.

**Figure 2.** The EMG timeline from the 1900s to the present



**Figure 3.** EMG signal detection and processing workflow, from **impulse detection** to **amplification and filtering** .Advanced EMG processing techniques, including **feature extraction**, **normalization**, and **pattern recognition** for diagnostics and rehabilitation

(intramuscular EMG) to detect these electrical signals. Surface electrodes measure electrical activity from the



muscle's surface, while intramuscular electrodes provide more detailed information from within the muscle [\[18\]](#page-18-12). In the Signal Amplification/Processing stage, the detected electrical signals are typically very small and require amplification. Amplifiers increase the signal strength for accurate recording and analysis. The amplified signals are then processed to filter out noise and other interference, including artifacts from external sources or other muscles. EMG signal processing techniques enhance the accuracy of muscle activity data by amplifying weak signals, removing noise through filtering, and converting signals to a unipolar format via rectification [\[19\]](#page-18-13). Smoothing helps reduce variability, while feature extraction provides meaningful parameters for analysis. Normalization standardizes data, and advanced methods like time-frequency analysis and pattern recognition offer insights into muscle activity dynamics and applications [\[20\]](#page-18-14). These processing techniques are essential for converting raw EMG data into valuable information, enabling accurate assessment of muscle activity and effective applications in clinical diagnostics, rehabilitation, sports science, and ergonomics [\[21\]](#page-19-0). The Signal Amplification/Processing stage encompasses several key processes: amplification to enhance signal strength, filtering to remove noise and interference, rectification to convert AC signals to DC, smoothing to stabilize signal fluctuations, feature extraction to identify important signal characteristics, normalization to adjust the signal to a common scale, time-frequency analysis to examine the signal in both domains and pattern recognition to classify and interpret muscle activity patterns.

The purpose of amplification is to enhance the strength of the weak EMG signals, making them suitable for accurate measurement. This is achieved by using amplifiers that increase the signal strength, ensuring that the EMG data can be further analyzed. It is important that amplification is carefully controlled to avoid distorting the signal [\[22\]](#page-19-1). Filtering is used to remove noise and unwanted interference from the EMG signal [\[23\]](#page-19-2). Techniques such as low-pass, highpass, band-pass, and notch filters help to eliminate artifacts and noise, including electrical interference and movement artifacts. This process isolates the relevant muscle activity from the background noise, improving the clarity of the signal [\[24\]](#page-19-3). Rectification converts the bipolar EMG signal into a unipolar form by taking the absolute value of the signal. This step is necessary because the raw EMG signal includes both positive and negative values, which can complicate analysis. By converting the signal to a unipolar format, it becomes easier to analyze and interpret [\[25\]](#page-19-4). Smoothing is applied to make the signal more interpretable by reducing variability and noise. Methods such as moving average or low-pass filtering are used to create a continuous curve representing

the overall trend of muscle activity. This helps in visualizing and analyzing muscle performance more clearly [\[26\]](#page-19-5). Feature extraction involves calculating parameters such as amplitude, frequency, and duration of muscle activity to extract meaningful information from the EMG signal. Common features include root mean square (RMS), mean absolute value (MAV), and frequency domain measures like median frequency. These features are used to assess muscle function, fatigue, and coordination [\[27\]](#page-19-6).

Normalization accounts for variations in EMG signal amplitude due to differences in electrode placement or muscle size. This is done by scaling the EMG data relative to a reference signal or maximum voluntary contraction (MVC). Normalization allows for standardized measurements, facilitating comparisons across different conditions or subjects [\[28\]](#page-19-7). Timefrequency analysis examines how the frequency content of the EMG signal changes over time. Methods such as wavelet transform are used to study the temporal and spectral characteristics of the EMG signal, providing insights into dynamic changes in muscle activity and fatigue [\[29\]](#page-19-8). Pattern recognition techniques are employed to classify and interpret complex EMG signals, particularly in applications like prosthetics and rehabilitation  $[30]$ . Machine learning algorithms are used to identify specific muscle activity patterns and classify them according to predefined categories. This approach is useful in advanced applications such as control of assistive devices and neuromuscular diagnostics [\[31\]](#page-19-10).

Finally, in Data Analysis, the processed EMG signals are examined to assess muscle activity. This analysis involves evaluating characteristics such as amplitude (strength) and frequency (rate) of the electrical activity to gain insights into muscle function, coordination, and performance. By measuring these electrical signals, EMG provides valuable information about muscle activity, which is crucial for diagnosing neuromuscular disorders, designing rehabilitation programs, and studying muscle function in various contexts [\[32\]](#page-19-11).

# 2.2. Types of EMG

The EMG can be categorized into two main types: surface EMG and intramuscular EMG. As shown in Figure 4, each type has distinct methods of measuring muscle electrical activity and is used for different applications [\[33\]](#page-19-12).

**Surface EMG (sEMG).** the skin over the muscle of interest. These electrodes detect the electrical activity generated by muscle contractions. Surface EMG is commonly used for assessing general muscle function, monitoring rehabilitation progress, studying muscle coordination, and evaluating ergonomics in work environments. It is also widely utilized in sports





**Figure 4. Surface EMG:** A non-invasive method using skin electrodes to detect muscle activity, commonly applied in rehabilitation, muscle coordination studies, ergonomics, and sports science. **Intramuscular EMG:** uses inserted electrodes for detailed analysis of specific muscles, often used in clinical diagnostics and research on neuromuscular disorders. [\[34\]](#page-19-13)

science for performance analysis and injury prevention. The primary advantage of surface EMG is that it is less invasive and more comfortable for the patient, allowing for broader muscle groups to be monitored simultaneously. However, it may be less precise in isolating specific muscles and can be affected by factors such as skin condition, electrode placement, and interference from other muscles [\[6\]](#page-18-0)[\[35\]](#page-19-14).

