

Review

AI-Based Personalization of 3D-Printed Hand Exoskeletons

Dariusz Mikołajewski ^{1,*} , Jakub Kopowski ¹ , Zbyszko Królikowski ¹, Jan Cybulski ¹, Bożena Skołod ²  and Izabela Rojek ¹ 

¹ Faculty of Computer Science, Kazimierz Wielki University, 85-064 Bydgoszcz, Poland; jakub.kopowski@ukw.edu.pl (J.K.); zbyszko.krolkowski@ukw.edu.pl (Z.K.); jan.cybulski@ukw.edu.pl (J.C.); izabela.rojek@ukw.edu.pl (I.R.)

² Department of Engineering Processes Automation and Integrated Manufacturing Systems, Faculty of Mechanical Engineering, Silesian University of Technology, 44-100 Gliwice, Poland; bozena.skolud@polsl.pl

* Correspondence: dariusz.mikolajewski@ukw.edu.pl

Featured Application

Possible practical applications include the planning and construction of 3D-printed exoskeletons, particularly for the upper limb.

Abstract

This article discusses advanced artificial intelligence (AI)-based strategies for the design and personalization of three-dimensionally (3D) fabricated hand exoskeletons, with a focus on adaptive, data-driven methodologies. It highlights the crucial role of intelligent personalization in improving user comfort, functional performance, and rehabilitation outcomes, particularly in medical and care settings. The proposed approach integrates biomechanical modeling, high-resolution 3D scanning, and machine learning (ML) algorithms to create exoskeleton systems tailored to the unique anatomical and motor characteristics of individual users. This article presents both a theoretical framework and practical implementation of AI-based adaptation, addressing key challenges such as precise anatomical fit, ergonomic optimization, and real-time responsiveness. Specific emphasis is placed on AI-based feedback mechanisms that enable continuous, dynamic adjustment of control parameters during device operation. Case studies illustrate the effectiveness of these techniques in improving performance and rehabilitation progress for individual users. By combining intelligent modeling, adaptive control, and additive manufacturing, this research advances the field of wearable robotics and points the way to more accessible, efficient, and fully personalized assistive technologies.

Keywords: artificial intelligence; machine learning; hand exoskeleton; wearable robots; personalisation; optimization; 3D printing; computational method; computational model; digital twin; decision support



Academic Editor: Claudio Belvedere

Received: 27 May 2026

Revised: 12 June 2026

Accepted: 1 July 2026

Published: 3 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Personalization of 3D-printed hand exoskeletons starts with acquiring anatomical data from the user through techniques such as 3D scanning, motion tracking, or parametric measurements. These data are then transformed into a digital model using CAD software, enabling precise adjustment of fit and range of motion [1]. Contemporary personalization approaches focus on developing adaptable parametric templates instead of fixed, single-use designs [2]. In practical applications, such templates allow clinicians and engineers to efficiently modify parameters such as finger length, joint spacing, and grip range to

suit individual users [3]. Material properties are also customized, with stiffness, flexibility, and weight carefully optimized according to the user's functional requirements and comfort needs [4]. Proprietary personalization techniques frequently employ algorithm-based fitting procedures that automatically adapt the exoskeleton geometry to the user's anatomy [5]. Certain systems further incorporate simulation tools to evaluate pressure distribution, joint alignment, and mechanical loading prior to fabrication. Machine learning (ML)-based personalization can enhance these processes by analyzing user feedback and performance metrics to continuously refine the design.

From a practical standpoint, iterative prototyping supports rapid testing and repeated adjustments of comfort, positioning, and actuation parameters [6]. Overall, personalized 3D-printed hand exoskeletons integrate theoretical principles of human biomechanics with advanced digital design workflows to create highly individualized assistive solutions [7].

Section 1.1 below establishes personalization as a fundamental requirement for 3D-printed, AI-based hand exoskeletons, as users differ in their anatomy, motor impairments, and rehabilitation needs. It explains how AI and 3D printing can work together to create personalized exoskeleton designs that improve fit, comfort, and functional performance. The discussion then links personalized design with improved rehabilitation outcomes, demonstrating why personalization is a key technological feature rather than an optional enhancement. Building on this foundation, Section 1.2 examines existing research and identifies limitations in current approaches to personalizing AI-based hand exoskeletons. The research gap stems from the lack of an integrated framework that comprehensively combines AI-based adaptation, user-specific design, and 3D printing technologies. Therefore, the novelty and contribution of the article are positioned as addressing this gap through a more advanced approach to personalized hand exoskeletons that improves personalization, usability, and rehabilitation effectiveness.

1.1. Personalization as a Key Feature of AI-Based 3D-Printed Exoskeletons

Patient-specific exoskeleton geometry can be designed based on 3D scans of the hand and forearm, ensuring an ergonomic fit and improved comfort during prolonged use [8,9]. AI algorithms can analyze patient-specific movement patterns and muscle activity to optimize the mechanical support provided by the device [10]. The personalization process also involves adjusting actuator force, joint stiffness, and range of motion based on the degree of motor impairment and rehabilitation goals [11]. ML systems can continuously update therapeutic parameters based on real-time patient progress and clinician feedback. Patient-specific rehabilitation programs supported by the exoskeleton can improve neuroplasticity through repetitive, adaptive, and task-oriented exercises [12]. AI-assisted monitoring allows clinicians to detect fatigue, compensatory movements, or incorrect exercise performance during therapy sessions [13]. Personalized rehabilitation strategies can increase patient motivation and adherence to treatment recommendations because exercises can be tailored to individual abilities and daily activities. The system can support collaborative goal setting between patients, physicians, physical therapists, and biomedical engineers by integrating measurable rehabilitation goals with an AI platform [14]. Common therapeutic goals may include restoring grip function, improving fine motor skills, reducing pain, and increasing independence in daily activities. In preventative medicine, personalized hand exoskeletons can reduce the risk of secondary musculoskeletal complications caused by immobilization or poor limb biomechanics [15]. This technology can also help prevent lifestyle diseases associated with a sedentary lifestyle and long-term disability by promoting active rehabilitation and functional movement. AI-based predictive analytics can identify early signs of muscle atrophy, joint contractures, or overuse syndromes before serious secondary changes develop [16]. Private cloud-based rehabilitation platforms can

facilitate remote monitoring and long-term adaptation of treatment plans for patients living outside specialized medical centers (Figure 1) [17].

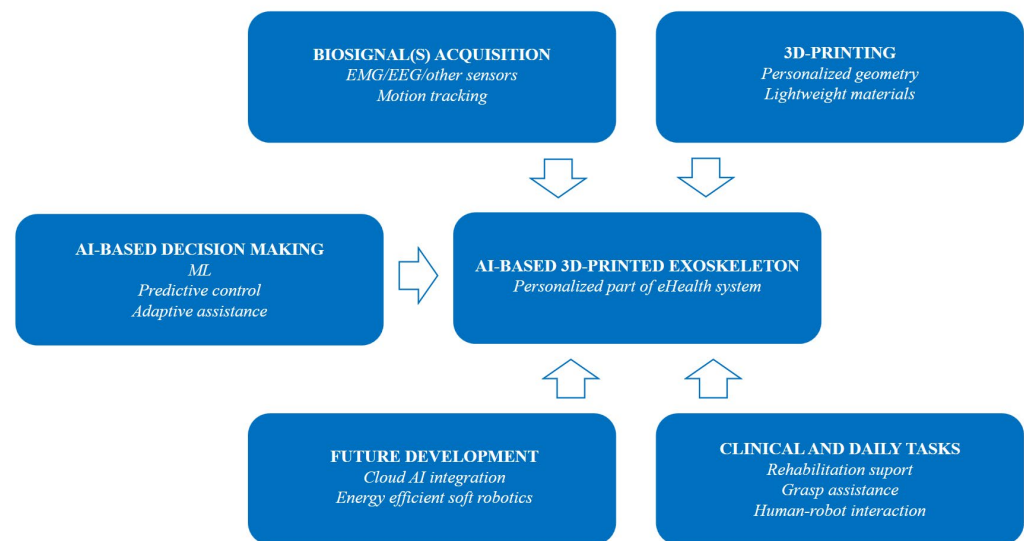


Figure 1. Personalization roles in AI-based 3D-printed hand exoskeleton.

1.2. Observed Research Gap, Novelty and Contribution

A major research gap in the customization of 3D-printed hand exoskeletons is the absence of a standardized framework for converting anatomical data into parametric and clinically validated design models [18]. Existing systems frequently depend on proprietary algorithms, limiting the ability of researchers to evaluate their accuracy, repeatability, and biomechanical reliability [19]. Comparative studies investigating the influence of different scanning technologies on customization quality and long-term user experience are also limited. In addition, many investigations involve only small participant groups, resulting in insufficient knowledge about how personalization performs across diverse hand sizes, functional impairments, and changes in user condition over time [20]. Another important limitation is the lack of transparent and dynamically integrated biomechanical modeling, as most current methods emphasize geometric fitting while neglecting joint kinematics, soft tissue interactions, and error analysis in fitting algorithms [21]. Furthermore, there is still a shortage of long-term clinical evidence, standardized validation metrics, and systematic approaches for incorporating user feedback into iterative personalization processes to determine whether customization truly enhances rehabilitation outcomes and user adherence [22–24].