**Intramuscular EMG.** involves inserting fine needle electrodes or wire electrodes directly into the muscle tissue. This method provides a more detailed view of the electrical activity within specific muscles. Intramuscular EMG is often used in clinical diagnostics to assess neuromuscular disorders and in research to study deep muscle function, motor unit activity, and precise muscle responses. It offers high-resolution data on muscle activity and can accurately detect activity from deep muscles or specific muscle fibers. However, it is invasive and may cause discomfort or pain. Additionally, it requires skilled electrode placement and can be more complex to perform and analyze compared to surface EMG [\[36\]](#page-19-15)[\[37\]](#page-19-16). As mentioned, each type of EMG has its own set of strengths and limitations, making them suitable for different diagnostic, research, and therapeutic purposes, summarized in Table 1.

#### **3. Rehabilitation and Movement Detection**

Rehabilitation and movement detection (Fig 5) are crucial components in designing effective therapeutic interventions for individuals recovering from injuries or managing chronic conditions. The integration of advanced techniques like EMG plays a significant role in enhancing these processes [\[38\]](#page-19-17). Together, effective rehabilitation and precise movement detection contribute to improved patient outcomes by enabling targeted interventions and providing real-time feedback on muscle function and movement [\[39\]](#page-19-18). Rehabilitation focuses on restoring function and improving the quality of life for patients with physical impairments. Techniques such as physical therapy, occupational therapy, and robotic-assisted therapy are employed to aid recovery. EMG provides valuable feedback on muscle activity and function, allowing therapists to tailor rehabilitation programs to the specific needs of each patient. By monitoring muscle activation patterns and adjusting therapeutic exercises based on EMG data, rehabilitation can be made more effective and personalized  $[40]$ .

Movement Detection involves tracking and analyzing movements to assess motor function and detect abnormalities. Techniques such as motion capture systems, wearable sensors, and EMG are used to monitor and evaluate movement patterns [\[41\]](#page-19-20). EMG, in particular, offers insights into muscle activation and coordination,





Table 1. Overview of EMG Types: Characteristics, Applications, Benefits, and Drawbacks [\[35\]](#page-19-14)[\[36\]](#page-19-15)[\[37\]](#page-19-16)



**Figure 5. Role of EMG in Rehabilitation and Movement Detection:** Rehabilitation methods, including physical, occupational, and robotic-assisted therapy, restore function. Movement detection uses tools like motion capture, wearable sensors, and EMG to monitor motor function

helping to identify issues such as muscle weakness or improper movement patterns. This information is crucial for diagnosing conditions, tracking recovery progress, and optimizing rehabilitation strategies [\[42\]](#page-19-21).

# 3.1. Role of EMG in Rehabilitation

EMG plays a key role in rehabilitation by providing detailed insights into muscle activity, essential for designing and optimizing therapeutic interventions [\[43\]](#page-19-22). As mentioned, EMG is a valuable tool in rehabilitation that enhances the ability to assess, monitor, and optimize muscle function, leading to more effective and personalized therapeutic interventions [\[44\]](#page-19-23)[\[45\]](#page-19-24). EMG significantly enhances rehabilitation by providing detailed assessments of muscle function and enabling personalized therapy through tailored exercises [\[46\]](#page-20-0). It offers real-time feedback on muscle activation, aiding in correcting movements and improving exercise accuracy [\[47\]](#page-20-1). Additionally, EMG helps monitor progress and supports motor learning, optimizing recovery outcomes. The role of EMG in rehabilitation, as illustrated in Figure 5, can be summarized as follows:

1. Assessment of Muscle Function: EMG helps assess muscle function by measuring electrical activity during contractions. This assessment allows therapists to identify muscle weaknesses, imbalances, or abnormal activity patterns, which



are crucial for developing targeted rehabilitation programs [\[48\]](#page-20-2).

- 2. Personalized Therapy: By analyzing EMG data, therapists can tailor rehabilitation exercises to the specific needs of each patient. This customization ensures that exercises effectively target the affected muscles and optimize recovery, enhancing the overall efficacy of the rehabilitation process [\[49\]](#page-20-3).
- 3. Real-Time Feedback: EMG provides real-time feedback on muscle activation, enabling patients and therapists to adjust exercises and techniques immediately. This feedback helps in correcting improper movements, improving exercise accuracy, and ensuring that the desired muscles are being effectively engaged [\[50\]](#page-20-4).
- 4. Progress Monitoring: Tracking changes in muscle activity over time through EMG allows therapists to monitor patient progress and adjust rehabilitation plans as needed. It helps in evaluating the effectiveness of interventions, identifying any deviations from expected recovery patterns, and making informed decisions about ongoing treatment [\[51\]](#page-20-5).
- 5. Enhancing Motor Learning: EMG data supports motor learning by providing feedback on muscle performance and coordination. This information aids patients in learning correct movement patterns and improving motor control, which is crucial for functional recovery [\[52\]](#page-20-6)[\[53\]](#page-20-7).