The concepts presented in this paper aim to address existing research gaps by introducing a unified and transparent framework for the personalization of 3D-printed hand exoskeletons that combines theoretical modeling with practical implementation. A central innovation is the integration of parametric anatomical templates with dynamic biomechanical simulation, allowing devices to be optimized not only for anatomical shape but also for movement behavior and load distribution patterns [25]. The proposed approach also establishes open and repeatable personalization workflows that make it possible to evaluate proprietary fitting algorithms without exposing protected intellectual property. In addition, the framework incorporates rapid user feedback loops supported by lightweight ML models, enabling continuous refinement of fit, comfort, and functionality [26]. Another important contribution is the introduction of standardized validation metrics and interoperable data structures that support comparisons across technologies, clinics, and research centers while facilitating collaborative development [27]. By combining transparent simulation tools with models of soft tissue interaction, joint kinematics, and force distribution,

the proposed system advances personalization from a largely manual customization process toward a rigorous, evidence-based engineering methodology linked to measurable rehabilitation outcomes [28,29].

This article examines innovative strategies for the design and personalization of robotic arm exoskeletons tailored to the specific needs of individual users. It emphasizes that personalization is essential for improving comfort, usability, and rehabilitation effectiveness, particularly in medical and assistive care applications [30]. The authors describe proprietary approaches that integrate biomechanical modeling, high-resolution 3D scanning, and adaptive algorithms to customize exoskeleton structures according to each patient's anatomy and motor capabilities. These integrated techniques enable accurate representation of joint alignment, muscle performance, and range of motion, factors that are often insufficiently addressed by conventional sizing methods [31]. The study further demonstrates that adaptive algorithms can continuously optimize design parameters using user feedback and real-time sensor information, thereby enhancing both device fit and long-term rehabilitation support [32]. In addition, the authors show that simulation-based personalization can predict pressure distribution and mechanical loading before fabrication, reducing repeated prototyping, improving safety, and supporting the development of scalable, evidence-based personalized exoskeleton systems [33,34].

This article explores both the theoretical principles and practical implementation of personalized hand exoskeletons, emphasizing the close relationship between these two aspects. It identifies key challenges associated with achieving accurate anatomical fitting, effective ergonomics, and responsive control systems adapted to individual users. A case study is presented to demonstrate how personalized design strategies directly influence device performance and research outcomes in wearable robotics. The authors further examine the integration of AI-driven feedback systems capable of dynamically adjusting control parameters in real time, enabling exoskeletons to respond more effectively to user needs and changing conditions [35]. The study shows that combining adaptive algorithms with biomechanical modeling can improve rehabilitation outcomes, enhance user comfort, support natural movement, and increase long-term acceptance of assistive devices [36]. Overall, the work contributes significantly to the field by merging advanced theoretical concepts with validated engineering approaches, outlining a promising direction for more accessible, efficient, and highly personalized hand exoskeleton technologies [37,38].

The aim of this study was to evaluate the extent to which current research, publication activity, and implementation opportunities are being leveraged in the development of personalized 3D-printed hand exoskeletons. As a secondary objective, the study also sought to determine whether findings from early-stage research can provide reliable indications regarding their potential clinical applicability and effectiveness.

2. Materials and Methods

2.1. Dataset

This bibliometric study aimed to explore the research landscape and to analyze the knowledge base and engineering practices underpinning the design, development, implementation, and operation of personalized 3D-printed hand exoskeletons. Bibliometric methods were employed to examine scientific publication databases and answer the following research questions (RQs):

- RQ1: What is the current research landscape, and how widely has this area been explored in the scientific literature?
- RQ2: Which research centers and collaboration networks are most active and who are the most prolific authors in this area of research?

- RQ3: What are the major research focuses and evolving thematic trends within the published literature?
- RQ4: To what extent do these studies correspond to the Sustainable Development Goals (SDGs)?

The analysis facilitated the identification of several key aspects, including the current state of knowledge, the emergence and evolution of research themes, publication sources (such as institutions, countries, and, where available, funding organizations), and the most influential authors and publications based on their scientific impact and significance. This approach offered a comprehensive overview of contemporary research directions and industrial developments within the studied domain of digital transformation. Moreover, the analysis and interpretation of bibliometric data contribute to ongoing scientific and clinical discourse, while providing a solid foundation for future research initiatives and technological advancements in this field.

2.2. Methods

For this study, four major bibliographic databases were analyzed: Web of Science (WoS), Scopus, PubMed, and dblp. These databases were selected due to their broad coverage and comprehensive citation data, which enable robust bibliometric analyses within the selected research domain (Figure 2). To ensure relevance, search filters were applied to restrict results to original research and review articles published in English. After this filtering stage, all retrieved records were manually screened according to predefined inclusion criteria, yielding the final dataset used for analysis. The review process involved three independent reviewers, who evaluated each article for inclusion or exclusion. Any discrepancies in assessment were resolved through discussion and consensus among at least two of the three reviewers.

Subsequently, key characteristics of the dataset were analyzed, including leading authors, research groups and institutions, countries of origin, thematic clusters, and emerging research trends. This enabled the mapping of the development of core terminology and significant scientific contributions within the investigated field. Where possible, temporal analyses were conducted to examine the evolution of research trends over time, while publications were organized into thematic clusters to identify relationships among different research areas.

This methodology facilitated the identification of the most significant topics and subdisciplines within the analyzed research domain.

The study selection process adhered to the PRISMA 2020 framework (ten core items). After removing duplicates, records retrieved from database searches were screened for relevance. Titles and abstracts were assessed based on predefined inclusion and exclusion criteria, followed by full-text evaluation of potentially eligible studies. Only studies fulfilling all eligibility criteria were included in the final review and subsequent bibliometric analysis.

The study was conducted in accordance with selected components of the PRISMA 2020 guidelines [39] for bibliographic reviews, with the PRISMA 2020 Checklist included in the Supplementary Materials. The following elements were considered: rationale (Item 3), objectives (Item 4), eligibility criteria (Item 5), information sources (Item 6), search strategy (Item 7), selection process (Item 8), data collection process (Item 9), synthesis methods (Item 13a), synthesis results (Item 20b), and discussion (Item 23a).

Bibliometric analysis was performed using analytical tools integrated within the Web of Science (WoS), Scopus, PubMed, and dblp databases. The adopted review methodology enabled detailed categorization of publications according to concepts (keywords), research

areas, authors and research groups, institutional affiliations, countries, document types, and publication sources.

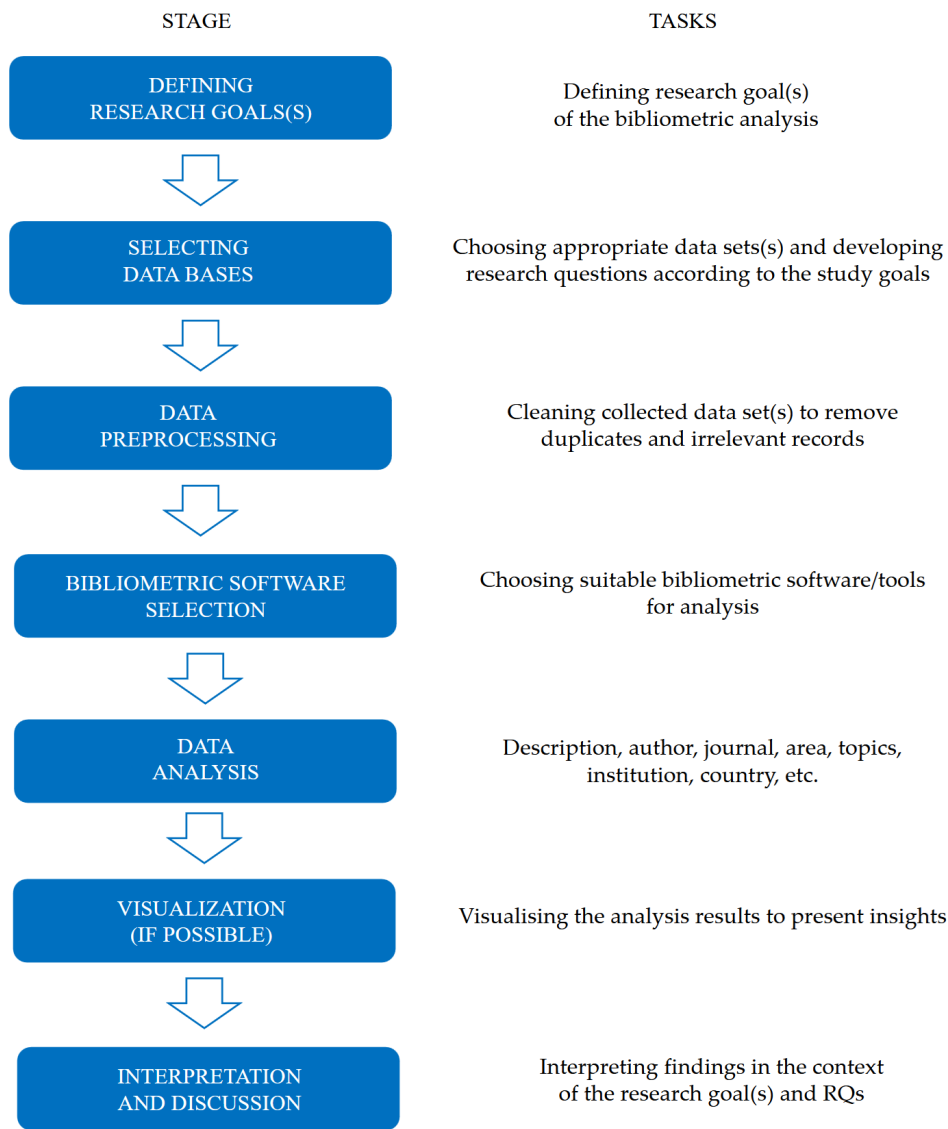


Figure 2. Methodology for bibliometric analysis used in this study (author-developed approach).

2.3. Data Selection

In the Web of Science (WoS) database, searches were conducted using the “Subject” field, which encompasses titles, abstracts, keywords, and supplementary keywords. In Scopus, the search was performed across article titles, abstracts, and keywords, while in PubMed and dblp, searches were based on manually defined keyword sets. Across all databases, articles were retrieved using optimized keyword-driven search strategies: “additive manufacturing” AND exoskeleton AND personalisation OR personalization (Figure 3).

The selected publication set was further subjected to a verification stage involving manual re-screening, during which irrelevant records and duplicate entries were excluded, resulting in the final sample size (Figure 4). To ensure the reliability and validity of the included studies, a combination of quality assessment approaches was employed.

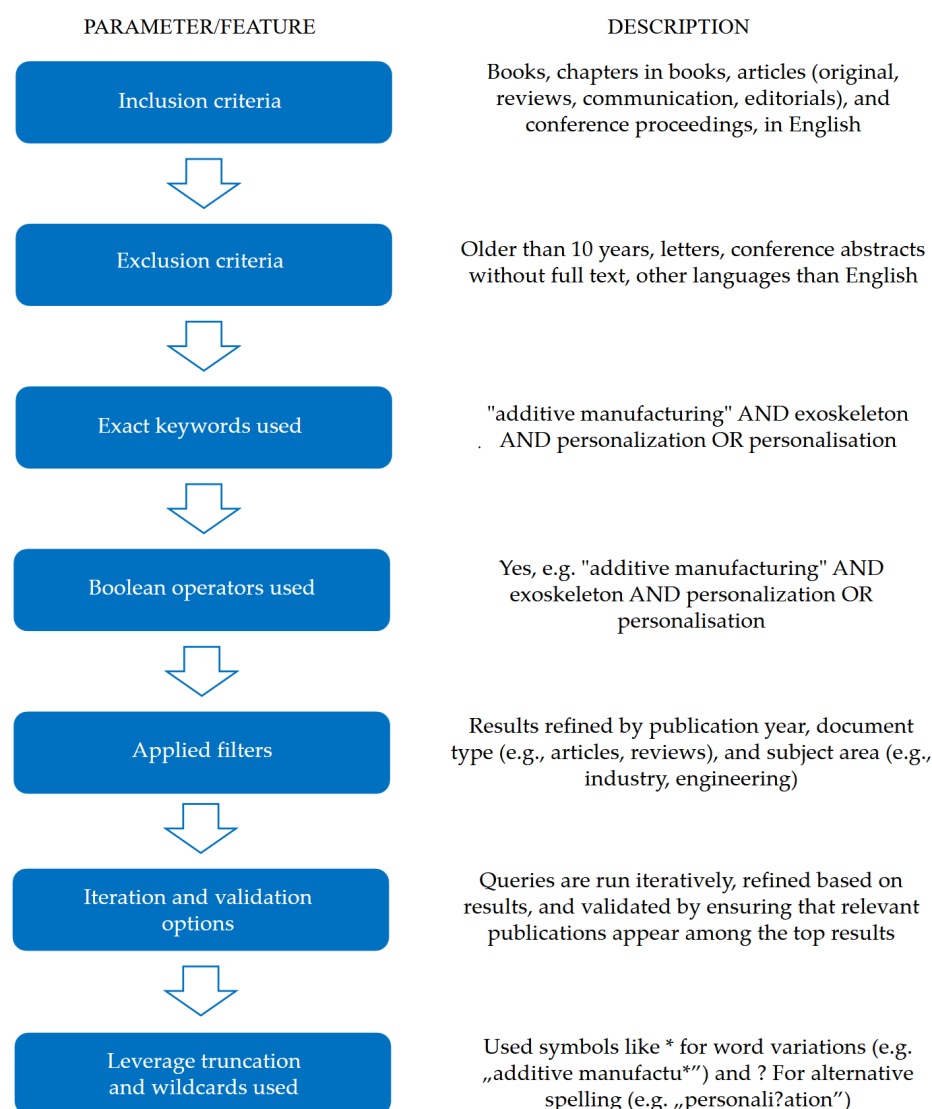


Figure 3. Search strategy employed across all four databases.

The PRISMA 2020 flow diagram presented above provides a transparent, step-by-step overview of the processes involved in identifying, screening, assessing, and ultimately including studies in the review, thereby ensuring methodological rigor and reproducibility. The process begins with the identification phase, during which records are retrieved from databases and other sources, capturing the full set of potentially relevant literature prior to duplicate removal.

The subsequent screening phase involves evaluating titles and abstracts against predefined eligibility criteria, excluding studies not directly related to wearable devices, machine learning, or digital transformation technologies. In the eligibility phase, the full texts of the remaining articles are assessed in detail with regard to methodological quality, adequacy of data collection and security, and relevance to topics such as additive manufacturing and 3D printing. Finally, the inclusion phase reports the number of studies retained after the exclusion process, forming the evidence base used for subsequent synthesis and analysis.

This interpretation of the PRISMA diagram enhances the transparency of the review process by not only illustrating the scope of the analyzed literature but also clearly outlining the rationale for exclusions at each stage. Consequently, it strengthens the credibility and validity of the study's conclusions.

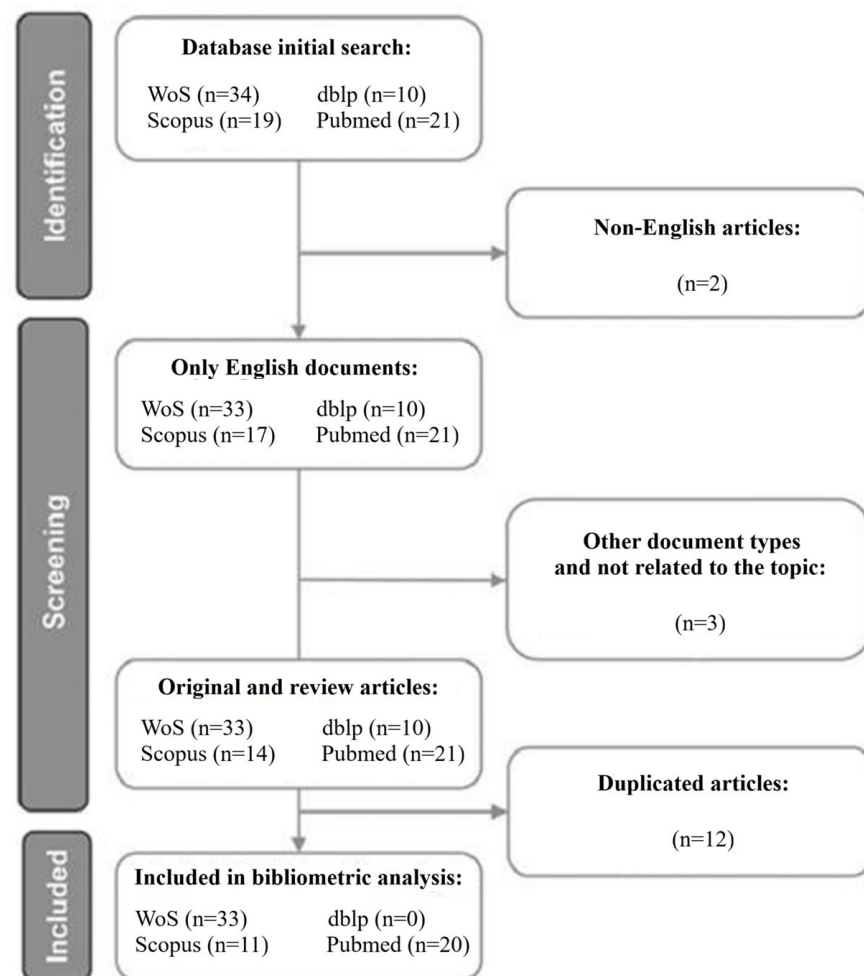


Figure 4. PRISMA flowchart.