# 3.2. Challenges in Detecting Interrupted Movements

The wrist and hand are crucial in rehabilitation because they play a key role in daily activities and overall functionality. Effective rehabilitation of these areas can significantly impact a person's ability to perform essential tasks such as writing, eating, and self-care. Improving wrist and hand function enhances dexterity, strength, and coordination, which are vital for maintaining independence and quality of life. Additionally, rehabilitation targeting these areas can address issues such as pain, weakness, or limited range of motion, contributing to better overall physical and emotional well-being. Detecting interrupted movements poses several challenges, such as signal interference, variable muscle activation, and complex movement patterns(Fig 10). Overcoming these issues necessitates the use of advanced signal processing techniques, meticulous calibration of measurement equipment, and the application of sophisticated algorithms for precise detection and analysis  $[21][54]$  $[21][54]$ . Signal interference, including noise and artifacts, can obscure EMG signals, complicating the accurate detection and analysis of muscle activity

during interrupted movements. Variable muscle activation patterns, which can be inconsistent during interruptions, further complicate the identification of movement disruptions and hinder precise detection [\[55\]](#page-20-9). Additionally, complex or multi-joint movements may produce overlapping muscle signals, making it difficult to isolate and accurately interpret specific interruptions in movement. Addressing these challenges involves sophisticated signal processing techniques, careful calibration of measurement equipment, and advanced algorithms for precise analysis [\[56\]](#page-20-10)[\[57\]](#page-20-11).

# 3.3. Importance of Accurate Detection in Wrist and Hand Rehabilitation

Accurate detection in wrist and hand rehabilitation is essential for creating effective, personalized treatment plans, optimizing recovery, preventing re-injury, and enhancing patient feedback and engagement [\[58\]](#page-20-12)[\[59\]](#page-20-13).

As shown in Figure 6, effective treatment planning is facilitated by the precise detection of muscle activation and movement patterns, allowing therapists to tailor rehabilitation programs specifically to the patient's needs. This ensures that exercises are targeted and effective, addressing the exact impairments or deficits [\[60\]](#page-20-14)[\[61\]](#page-20-15). Accurate detection also helps in optimizing recovery by monitoring progress and adjusting treatments as necessary. By understanding how well a patient is performing movements, therapists can make informed decisions about advancing or modifying rehabilitation strategies, thus improving recovery outcomes [\[62\]](#page-20-16)[\[63\]](#page-20-17). Additionally, proper detection and analysis of movement patterns help prevent re-injury by identifying risky techniques that could lead to setbacks. This enables the implementation of corrective measures to promote safer rehabilitation practices [\[64\]](#page-20-18). Furthermore, real-time, accurate feedback on muscle activity and movement enhances patient engagement and adherence to rehabilitation programs, as patients gain a better understanding of their progress and can make adjustments based on precise, actionable information  $[50][65]$  $[50][65]$ .

#### **4. Robotic Arm Approaches in Rehabilitation**

Robotic arm approaches in rehabilitation offer advanced solutions for assisting and enhancing the recovery of individuals with motor impairments. These approaches leverage robotics technology to provide targeted, controlled, and repetitive movements that are crucial for effective rehabilitation [\[66\]](#page-20-20)[\[67\]](#page-20-21). The arm approach in rehabilitation encompasses several key elements: Assisted Movement, Rehabilitation Therapy, Repetitive Task Training, Real-Time Feedback, Customization and Adaptability, and Integration with EMG. These elements are described as follows:





**Figure 6.** The role of EMG in wrist and hand rehabilitation, (A) enabling effective treatment planning, (B) optimized recovery, (C) re-injury prevention, and (D) enhanced patient feedback through accurate detection and real-time muscle activity insights

- 1. Enhancing Motor Learning: Robotic arms can provide physical support and assistance during movement exercises, helping patients perform tasks they might otherwise struggle with. This support is particularly beneficial for individuals with severe motor impairments, as it allows them to engage in therapeutic activities that promote motor learning and recovery [\[68\]](#page-20-22).
- 2. Rehabilitation Therapy: Robotic arms can be programmed to deliver customized therapeutic interventions based on the patient's needs. They offer precise control over movement patterns and resistance levels, enabling therapists to design and adjust rehabilitation protocols tailored to individual progress and recovery goals [\[69\]](#page-20-23).
- 3. Repetitive Task Training: Repetitive and repetitive task training is a core component of many robotic rehabilitation systems. Robotic arms can perform consistent, repetitive movements, which are essential for motor learning and neuroplasticity. This repetitive training helps reinforce motor pathways and improve functional outcomes [\[70\]](#page-20-24).
- 4. Real-Time Feedback: Advanced robotic systems often include sensors and feedback mechanisms that provide real-time data on patient performance [\[71\]](#page-21-0). This feedback can be used to monitor

progress, adjust rehabilitation protocols, and provide patients with immediate insights into their movement quality and effectiveness [\[72\]](#page-21-1).

- 5. Customization and Adaptability: Robotic arms can be adapted to different types of rehabilitation exercises and can be customized to meet the specific needs of each patient [\[73\]](#page-21-2). This flexibility allows for a wide range of therapeutic activities, from fine motor skill training to gross motor function exercises [\[74\]](#page-21-3).
- 6. Integration with EMG: Combining robotic arms with electromyography (EMG) technology enhances the rehabilitation process by providing detailed information on muscle activity. This integration allows for more precise adjustments to the robotic assistance based on real-time muscle performance, improving the overall effectiveness of the therapy [\[75\]](#page-21-4).

Robotic arms in rehabilitation provide crucial support through assisted movement, tailored therapeutic interventions, and repetitive task training, which enhances motor learning and recovery. They offer realtime feedback to monitor progress and adjust protocols while their customization and adaptability cater to individual patient needs. Integrating these systems with EMG technology further refines the rehabilitation



process by allowing precise adjustments based on muscle activity.