3. Results

Table 1 and Figures 5–7 present a general summary of the bibliographic analysis results. The review analyzed 64 articles published between 2020 and 2025. Studies published prior to 2020 were excluded because the personalization of 3D-printed exoskeletons is an emerging area of research. Moreover, the integration of AI and advanced 3D printing technologies into the digital transformation of manufacturing has become widespread only in recent years. Older studies may contribute outdated approaches or technologies that fail to reflect present-day capabilities or trend. Therefore, limiting the review to the 2020–2025 period ensures a focus on the most relevant, innovative, and technically viable approaches.

Table 1. Overview of findings from bibliographic analyses conducted in WoS, Scopus, PubMed, and dblp.

Parameter/Feature	Value
Dominant publication types	Conference papers (50.00%), book chapters (25.00%), reviews (25.00%)
Dominant science areas	Engineering (42.9%)
Dominant countries/territories	None were detected
Dominant scientists	None were detected
Dominant affiliations	None were detected
Dominant funders (where information available)	None were detected
Dominant SDGs	Industry, Innovation and Infrastructure; Good Health and Well-Being

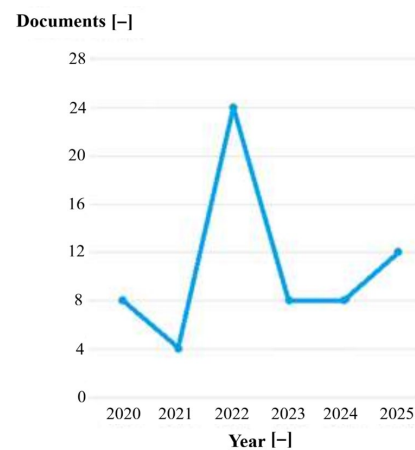


Figure 5. Publications by year.

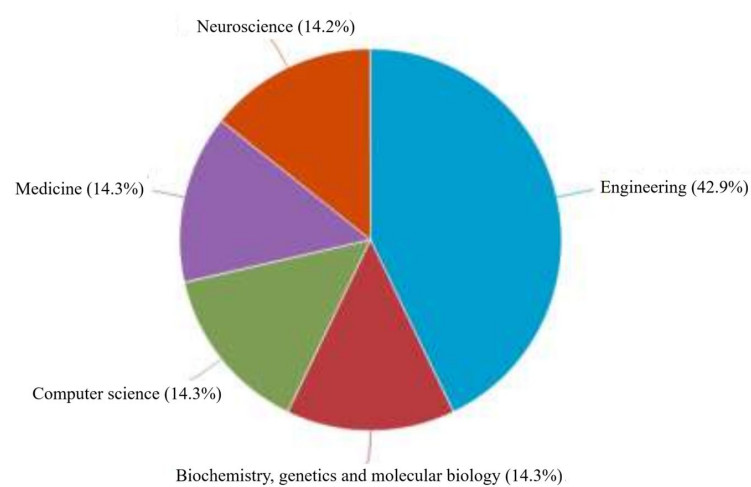


Figure 6. Publications by area.

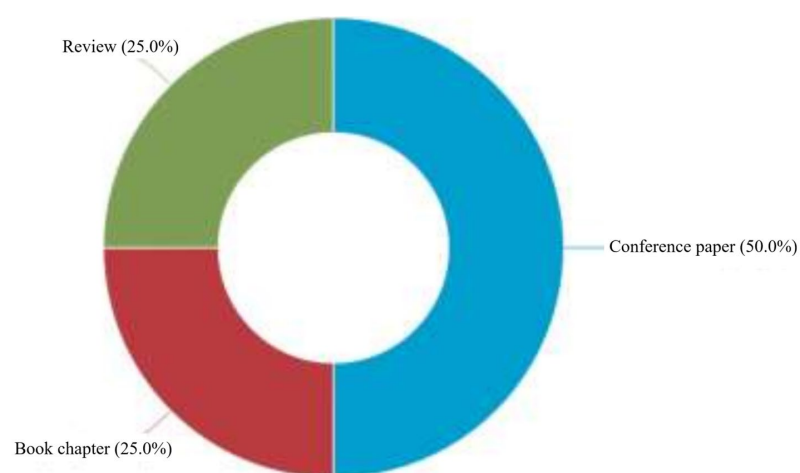


Figure 7. Publications by type.

The review shows that research on AI-based personalization of 3D-printed hand exoskeletons remains a developing field, with the available literature consisting primarily of conference papers (50%), followed by book chapters (25%) and review articles (25%). Engineering was identified as the dominant research area (42.9%), reflecting the strong technological focus on device design, optimization, and manufacturing processes. Unlike more mature research areas, no leading countries, institutions, researchers, or funding

organizations were identified, indicating a fragmented and still evolving global research landscape. The most common affiliations were:

- Kazimierz Wielki University (three publications);
- RIKEN and Kyushu Institute of Technology (two publications each).

The most common authors were I. Rojek, D. Mikołajewski, and J. Kopowski (three publications each). The most common funders were:

- Kazimierz Wielki University (three publications);
- Japan Society for the Promotion of Science and Kitakyushu Foundation for the Advancement of Industry, Science, and Technology (two publications each).

The main finding of the review is that AI-based personalization and additive manufacturing have significant potential to improve the fit, functionality, and accessibility of hand exoskeletons, while supporting the Sustainable Development Goals related to Health and Well-Being and Industry, Innovation and Infrastructure. In addition to existing reviews, this study provides a bibliometric perspective that maps publication patterns, scientific contributions, and research gaps, rather than focusing solely on technical performance or clinical outcomes. These findings shed new light on the maturity of this field, reveal the lack of recognized research leaders, and highlight opportunities for broader international collaboration and strategic investment in personalized rehabilitation technologies.

These bibliometric findings imply that the predominance of conference papers may reflect a field that is still in the conceptual development stage and has yet to strongly emphasize industrial validation. Most studies originated from the engineering domain, which further points to an early level of technological maturity. No dominant countries, highly prolific researchers, or leading institutions were identified, indicating a fragmented research landscape. Nevertheless, the Sustainable Development Goals (SDGs) most frequently associated with the literature reveal a strong healthcare orientation, particularly in relation to “innovation and industrial infrastructure” and “good health and well-being”.

Key current research areas include personalized biomechanical modeling, additive manufacturing, AI-based motion control, the integration of sensors with adaptive feedback systems, and AI-based rehabilitation strategies.

3.1. Personalized Biomechanical Modeling

AI-based personalized biomechanical modeling for customizing 3D-printed hand exoskeletons has evolved from generic kinematic templates to patient-specific digital twins of the musculoskeletal and neuromotor systems (Figure 8). The development of personalized biomechanical modeling in AI-based hand exoskeletons has gone through several distinct stages. Early systems relied on kinematic templates that utilized generalized models of hand anatomy and motion, providing basic functionality but limiting the scope for individual adaptation. The introduction of 3D scanning technology enabled the creation of patient-specific geometry, improving device fit, comfort, and biomechanical accuracy. The subsequent integration of sensors such as force, motion, and electromyography enabled real-time monitoring of user performance and adaptive control of exoskeleton functions. More recently, combining AI with biomechanical modeling has enabled data-driven optimization of movement assistance, anticipation of user needs, and continuous personalization based on individual characteristics. The latest stage involves the development of DTs, which create dynamic virtual representations of the user–exoskeleton system based on physics and biomechanics, enabling simulation, remote monitoring, and highly personalized rehabilitation planning.

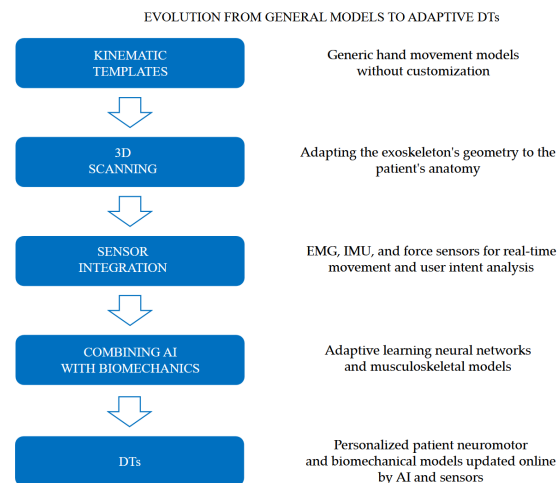


Figure 8. Stages of development of personalized biomechanical modeling within AI-based hand exoskeletons.

Modern systems integrate medical imaging, optical scanning, wearable sensors, and motion capture technology to create personalized anatomical models of bones, tendons, joints, and soft tissues with sub-millimeter precision [40]. Cutting-edge ML processes leverage electromyography, inertial measurement units, and force sensors to infer user intent and estimate muscle activation patterns in real time [41]. Physics-based neural networks and differentiable biomechanical simulators are increasingly being used to combine data-driven learning with the anatomically constrained dynamics of the hand [42]. Modern exoskeleton designs utilize topological optimization and generative AI to automatically adapt 3D-printable structures to the patient's morphology, residual motor function, and rehabilitation goals [43]. Adaptive control frameworks based on ML and model predictive control now continuously personalize support levels, taking into account fatigue, spasticity, and task performance [44]. Researchers are also developing closed-loop systems in which biomechanical models are updated online using streaming sensor data, enabling long-term co-adaptation between the user and the exoskeleton [45]. High-fidelity finite element models are being implemented to predict local pressure distribution, tendon loading, and skin–device interaction, improving comfort and reducing the risk of injury [46]. Cloud-connected rehabilitation platforms are increasingly combining biomechanical personalization with federated learning, allowing models to improve collectively without revealing sensitive patient data [47]. Despite these advances, significant challenges remain in achieving clinically validated accuracy, cost-effective measurement, robust generalization across pathologies, and computational efficiency in wearable devices [48]. The current state of the art combines AI, additive manufacturing, biomechanics, soft robotics, and digital healthcare technologies to produce highly customized, adaptive, and scalable hand exoskeletal systems for rehabilitation and assistive applications.

Personalization begins with capturing the user's hand geometry through 3D scanning, enabling the exoskeleton to match the individual's anatomical dimensions with high precision. Proper alignment between the exoskeleton joints and the user's natural joints is essential for minimizing discomfort and reducing unnecessary mechanical resistance [49]. Personalized finger splints and support structures are developed to accommodate the unique curvature, length, and rotational movement patterns of the fingers (see Figure 5 for a digit case study). Personalization also includes adjusting actuation forces according to the user's muscle strength, range of motion, and physical limitations [50]. Material properties, such as stiffness and flexibility gradients, are selected to satisfy individual comfort and durability requirements [51]. In addition, weight distribution is optimized to prevent

excessive strain on the hand and forearm during use [52]. Control interfaces—whether mechanical, myoelectric, or sensor-based—are adapted to the user’s motor capabilities and cognitive preferences. Grip configurations and functional tasks are further tailored to support the user’s daily activities, occupational demands, and rehabilitation objectives [53]. Ergonomic padding and contact surfaces are carefully designed to minimize pressure points and maintain comfort during extended wear [54]. The device’s visual appearance, including color, texture, and overall design, may also be personalized to improve user acceptance and satisfaction. Attachment systems, such as straps or custom sockets, are configured for convenient donning and doffing based on the user’s mobility level [55]. Software parameters controlling movement speed, assistance intensity, and safety thresholds are calibrated individually for each user. Personalization additionally emphasizes modularity, allowing components to be replaced or adjusted as the user’s abilities evolve over time [56]. Where sensory feedback systems are integrated, they are tuned to the user’s sensory thresholds and rehabilitation needs [57]. Overall, personalization supports long-term adaptability, ensuring that the exoskeleton can continue to evolve alongside changes in the user’s physical condition, lifestyle, and therapeutic progress [58].

3.2. Additive Manufacturing in Exoskeletons

Additive manufacturing (AM) for AI-personalized, 3D-printed hand exoskeletons has evolved into a highly adaptive manufacturing paradigm, enabling the creation of patient-specific assistive and rehabilitation devices with complex biomechanical geometry [58]. Cutting-edge workflows combine 3D scanning, medical imaging, and parametric CAD systems to generate anatomically accurate exoskeleton structures tailored to the dimensions and ranges of motion of individual users [59]. AI is increasingly being integrated with generative design processes to optimize lattice structures, joint placement, and load distribution while minimizing device weight and material consumption (Figure 9). Multimaterial AM now enables the simultaneous printing of rigid structural elements and soft, flexible interfaces, improving comfort, flexibility, and ergonomic interaction with the human hand [60,61]. Advanced polymers, carbon fiber-reinforced composites, thermoplastic polyurethanes, and bioinspired metamaterials are being used to enhance durability, flexibility, and fatigue resistance in wearable exoskeleton systems [62]. ML models are also being used to predict mechanical performance and print quality, reducing manufacturing defects and enabling rapid iteration of custom designs. Recent advances in embedded electronics printing enable the direct integration of sensors, conductive pathways, and flexible actuators into exoskeleton components during manufacturing. Topology optimization and ML-assisted structural adaptation are increasingly being used to create lightweight architectures that maintain biomechanical performance while improving actuation responsiveness [63,64]. Cloud-connected manufacturing ecosystems support remote personalization processes, where patient motion data is continuously analyzed and transformed into updated printable exoskeleton configurations. Despite significant progress, limitations remain regarding printing speed, material biocompatibility, long-term reliability, actuator integration, and standardization of clinically validated manufacturing processes [65–67]. The evolution of intelligent AM and biomechanical personalization has evolved from conventional 3D printing toward adaptive AI-based DTs. Initially, conventional AM focused on producing standardized components with limited consideration of individual biomechanical characteristics. The advent of mass customization enabled the production of patient-specific hand exoskeletons tailored to anatomical and functional requirements through digital design and flexible manufacturing processes. The next stage involved AI-assisted optimization, where ML algorithms refined the structural design, material distribution, and device performance based on user-specific data. Functional

integration further advanced this field by combining embedded sensors, data acquisition systems, and biomechanical models to enable real-time monitoring and adaptive control of exoskeleton performance. The most advanced stage is the smart additive manufacturing ecosystem, where AI, AM, sensor networks, and digital twins operate as an interconnected framework that continuously updates personalized biomechanical models and supports predictive, adaptive, and highly individualized rehabilitation.

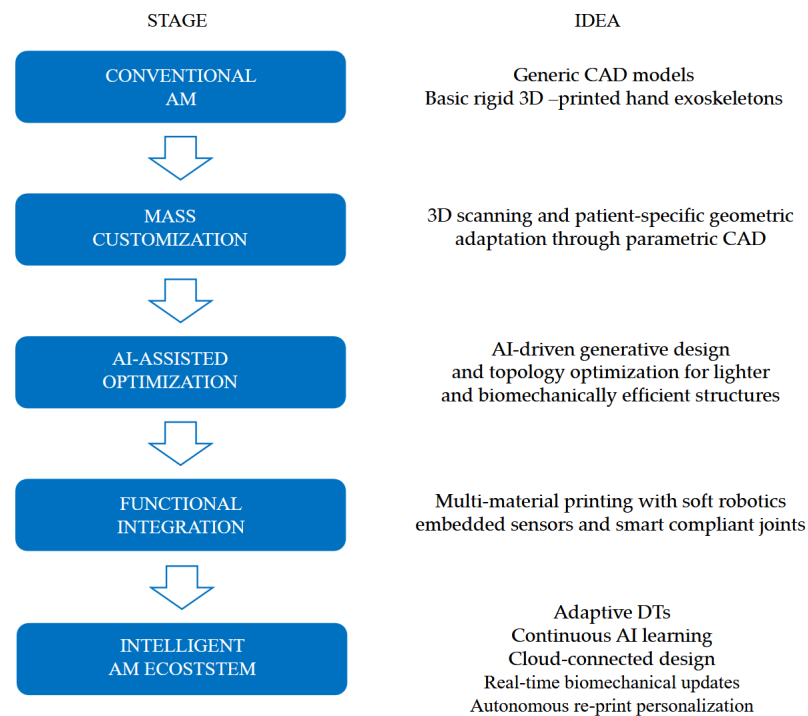


Figure 9. Evolution pathway of intelligent additive manufacturing and biomechanical personalization: from conventional 3D printing to AI-driven adaptive biomechanical DTs.

Material customization involves the selection of polymers or composite materials with levels of stiffness, flexibility, and durability that match the user’s specific functional requirements and comfort preferences. The use of gradient materials and multimaterial 3D printing makes it possible to combine rigid structural support with soft cushioning in targeted areas corresponding to the user’s anatomical pressure points. Technological customization starts with high-resolution hand scanning or profiling using sensors, allowing detailed capture of hand geometry and accurate anatomical fitting [68]. Parametric CAD modeling then enables automatic adaptation of dimensions, joint alignment, and finger curvature based on measured or scanned hand data [69]. Advanced additive manufacturing techniques, including fused filament fabrication and resin-based printing, support the creation of lightweight structures optimized for the user’s strength and dexterity [70]. In addition, embedded sensor arrays can be individually configured so that force, motion, or EMG sensors are positioned at locations where the user produces the most reliable signals.