#### 4.1. Overview of Robotic Arm Systems

Robotic arm systems in rehabilitation are advanced technological solutions designed to assist individuals in regaining motor function and improving mobility. These systems incorporate various components and technologies to deliver controlled, repetitive, and tailored therapeutic interventions. Robotic arm systems provide a versatile and advanced approach to rehabilitation, offering customized, controlled, and effective therapeutic solutions to support patient recovery and enhance motor function [\[76\]](#page-21-5)[\[77\]](#page-21-6).

As depicted in Figure 7, the robotic arm is comprised of six key elements: Components, Control Mechanisms, Sensors and Feedback, Types of Systems, Therapeutic Applications, and Integration with Other Technologies. Each of these elements plays a crucial role in the functionality and effectiveness of the robotic arm, as detailed below:

- 1. Components: Robotic arm systems typically include a robotic arm or manipulator, which provides physical support and guidance during movement exercises [\[78\]](#page-21-7). These systems often feature adjustable joints, actuators, and sensors that enable precise control and adaptability to different rehabilitation tasks [\[79\]](#page-21-8).
- 2. Control Mechanisms: The control mechanisms of robotic arm systems can range from manual controls operated by therapists to automated systems that adjust based on real-time data. These mechanisms allow for customized resistance, movement patterns, and exercise protocols tailored to individual patient needs [\[80\]](#page-21-9).
- 3. Sensors and Feedback: Many robotic arm systems are equipped with sensors that monitor movement, force, and muscle activity. This data is used to provide real-time feedback on the patient's performance, helping therapists adjust the therapy parameters and track progress [\[81\]](#page-21-10).
- 4. Types of Systems: Robotic arm systems can vary widely in design and functionality. Some systems are designed for upper extremity rehabilitation, focusing on the arm and hand, while others may support lower extremity rehabilitation or full-body movement [\[82\]](#page-21-11). Systems can also be stationary or mobile, depending on the therapeutic needs [\[83\]](#page-21-12)
- 5. Therapeutic Applications: These systems are used in various rehabilitation settings, including clinical environments and home therapy. They

support a range of therapeutic activities, from passive movement assistance to active exercise training, aiming to improve strength, coordination, and functional mobility [\[84\]](#page-21-13).

6. Integration with Other Technologies: Robotic arm systems are often integrated with other technologies, such as EMG, for enhanced functionality. This integration allows for more precise adjustments based on muscle activity data, improving the effectiveness of rehabilitation [\[85\]](#page-21-14).

#### 4.2. Integration of EMG with Robotic Arms

Integrating EMG with robotic arm systems enhances the precision and effectiveness of rehabilitation therapies by combining real-time muscle activity data with controlled robotic assistance (Fig 9). The integration of EMG with robotic arms represents a significant advancement in rehabilitation technology, offering a more responsive, precise, and personalized approach to improving muscle function and recovery [\[70\]](#page-20-24)[\[86\]](#page-21-15) (Fig 8).

Real-time muscle monitoring is a key feature of EMG sensors, which continuously provide data on muscle activation  $[87]$ . This allows the robotic arm to adjust its responses in real-time, delivering tailored assistance based on the patient's current muscle performance and improving the accuracy of therapeutic interventions. By analyzing EMG signals, robotic arms can customize their support to match the patient's muscle strength and activation patterns, ensuring that exercises are suited to the individual's functional abilities and making rehabilitation both challenging and achievable. The integration of EMG also enables dynamic feedback on muscle activity, allowing the robotic system to modify its movements or resistance based on the patient's performance, which helps maintain optimal levels of difficulty and support, thereby enhancing therapy effectiveness. Combining EMG with robotic arms enhances the precision of therapeutic exercises by finetuning the arm's movements to target specific muscles accurately. Additionally, this integration provides valuable data for monitoring progress over time, allowing therapists to track changes in muscle activity, adjust therapy accordingly, and better understand the patient's recovery trajectory. The synergy between EMG and robotic arms also facilitates adaptive training, where the robotic system learns and adapts to the patient's evolving needs, supporting progressive rehabilitation and helping patients gradually improve their muscle function and motor skills [\[88\]](#page-21-17)[\[89\]](#page-21-18)[\[90\]](#page-21-19).



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**Figure 7.** Robotic arm systems in rehabilitation feature adjustable arms, real-time feedback sensors, and EMG integration, enhancing adaptability and effectiveness in various therapeutic settings



**Figure 8.** EMG-driven robotic arms in rehabilitation enhance therapy precision and effectiveness by combining (A) real-time muscle monitoring, (B) personalized assistance, (C) adaptive training, (D) progress tracking, and (E) improved therapeutic accuracy. This integration provides a tailored and responsive approach to patient recovery

# 4.3. Benefits of Using Robotic Arms in Rehabilitation

Robotic arms offer several key benefits in rehabilitation, enhancing the effectiveness and efficiency of therapeutic interventions. Figure 9 shows the use of robotic arms in rehabilitation offers significant advantages by providing precise, consistent, and personalized therapy, enhancing patient engagement, and improving overall outcomes in motor function recovery [\[91\]](#page-21-20)[\[92\]](#page-21-21).