3.3. AI-Based Motion Control

AI-based motion control in personalized, 3D-printed hand exoskeletons has evolved into highly adaptive human–machine interaction systems capable of interpreting user intent and dynamically adjusting support in real time. Modern control architectures integrate electromyography, inertial sensors, force measurement, and vision-based tracking to capture precise biomechanical and neuromuscular signals from individual users. Deep learning (DL) algorithms are increasingly being used to decode complex hand movement intentions from noisy biological signals, enabling more natural and intuitive exoskeleton

operation. Reinforcement learning (RL) methods are being used to continuously optimize the assistance strategy based on user performance, fatigue, rehabilitation progress, and task-specific movement patterns. State-of-the-art systems combine biomechanical modeling with AI-based predictive control to synchronize actuator behavior with the user's natural joint trajectories and muscle activation dynamics. Hybrid controllers combining model predictive control, adaptive impedance control, and neural network-based estimation improve both movement precision and safety during physical interactions. Real-time personalization is increasingly supported by online learning algorithms that continuously update control parameters using streaming feedback from the user's sensors. Researchers are also developing shared control paradigms in which the exoskeleton autonomously compensates for impaired motor function while maintaining voluntary user participation. Soft robotic actuators and compliance mechanisms are being integrated with AI control systems to provide smoother, safer, and more biomimetic hand support. Despite rapid progress, challenges remain in achieving robust generalization for all users, reducing calibration requirements, minimizing computational latency, and ensuring long-term clinical reliability. Control personalization focuses on optimizing actuation parameters—such as torque, speed, and motion constraints—to align the device with the user's natural movement patterns [71]. AI-driven adaptive algorithms analyze the user's everyday motions and dynamically modify assistance levels in real time, improving precision while minimizing fatigue [72]. ML techniques further enhance personalization by recognizing individual movement characteristics, compensating for tremors, and anticipating intended actions before they are executed [73]. In addition, closed-loop AI systems combine sensory input with behavioral data to continuously refine exoskeleton responsiveness, enabling a highly adaptive and individualized assistive experience [74]. The current state of the art therefore reflects the convergence of AI, biomechanics, wearable sensors, soft robotics, and adaptive control engineering towards intelligent, patient-specific hand exoskeletons capable of responsive and autonomous movement assistance.

3.4. Integration of Sensors with Adaptive Feedback Systems

The integration of sensors with adaptive feedback systems in AI-personalized, 3D-printed hand exoskeletons has evolved toward multimodal closed-loop architectures capable of continuously monitoring the user's biomechanics and device performance. Modern systems combine electromyographic sensors, inertial measurement units, force sensors, deflection sensors, pressure sensors, and optical tracking technologies to capture detailed information about hand movement and muscle activity [75]. These heterogeneous sensor streams are increasingly being combined using AI algorithms that estimate user intentions, detect movement anomalies, and predict the need for motor assistance in real time [76]. Adaptive feedback controllers use this information to dynamically adjust actuator force, joint stiffness, and movement trajectory based on the patient's biomechanical status and rehabilitation progress [77]. Recent advances in soft and flexible electronics enable sensors to be embedded directly into the structures of 3D-printed exoskeletons, improving wearer comfort and signal fidelity [78]. ML methods such as recurrent neural networks, transformers, and reinforcement learning are being used to model movement patterns over time and optimize responsive assistance strategies [75,76,79,80]. State-of-the-art systems increasingly incorporate haptic and vibrotactile feedback mechanisms that provide users with sensory input, enhancing motor learning, coordination, and engagement during rehabilitation exercises [81,82]. Cloud-connected adaptive platforms can analyze sensor data longitudinally to continuously refine personalization models and support remote monitoring through observation. Researchers are also integrating digital twin frameworks, where real-time sensor feedback updates personalized biomechanical simulations for predictive

alized behaviors of the musculoskeletal and neuromotor systems to predict rehabilitation outcomes and guide therapy adaptations [85]. Gamification and AI-based virtual reality environments are being integrated with hand exoskeletons to improve patient engagement, stimulate neuroplasticity, and increase adherence to long-term rehabilitation programs [86]. Cloud-connected rehabilitation ecosystems support remote therapy and telerehabilitation, allowing clinicians to continuously monitor patient progress and update treatment strategies through longitudinal data analysis [87]. It is difficult to predict that exoskeletons will replace existing Safe Patient Handling and Mobility programs; instead, they are expected to serve as a complementary component of these multifaceted initiatives. Emerging exoskeleton technologies may be particularly suitable for use in uncontrolled or specialized healthcare environments. Different healthcare settings impose distinct expectations and requirements for hand exoskeleton applications. Furthermore, the introduction of certain personalized patient-assistive exoskeletons during treatment and rehabilitation may contribute to reducing the risk of musculoskeletal disorders among healthcare workers [88]. Hybrid rehabilitation frameworks combining robotic assistance, haptic feedback, and cognitive interaction enhance motor relearning and facilitate more natural sensorimotor integration [89]. Recent advances in explainable AI also help clinicians interpret rehabilitation decisions made by adaptive algorithms, increasing confidence, transparency, and clinical utility [90]. Despite significant progress, challenges remain in achieving large-scale clinical validation, reducing calibration complexity, ensuring interoperability between devices, and maintaining affordability for widespread healthcare implementation.

In summary, AI-based personalization of 3D-printed hand exoskeletons represents a significant advance in rehabilitation engineering, enabling devices to be tailored to the anatomical and functional requirements of individual users. Recent research has demonstrated the use of AI algorithms combined with 3D scanning and additive manufacturing to generate personalized exoskeleton geometries that improve comfort, fit, and movement precision compared to conventional, standardized designs. For example, ML models can analyze hand dimensions and patient-specific movement patterns to optimize joint alignment and actuator placement, thereby increasing the effectiveness of rehabilitation for stroke survivors and people with neuromuscular disorders. In the scientific literature, researchers have also explored AI-based adaptive control systems that continuously adjust the level of assistance based on real-time sensor feedback, enabling personalized rehabilitation programs that evolve with the patient's progress. A key advantage of combining AI with 3D printing is the ability to deliver highly personalized devices with relatively low production costs and reduced lead times. Another benefit is the potential improvement in user compliance, as personalized exoskeletons are generally more comfortable and better suited for long-term therapeutic use. However, these technologies also pose a number of challenges, including the need for large and diverse datasets to train reliable AI models and ensure precise personalization. Furthermore, the performance of AI algorithms can be limited by sensor noise, data quality issues, and patient variability, which can impact the reliability of adaptive control strategies. From a manufacturing perspective, although 3D printing enables rapid personalization, material limitations and durability issues can limit the long-term performance of lightweight exoskeleton designs. Therefore, the current research trend is focused on integrating advanced AI techniques, robust sensor systems, and improved additive manufacturing materials to maximize the benefits of personalized hand exoskeletons while addressing their technical and clinical limitations.

4. Discussion

The relatively small number of publications suggests that the AI-based personalization of hand exoskeletons using closed and proprietary solutions is still in the early stages of

both theoretical and practical development. The limited availability of studies also points to challenges in ensuring transparency and reproducibility, as proprietary methods can restrict knowledge sharing and hinder open validation of models. In addition, the scarcity of research may reflect a high barrier to entry, including the need for costly software, scanning technologies, and proprietary design workflows. The limited body of literature highlights a gap between rapidly advancing 3D printing technologies and their clinical translation into personalized assistive devices such as hand exoskeletons, potentially further influenced by regulatory, ethical, and data ownership concerns that slow down open development and adoption.

In response to RQ1, research on the personalization of 3D-printed hand exoskeletons based on AI, wearable robotics, and additive manufacturing technologies has rapidly developed thanks to advances in AI, wearable robotics, and additive manufacturing technologies. A growing number of scientific publications indicate a growing interest in patient-specific rehabilitation devices capable of adapting to individual anatomical and functional needs. Current research focuses primarily on intelligent control systems, motion prediction, biomechanical adaptation, and the integration of sensor-based feedback mechanisms. Although publication activity has increased significantly in recent years, this field is still evolving and requires broader clinical validation, standardized evaluation protocols, and long-term usability studies.

In response to RQ2, the most visible research centers are typically associated with institutions specializing in biomedical engineering, rehabilitation robotics, AI, and digital health technologies. Leading authors in this field are recognized for their high citation rates, interdisciplinary research achievements, and participation in international collaborative projects related to assistive robotics and personalized healthcare systems. Collaborative networks typically include partnerships between universities, hospitals, engineering laboratories, and technology companies working on human–machine interaction and intelligent rehabilitation systems. International collaboration is particularly strong in Europe, North America, and Asia, fostering the exchange of expertise in AI algorithms, 3D printing technology, and clinical rehabilitation practices.

In response to RQ3, key research areas include AI-based motion control, personalized biomechanical modeling, additive manufacturing, wearable rehabilitation robotics, and the integration of sensors with adaptive feedback systems. Recent thematic trends emphasize ML techniques to predict user movement patterns and optimize rehabilitation exercises in real time. Publications are increasingly exploring the use of lightweight and customizable 3D-printed structures designed to improve patient comfort, functionality, and adherence during therapy. Another significant trend is the integration of digital health technologies, cloud-based monitoring, and intelligent data analysis to support remote rehabilitation and personalized treatment strategies.