The benefits of using robotic arms in rehabilitation can be outlined as follows:

- 1. Precision and Control: Robotic arms provide precise and controlled movements, allowing for accurate targeting of specific muscles and joints. This precision ensures that rehabilitation exercises are performed correctly, crucial for effective recovery and preventing further injury.
- 2. Consistent Repetition: Robotic systems can deliver consistent and repetitive movements, which are essential for motor learning and neuroplasticity. Repetitive task training helps reinforce motor pathways and improve functional outcomes, aiding in the recovery of motor skills and coordination.
- 3. Personalized Therapy: Advanced robotic arms can be programmed to tailor rehabilitation exercises to the individual's needs and progress. This customization ensures that the therapy is adapted to the patient's functional abilities and recovery goals, optimizing the effectiveness of the intervention.





**Figure 9.** EMG and Robotic robotic arm integration and benefits in rehabiation

- 4. Real-Time Feedback: Many robotic arm systems are equipped with sensors that provide real-time feedback on movement and muscle activity. This immediate feedback helps patients and therapists monitor progress, adjust therapy protocols, and make informed decisions about the rehabilitation process.
- 5. Enhanced Motivation: Robotic arms often incorporate interactive elements and gamified therapies that can increase patient engagement and motivation. The interactive nature of these systems can make rehabilitation exercises more enjoyable and encourage consistent participation.
- 6. Reduced Therapist Burden: By automating certain aspects of therapy, robotic arms can reduce the physical burden on therapists and allow them to focus on other aspects of patient care. This efficiency can also enable therapists to manage more patients and deliver high-quality care [\[93\]](#page-21-22).
- 7. Safe and Controlled Environment: Robotic systems provide a safe and controlled environment for rehabilitation, reducing the risk of falls or injuries during exercises. The robotic arm's support helps patients perform movements with minimal risk, particularly for those with significant motor impairments [\[94\]](#page-21-23).
- 8. Objective Measurement: Robotic arms can objectively measure and record various aspects of performance, such as movement range, speed, and force. This data allows for accurate assessment of progress and the effectiveness of rehabilitation strategies [\[95\]](#page-22-0).

As mentioned, Robotic arms in rehabilitation offer several key benefits. They provide precise and controlled movements for accurate targeting of muscles and joints, which is crucial for effective recovery and injury prevention. The systems deliver consistent and repetitive tasks that support motor learning and neuroplasticity, while advanced programming allows for personalized therapy tailored to individual needs and progress. Additionally, real-time feedback from sensors helps monitor and adjust therapy, enhancing motivation through interactive elements, reducing therapist burden, and ensuring a safe, controlled environment with objective performance measurements.

# **5. Detection of Interrupted Wrist and Hand Movements**

Detecting interrupted wrist and hand movements is critical for effective rehabilitation and understanding motor function. This process involves identifying and analyzing disruptions in movement patterns, which can provide insights into the underlying motor impairments and inform therapeutic strategies. detecting interrupted wrist and hand movements is essential for diagnosing motor impairments, optimizing rehabilitation strategies, and improving patient outcomes. Advanced detection techniques and real-time monitoring play a crucial role in ensuring effective and personalized therapeutic interventions  $[96]$ .

As it shown in Figure 10, Various techniques are employed to detect interrupted movements, including electromyography (EMG), motion capture systems, and wearable sensors. EMG measures muscle activity to identify irregularities, while motion capture and sensors track movement patterns to detect disruptions [\[97\]](#page-22-2)[\[98\]](#page-22-3). Detecting interruptions can be challenging due to factors such as signal interference from noise and artifacts, variable muscle activation patterns, and complex movement dynamics. These factors can complicate the identification and analysis of movement disruptions [\[99\]](#page-22-4). Integrating data from multiple sources, such as EMG and motion sensors, can improve





**Figure 10.** Techniques and challenges in detecting interrupted wrist and hand movements. The figure highlights EMG, motion capture systems, and wearable sensors for detection, challenges like signal interference, and the role of robotic arms in enhancing precision, real-time feedback, and data integration for improved rehabilitation outcomes

the accuracy of detection. Combining these data sources allows for a more comprehensive understanding of movement interruptions and their impact on rehabilitation [\[100\]](#page-22-5)[\[101\]](#page-22-6). Advanced systems enable real-time monitoring of wrist and hand movements, providing immediate feedback on any interruptions. This capability allows for timely adjustments to therapy and better tracking of patient progress [\[102\]](#page-22-7). As the Application in Rehabilitation, Accurate detection of movement interruptions helps in designing targeted rehabilitation interventions. By understanding specific disruptions, therapists can customize exercises and adjust therapy protocols to address the exact impairments and improve recovery outcomes [\[103\]](#page-22-8). The detection of interrupted movements provides valuable feedback for both patients and therapists. This feedback can be used to correct improper techniques, enhance exercise effectiveness, and facilitate better engagement in the rehabilitation process [\[104\]](#page-22-9)[\[105\]](#page-22-10)].

# 5.1. Mechanisms of Movement Interruption

Movement interruptions can occur due to various mechanisms, each affecting the ability to perform smooth and coordinated wrist and hand movements. Understanding these mechanisms is essential for effective diagnosis and rehabilitation. Understanding these mechanisms helps in diagnosing the underlying causes of movement interruptions and tailoring rehabilitation strategies to address specific issues, ultimately improving motor function and overall movement quality [\[106\]](#page-22-11)[\[107\]](#page-22-12). The Movement Interruption mechanism includes the following categories:

- 1. Neuromuscular Factors: Interruptions may result from deficits in the neuromuscular system, such as impaired motor control or muscle weakness. Conditions like stroke, nerve injuries, or neuromuscular disorders can disrupt the transmission of signals from the brain to the muscles, leading to inconsistent or incomplete movement
- 2. Motor Planning and Coordination: Difficulties in motor planning and coordination can lead to interruptions. Issues with the brain's ability to plan and execute complex movements can cause problems with initiating, sustaining, or adjusting movements, resulting in breaks or irregularities in motion.
- 3. Muscle Fatigue: Prolonged or intense activity can cause muscle fatigue, leading to interruptions in movement. As muscles become tired, their ability to maintain force and control diminishes, resulting in less smooth or interrupted motion



- 4. Joint or Tendon Restrictions: Physical restrictions in the joints or tendons, such as stiffness or limited range of motion, can interrupt smooth movements. Conditions like arthritis or tendonitis may affect joint flexibility and tendon function, causing disruptions in movement.
- 5. Sensory Feedback Disruptions: Proper movement requires accurate sensory feedback from the environment and body. Disruptions in sensory feedback, whether due to peripheral nerve damage or sensory processing issues, can impair the ability to adjust movements in real time, leading to interruptions
- 6. External Factors: External factors such as environmental conditions or improper ergonomics can also contribute to movement interruptions. For example, an awkward hand position or an unsuitable work environment may lead to inefficient movements and frequent interruptions [\[108\]](#page-22-13).

Movement interruptions can arise from several factors: Neuromuscular issues, such as motor control impairments or muscle weakness, can disrupt signal transmission from the brain to the muscles, leading to inconsistent movements. Problems with motor planning and coordination may cause difficulties in initiating or sustaining complex movements, resulting in irregular motion. Muscle fatigue from prolonged activity reduces muscle control and smoothness of movement. Joint or tendon restrictions, such as stiffness from arthritis, can limit the range of motion and disrupt movement. Sensory feedback disruptions due to nerve damage or processing issues impair real-time movement adjustments. Additionally, external factors, such as poor ergonomics or environmental conditions, can lead to inefficient movements and interruptions.

# 5.2. EMG Techniques for Detecting Interruptions

Electromyography (EMG) techniques are crucial for detecting interruptions in wrist and hand movements by providing insights into muscle activity patterns which are described as below:

- 1. Signal Analysis: EMG signal analysis involves examining muscle electrical activity during movements. By analyzing the amplitude and frequency of EMG signals, disruptions in muscle activation can be identified. Irregularities or deviations from normal patterns indicate possible interruptions.
- 2. Time-Domain Analysis: This method examines EMG signals over time to detect interruptions. Techniques such as root mean square (RMS) and mean absolute value (MAV) quantify muscle

activity. Sudden changes or inconsistencies in these values can reveal movement interruptions.

- 3. Frequency-Domain Analysis: Frequency-domain analysis assesses the frequency components of EMG signals using power spectral density (PSD) analysis. Shifts in frequency content or power distribution can indicate disruptions in muscle activity or coordination.
- 4. Wavelet Transform: Wavelet transform offers a time-frequency analysis of EMG signals, revealing how muscle activity varies over time and frequency. This technique helps identify transient interruptions or abnormal patterns in muscle activity.
- 5. Pattern Recognition: Advanced pattern recognition techniques use machine learning algorithms to classify and interpret complex EMG data. These algorithms can detect specific patterns associated with movement interruptions and classify them effectively.
- 6. Real-Time Monitoring: Real-time EMG monitoring systems provide immediate feedback on muscle activity, allowing for the detection of interruptions as they happen. This enables timely adjustments to therapeutic interventions and exercises.
- 7. Integration with Other Sensors: Combining EMG with other sensors, such as accelerometers or motion capture systems, enhances the accuracy of detecting interruptions. This integrated approach provides a comprehensive view of both muscle activity and movement dynamics [\[109\]](#page-22-14)[\[110\]](#page-22-15).

These EMG techniques enable accurate detection and analysis of interrupted wrist and hand movements, facilitating more effective diagnosis and tailored rehabilitation strategies.

# 5.3. Role of Robotic Arms in Enhancing Detection

Robotic arms play a significant role in enhancing the detection of interrupted wrist and hand movements by providing precise, controlled, and integrated systems for monitoring and analysis. Overall, robotic arms enhance the detection of interrupted wrist and hand movements by providing precise control, integrating advanced sensors, and offering real-time feedback. This leads to more accurate detection, detailed analysis, and improved rehabilitation outcomes [\[111\]](#page-22-16)[\[112\]](#page-22-17). The role of robotic arms in enhancing detection (Fig 10) can be described as follows:

1. Precision in Movement: Robotic arms offer highly accurate and consistent movement control,



which is crucial for detecting subtle interruptions in wrist and hand movements. The precision of robotic systems ensures that even minor deviations from intended movement patterns can be identified and analyzed [\[113\]](#page-22-18).