In response to RQ4, research on personalized, 3D-printed, AI-based hand exoskeletons significantly supports SDG 3 (Good Health and Well-Being) by improving rehabilitation outcomes and quality of life for people with motor impairments. The development of intelligent assistive technologies also contributes to SDG 9 (Industry, Innovation and Infrastructure) through innovations in robotics, AI, and additive manufacturing. Furthermore, this research aligns with SDG 10 (Reducing Inequalities) by promoting more accessible, affordable, and personalized rehabilitation solutions for diverse patient groups. The interdisciplinary and international nature of this research further reflects SDG 17 (Partnerships for the Goals), highlighting the importance of scientific collaboration and knowledge exchange in the development of healthcare technologies.

Integrating AI-based personalization into 3D-printed hand exoskeletons raises significant ethical issues related to data privacy, algorithm transparency, and equitable access to

assistive technologies. A personalized design approach relies on the collection and processing of user-specific anatomical and functional data, making secure data management and informed consent essential. From an energy perspective, AI-based optimization and additive manufacturing can reduce material waste and production inefficiencies compared to conventional manufacturing methods, although computational processes and 3D printing still consume significant energy resources. Sustainability benefits stem from the ability to produce personalized devices on demand, minimize excess inventory, reduce transportation requirements, and enable more efficient material use. Responsible implementation of AI and additive manufacturing requires balancing technological innovation with ethical safeguards, energy-efficient practices, and long-term environmental sustainability concerns.

4.1. Limitations

Current research on AI-based personalization of 3D-printed hand exoskeletons is limited by technical, financial, clinical, and regulatory challenges, requiring further interdisciplinary research. Research on AI-based personalization of 3D-printed hand exoskeletons is limited by the small number of available long-term clinical trials. Many studies use small sample sizes, which reduces the reliability and generalizability of study results. Variations in patient conditions, hand anatomy, and rehabilitation goals make it difficult to standardize experimental methods and compare results across studies. The accuracy of AI personalization is highly dependent on the quality and quantity of training data used in ML models. Limited access to diverse medical datasets can increase the risk of algorithmic errors and reduce system performance for certain user groups. Researchers also face technical challenges related to sensor integration, motion tracking accuracy, and real-time adaptation of exoskeleton systems. The high cost of advanced 3D printers, AI software, and test equipment can limit research opportunities for smaller institutions. Another limitation is the lack of widely accepted global standards and regulations for AI-powered personalized medical devices. Many studies focus primarily on short-term improvements in functionality rather than long-term usability, durability, and psychological impact on users [91]. Concerns about cybersecurity and data privacy may also limit data sharing and collaboration between institutions.

4.2. Proposed Roadmap

We proposed an actionable, time-phased roadmap (short-, mid-, and long-term) that outlines specific activities, expected deliverables, key stakeholders, and measurable success indicators to address the previously identified gaps (Figure 11).

Short-term activities (0–12 months) focus on establishing foundational elements and promoting reproducible research practices. These include developing a minimal standardized dataset and metadata schema for personalization research, covering 3D scans, anthropometric data, pathology labels, sensor recordings, printing parameters, and post-fitting outcomes, with deliverables such as a sample dataset, and success defined by adoption by at least three research groups. Another task involves conducting multi-site pilot studies that compare different scanning technologies and measurement protocols using a shared participant cohort to quantify measurement variability, resulting in a comparative technical report and clearly defined error bounds for each modality. In addition, standardized validation metrics will be defined and published, including measures such as fit accuracy, pressure hotspots, range-of-motion alignment, actuation efficiency, and user comfort scores, accompanied by a concise technical standard document, with success indicated by adoption as a baseline in subsequent publications. Finally, open-source reference parametric models and example CAD templates will be created under permissive licensing to support reproducible morphing experiments, delivered via a Git repository containing templates

and sample scripts, with success measured by at least 50 documented uses within the first 12 months.

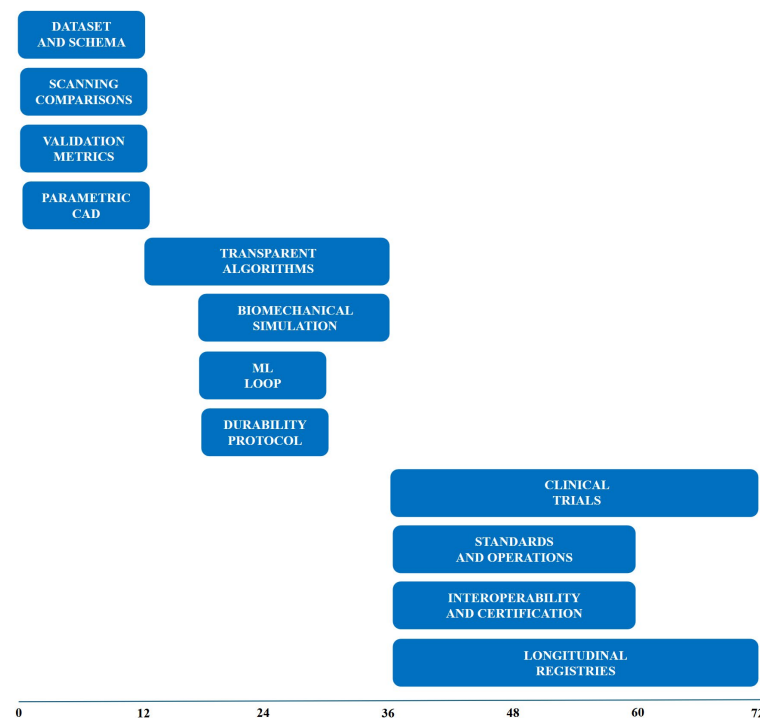


Figure 11. Gantt chart concerning personalization of 3D-printed hand exoskeletons.

Mid-term activities (1–3 years) focus on improving transparency, advancing biomechanical modeling, and enabling iterative personalization workflows. One key task is the development and benchmarking of open, transparent fitting algorithms that convert scan and measurement data into parametric models, alongside comparisons with proprietary approaches where possible, resulting in a benchmark suite and leaderboard, with success measured by a published benchmark study and fully reproducible results.

Another objective is to incorporate dynamic biomechanical simulation into the personalization loop, including soft tissue interaction, tendon and joint kinematics, and simplified musculoskeletal loading, and to validate these simulations using instrumented prototypes; deliverables include a simulation toolkit and validation dataset, with success defined by strong correlation between predicted and measured pressure and joint alignment within predefined tolerances. In parallel, iterative, data-driven personalization pipelines will be developed to integrate short-term user feedback (e.g., comfort and functional performance metrics) and automatically adjust parameters using lightweight ML models, supported by prototype pipelines and case studies, with success indicated by measurable improvements in comfort and function across at least 10 users after a single iteration. Additionally, standardized durability and real-world testing protocols will be established to assess fatigue, repeated donning and doffing, and environmental effects on personalized prints, alongside systematic documentation of failure modes, with deliverables including testing protocols and a shared result database, and success defined by the identification of the three most common failure causes and corresponding mitigation strategies.

Long-term activities (3+ years) focus on evaluating clinical impact, establishing standards, and achieving ecosystem maturity. A primary goal is to conduct medium-scale clinical trials comparing rigorously personalized exoskeletons with non-personalized controls to assess improvements in rehabilitation outcomes, user adherence, and quality of life across different pathologies; deliverables include randomized or matched clinical studies

with defined outcome measures, with success indicated by statistically significant improvements in primary endpoints or identifiable benefits in specific subgroups. Another key task is collaboration with standards organizations and regulatory bodies to define validation criteria, data privacy requirements, and interoperability specifications for personalization workflows, including APIs, data formats, and reporting structures; outputs include draft standards and regulatory submissions, with success measured by the adoption of at least one recognized standard or regulatory guideline referencing these criteria. In parallel, the development of an ecosystem combining proprietary and open tools will be supported through a certification framework (e.g., a “benchmarked” label), enabling vendors to demonstrate performance against standardized tests while maintaining intellectual property protection; deliverables include a certification program and a list of certified products, with success defined by participation of major vendors and independent auditing by third-party laboratories. Finally, longitudinal registries and post-market surveillance systems will be established to connect personalization decisions with long-term device performance and clinical outcomes, supporting continuous improvement and safety monitoring; deliverables include a privacy-preserving registry infrastructure and an initial multi-year dataset, with success measured by the ability to detect rare failure modes and demonstrate iterative improvements in design best practices.