- 2. Integrated Sensors: Many robotic arms are equipped with advanced sensors, including force sensors, accelerometers, and EMG electrodes. These sensors collect comprehensive data on muscle activity, joint forces, and movement dynamics, providing a detailed understanding of any interruptions [\[114\]](#page-22-19).
- 3. Real-Time Feedback: Robotic arms with real-time monitoring capabilities provide immediate feedback on movement and muscle performance. This allows for the instant detection of interruptions and enables timely adjustments to therapeutic protocols based on current data [\[115\]](#page-22-20).
- 4. Adaptive Response: Robotic arms can be programmed to adjust their support and resistance in response to detected interruptions. This adaptive capability helps in maintaining the effectiveness of rehabilitation exercises and ensuring that the therapy remains aligned with the patient's needs [\[116\]](#page-22-21).
- 5. Enhanced Data Collection: The integration of robotic arms with EMG and other sensing technologies facilitates the collection of extensive and high-resolution data. This data can be used to perform in-depth analyses of movement patterns and interruptions, leading to more accurate diagnoses and treatment plans [\[117\]](#page-22-22)[\[118\]](#page-22-23).
- 6. Consistent Testing Conditions: Robotic arms provide a controlled environment for performing rehabilitation exercises, minimizing variability in testing conditions. This consistency helps in accurately detecting and analyzing movement interruptions without external influences affecting the results [\[119\]](#page-22-24)[\[120\]](#page-22-25).
- 7. Detailed Analysis: Robotic systems can integrate and analyze data from multiple sources, such as EMG signals and movement trajectories. This comprehensive analysis allows for a deeper understanding of how interruptions impact overall motor function and aids in developing targeted rehabilitation strategies [\[121\]](#page-22-26).
- 8. Enhanced Patient Interaction: Some robotic arms include interactive features and feedback mechanisms that engage patients more effectively. By offering visual or auditory feedback, these systems can assist patients in understanding

and correcting interruptions in their movements [\[122\]](#page-23-0).

#### **6. Case Studies and Applications**

The integration of robotic arms and EMG techniques has been widely explored in various clinical and research settings, leading to significant advancements in rehabilitation [\[123\]](#page-23-1). As the key case studies and applications some notable achievements are as follows:



**Figure 11.** Key case studies of robotic arms and EMG integration in rehabilitation. Applications include (A) stroke rehabilitation, (B) post-surgical recovery, (C) spinal cord injury therapy, (D) sports performance enhancement, (E) chronic pain management, and (F) pediatric rehabilitation, demonstrating the effectiveness of combining robotic assistance with EMG monitoring for improved motor function and recovery outcomes

1. Stroke Rehabilitation: In a study focused on stroke rehabilitation, robotic arm systems were employed to assist patients with hand and wrist exercises (Fig 11A). The use of EMG sensors



provided real-time feedback on muscle activity, allowing for the adaptation of robotic assistance based on individual muscle performance. This approach led to improved motor recovery and functionality in stroke patients, demonstrating the effectiveness of combining robotic support with EMG monitoring.[\[124\]](#page-23-2)[\[125\]](#page-23-3).

- 2. Post-Surgical Hand Recovery: After hand surgery, patients often experience challenges with movement and strength. Robotic arm systems, integrated with EMG technology, were used to deliver controlled and repetitive exercises (Fig 11B). The EMG data helped tailor the rehabilitation protocol to each patient's muscle recovery progress, resulting in enhanced strength and dexterity during the post-surgical recovery period [\[126\]](#page-23-4).
- 3. Spinal Cord Injury Rehabilitation: A case study involving spinal cord injury patients utilized robotic arms to facilitate upper limb exercises. EMG techniques were used to monitor muscle activation and adjust robotic support accordingly (Fig 11C). This integration helped improve motor function and muscle coordination, showcasing the benefits of robotic and EMG technologies for severe motor impairments [\[127\]](#page-23-5).
- 4. Sports Performance and Injury Prevention: In sports science, robotic arms and EMG sensors were used to analyze athletes' hand and wrist movements. The technology helped identify and address interruptions in movement patterns, leading to the development of targeted training programs that enhanced performance and reduced injury risk (Fig 11D). This application highlights the role of these technologies in optimizing athletic performance and preventing injuries [\[128\]](#page-23-6).
- 5. Chronic Pain Management: Robotic arm systems, combined with EMG monitoring, were applied in managing chronic pain conditions affecting the wrist and hand. The technology allowed for controlled exercise therapy, with real-time EMG data guiding the adjustments based on pain levels and muscle activity (Fig 11E). This approach improved pain management and functional outcomes for individuals with chronic conditions [\[129\]](#page-23-7).
- 6. Pediatric Rehabilitation: For children with developmental disorders affecting hand and wrist movements, robotic arms and EMG sensors were used to provide engaging and interactive therapy (Fig 11F). The real-time feedback and adaptive therapy facilitated developmental milestones and

improved motor skills, demonstrating the benefits of these technologies in pediatric rehabilitation [\[130\]](#page-23-8).

These case studies and applications illustrate the diverse and impactful uses of robotic arms and EMG techniques in rehabilitation. They demonstrate the potential of these technologies to enhance recovery, optimize therapeutic interventions, and improve patient outcomes across various conditions and therapeutic contexts.

High costs associated with robotic arms and EMG systems limit their accessibility for many patients and facilities, necessitating efforts to make these technologies more affordable. The complexity of operating these systems poses challenges, but simplifying user interfaces and providing thorough training can improve usability. There is a lack of long-term data on their effectiveness, requiring more longitudinal studies to assess sustained impact. Variability in patient responses highlights the need for more personalized and adaptive systems. Better integration with traditional therapies and addressing technical issues like signal interference and sensor accuracy are also crucial. Improvements in these areas will enhance the effectiveness and accessibility of robotic and EMG technologies in rehabilitation [\[134\]](#page-23-9)[\[135\]](#page-23-10).

# **7. Technological Advancements and Future Directions**

Advancements in manufacturing and materials are expected to reduce the costs of robotic arms and EMG systems, increasing their accessibility [\[136\]](#page-23-11) . Future developments aim to simplify user interfaces, making these technologies easier to operate and calibrate [\[137\]](#page-23-12). Long-term studies, supported by advanced data analytics and AI, will provide deeper insights into the sustained impact of these therapies. Personalized rehabilitation will benefit from sophisticated algorithms and AI to tailor treatments to individual needs. Integrating robotic and EMG technologies with traditional therapies will offer a more comprehensive rehabilitation approach. Innovations in sensors and wireless communication will address technical limitations, enhancing performance and reliability [\[138\]](#page-23-13).

Recent innovations in EMG signal processing include advanced algorithms for noise reduction and enhanced signal clarity, improving the accuracy of muscle activity detection. Machine learning techniques are increasingly being used to analyze complex EMG data, enabling better interpretation of muscle patterns and movement intentions. Real-time processing advancements allow for immediate feedback during rehabilitation exercises, facilitating more dynamic and responsive adjustments. Additionally, wearable and wireless EMG systems are being developed to provide greater flexibility and





Table 2. Case Studies and Applications of Robotic Arms and EMG in Rehabilitation [\[131\]](#page-23-14)[\[132\]](#page-23-15)[\[133\]](#page-23-16)

comfort for patients while maintaining high-quality data collection [\[139\]](#page-23-17)[\[140\]](#page-23-18).

The future of robotic arms in rehabilitation is marked by greater integration with AI and adaptive control systems, which will allow for more precise and personalized therapeutic interventions. Advances in robotics will lead to more versatile and user-friendly devices capable of accommodating a wider range of patient needs and rehabilitation goals. Developments in soft robotics and flexible materials will make robotic arms more adaptable and comfortable for extended use. Enhanced connectivity and data integration will also facilitate better coordination between robotic systems and other therapeutic modalities [\[141\]](#page-23-19). The potential for personalized rehabilitation programs is expanding with advancements in data analytics and AI, which enable tailored therapeutic approaches based on individual patient profiles and progress. Personalized algorithms can adapt rehabilitation exercises in real time, responding to changes in muscle function and recovery rates. Integration with wearable technology allows for continuous monitoring and adjustment of therapy programs, enhancing their effectiveness. As these technologies evolve, they promise to provide more customized, efficient, and engaging rehabilitation experiences, ultimately leading to improved patient outcomes and satisfaction [\[142\]](#page-23-20).



#### **8. Challenges and Limitations**

Integrating EMG systems with robotic arms involves addressing several technical challenges, including issues related to signal interference, hardware malfunctions, and sensor accuracy. Additionally, patientspecific factors, such as individual variations in muscle function and movement patterns, must be considered to ensure effective therapy. Cost and accessibility issues also play a significant role, as the high expense of advanced technologies can limit their availability and restrict patient access (Fig 12).

Considering the Technical Challenges in EMG and Robotic Integration, Integrating EMG systems with robotic arms presents several technical challenges, including signal interference, hardware malfunctions, and limitations in sensor accuracy. Ensuring precise synchronization between EMG data and robotic control requires ongoing advancements in signal processing and system engineering. Additionally, maintaining reliability and performance in varying clinical environments remains a significant challenge [\[143\]](#page-23-21).With respect to Patient-Specific Factors, Individual differences in muscle function, movement patterns, and rehabilitation needs can impact the effectiveness of EMG and robotic therapies [\[144\]](#page-23-22). Variability among patients may require highly adaptable and personalized approaches, which can complicate the development and implementation of standardized treatment protocols. Addressing these factors demands flexible and adaptive systems that can accommodate a wide range of patient profiles [\[145\]](#page-23-23)[\[146\]](#page-23-24). By the Cost and Accessibility Issues, The high costs associated with advanced robotic arms and EMG technologies limit their availability in many healthcare settings. This financial barrier can restrict access for patients who could benefit from these innovative therapies. Efforts to reduce costs through technological advancements and more efficient manufacturing processes are crucial for improving accessibility and expanding the reach of these technologies [\[147\]](#page-23-25)[\[148\]](#page-23-26).

#### **9. Conclusion**

Electromyography (EMG) is a diagnostic technique used to measure and record the electrical activity produced by muscles. It involves placing electrodes on the skin or inserting them into muscle tissue to detect electrical signals generated during muscle contractions. EMG is commonly employed to assess muscle function, diagnose neuromuscular disorders, and evaluate the effectiveness of treatments or rehabilitation exercises.

This technique provides valuable insights into muscle activity patterns, helping clinicians understand muscle performance and identify abnormalities. The integration of robotic arms with EMG technologies has shown significant potential in enhancing rehabilitation outcomes through precise monitoring of muscle activity and adaptive robotic support. Key findings highlight their effectiveness in various applications, including stroke recovery, post-surgical hand therapy, spinal cord injury rehabilitation, sports performance, chronic pain management, and pediatric developmental disorders.

Despite these advantages, challenges such as high costs, technical complexities, and variability in patient responses persist. Integrating robotic arms with EMG systems has the potential to revolutionize rehabilitation practices by enabling more targeted and personalized therapies. Enhanced accuracy in muscle activity detection and real-time feedback can lead to more effective treatment plans, optimized recovery, and a reduced risk of re-injury. Additionally, these advancements may improve patient engagement and adherence through interactive and adaptive rehabilitation programs.

Future research should focus on addressing the technical challenges and limitations associated with robotic arms and EMG systems. This includes developing more cost-effective solutions, improving user interfaces, and conducting long-term studies to better understand their sustained impact. Investigating personalized rehabilitation approaches and integrating these technologies with traditional therapies will also be crucial. Furthermore, research into patient-specific factors and innovations in signal processing will enhance the effectiveness and accessibility of these advanced rehabilitation technologies.

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**Figure 12.** Challenges in EMG and robotic arm integration, including technical issues, patient-specific variability, and cost barriers limiting accessibility.

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