4.3. Technological Implications

AI-based personalization of 3D-printed hand exoskeletons is driving technological progress by improving personalization, automation, data analysis, and rehabilitation effectiveness. It can already be assessed that AI-based personalization of 3D-printed hand exoskeletons has significantly accelerated the technological development of assistive devices [92]. AI can analyze patient data to create highly personalized exoskeleton designs tailored to individual anatomical and functional needs. Integrating AI with 3D printing enables faster prototyping and more efficient manufacturing processes. ML algorithms can improve device performance by adapting movement support and rehabilitation exercises to the user’s progress over time. Advanced sensors integrated into exoskeletons can collect data in real time and enable AI systems to optimize movement control and comfort. Fuzzy logic, in particular, helps address uncertainties and data incompleteness. The technology supports the development of lightweight and ergonomic designs that improve usability and reduce patient fatigue. AI-based personalization can also increase the precision of rehabilitation therapy by adapting support levels to the patient’s abilities. Private cloud computing and digital modeling technologies (including digital twins (DTs)) facilitate the storage, sharing, and updating of personalized exoskeleton designs. The combination of AI and additive manufacturing is driving innovation in biomedical engineering, robotics, and human–computer interaction [93]. However, technological challenges remain, such as cybersecurity threats, software reliability, and the need for high-quality training data.

4.4. Economic and Practical Implications

AI-based personalization of 3D-printed hand exoskeletons could deliver significant economic and practical benefits by improving efficiency, reducing costs, and increasing the availability of personalized rehabilitation technologies. AI-based personalization of 3D-printed hand exoskeletons could reduce production costs by creating devices tailored to individual users with minimal material waste. The use of 3D printing allows for faster production compared to traditional methods, increasing the efficiency of medical device delivery. AI algorithms can optimize the design process by adapting the exoskeleton to the user’s anatomy and rehabilitation needs. Personalized devices can improve patient recovery outcomes, reducing long-term healthcare and rehabilitation costs. Hospitals

and clinics can benefit from shorter fitting procedures and fewer device modifications thanks to more precise personalization. The growing demand for AI-assisted medical technologies could stimulate economic growth in the biomedical engineering and additive manufacturing sectors. Research centers and companies developing AI-based exoskeletons could create new job opportunities for engineers, programmers, designers, and healthcare professionals. Digital manufacturing and local 3D printing can reduce transportation and warehousing costs because devices can be manufactured closer to patients. However, the initial investment in AI software, high-quality printers, and technical training can be costly for smaller healthcare facilities. Practical challenges also include maintaining device reliability, ensuring software updates, and meeting medical safety standards [94].

4.5. Societal Implications

AI-based personalization of 3D-printed hand exoskeletons has the potential to drive positive social change by promoting independence, inclusivity, and accessibility, while also raising concerns about equality, trust, and privacy. Personalizing 3D-printed hand exoskeletons with AI can improve the quality of life for people with physical disabilities or hand injuries. Personalized devices can increase user comfort and functionality, allowing them to perform daily activities more independently. Increased independence can boost self-confidence and reduce the social isolation often experienced by people with limited mobility. The technology can support integration in education and the workplace, helping users participate more actively in social and professional life. AI-based personalization can also improve rehabilitation outcomes, promoting faster reintegration into family and community life. The affordability of 3D printing can increase access to assistive technologies for people from disadvantaged communities. At the same time, unequal access to advanced AI systems and healthcare infrastructure can exacerbate social inequalities between different regions and social groups. Some users may have concerns about relying on AI systems to make decisions about healthcare and physical assistance. Collecting personal and biometric data for AI-based personalization may also raise privacy and surveillance concerns. Public acceptance of AI-based exoskeletons could lead to widespread adoption of these technologies in healthcare and rehabilitation programs [95].

4.6. Ethical and Legal Implications

The ethical and legal implications of AI-based 3D-printed hand exoskeletons personalization depend on a balance between innovation, patient safety, transparency, privacy, and regulatory accountability. AI-based personalization of 3D-printed hand exoskeletons raises significant ethical questions regarding the privacy and security of patient medical and biometric data. Developers and healthcare providers must ensure that AI systems collect and process sensitive information in compliance with data protection regulations and ethical standards. The use of AI in medical personalization can improve equity by providing devices tailored to individual physical needs and rehabilitation goals. However, biased training data can lead to unequal performance of exoskeleton systems across individuals of different ages, genders, or physical conditions. Legal regulations are necessary to determine liability in the event that an AI-personalized exoskeleton causes injury or malfunctions during medical use. Manufacturers, software developers, healthcare professionals, and patients may share responsibility depending on the design and use of the device, as defined by the Medical Devices Regulations (MDR) [96], ISO 13485 [97], and the AI Act. From an ethical perspective, patients should provide informed consent and understand how AI contributes to the personalization and performance of their exoskeleton. Transparency in the AI decision-making process, avoiding “black boxes,” and using eXplainable AI (XAI) are important for users and clinicians to trust the recommendations and adjustments made

by the system [98]. The integration of AI and additive manufacturing poses a number of regulatory and ethical challenges that transcend any specific application domain. One significant issue is data privacy, particularly when AI systems are trained using sensitive personal data such as anatomical scans, biometric data, or medical images, which may be subject to stringent data protection regulations such as the EU's General Data Protection Regulation (GDPR). A key regulatory question is whether the initial consent given by individuals for data collection also covers the secondary use of that data to train commercial AI models, or whether additional informed consent is required. Another significant challenge is algorithmic bias, as AI systems trained on non-representative datasets can generate designs or recommendations that perform unevenly across demographic groups, potentially leading to discriminatory outcomes. Liability is equally complex, as it may be unclear whether liability for a defective AI-generated product rests with the software developer, manufacturer, data provider, or end-user who implemented the design. The European Union Artificial Intelligence Act (AI Act) introduces a risk-based regulatory framework that requires transparency, documentation, human oversight, and risk management measures for certain categories of AI systems. Intellectual property law also faces new challenges in establishing ownership of AI-generated designs, especially when the degree of human creative input is limited. In many jurisdictions, copyright protection traditionally requires human authorship, creating uncertainty as to whether an AI-generated design model can qualify as independent intellectual property. Additive manufacturing further complicates enforcement because digital design files can be easily modified, shared, reproduced, and distributed across international jurisdictions with differing legal standards. Consequently, policymakers, lawyers, and industry stakeholders continue to debate how existing frameworks on privacy, intellectual property, product liability, and AI governance should evolve to address the specificities of AI-enabled additive manufacturing.

4.7. AI-Based Personalized Exoskeleton as Part of Neuroprosthetic System

AI-based personalization of a 3D-printed hand exoskeleton enables precise adjustment of the device to the anatomical structure and functional needs of a specific patient. The exoskeleton can be integrated with an advanced neuroprosthetic system that combines robotics, biosignal processing, and neural control technologies [99]. AI algorithms analyze electromyographic (EMG), electroencephalographic (EEG), or motion capture data to adapt movement assistance and rehabilitation strategies. 3D printing enables the rapid production of lightweight and patient-specific mechanical structures with complex ergonomic geometry. ML models continuously adapt grip strength, finger coordination, and movement trajectories to the user's motor skills and rehabilitation progress. The neuroprosthetic system can improve motor recovery in patients with stroke, spinal cord injury, or neuromuscular disorders by supporting repetitive and adaptive hand exercises. ML-based predictive control improves synchronization between the intended user movement and the response of the exoskeleton actuators. Cloud-connected data analysis platforms can enable long-term monitoring of rehabilitation outcomes and remote optimization of therapy parameters. Combining soft robotic materials with intelligent control systems enhances user comfort, safety, and natural interaction with everyday objects. Thus, the future development of personalized AI-based hand exoskeletons will contribute to the emergence of more autonomous, affordable, and clinically effective neuroprosthetic rehabilitation technologies (Figure 12) [100].

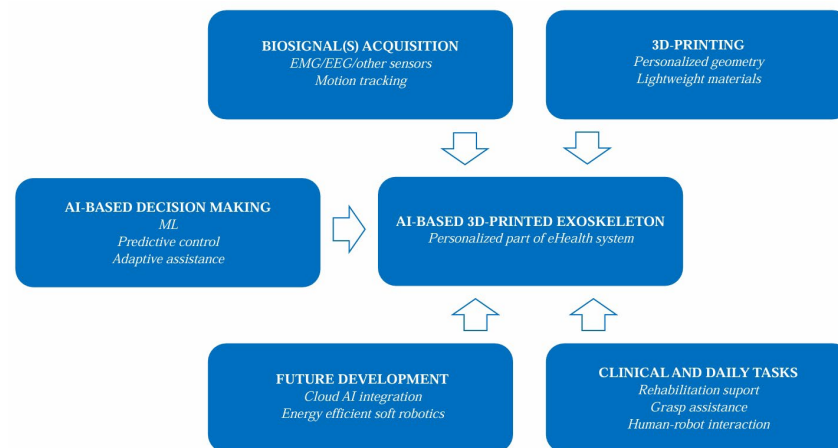


Figure 12. AI-based personalized 3D-printed hand exoskeleton as part of advanced neuroprosthetic system.

4.8. Energetic Issues

AI-based personalization of 3D-printed hand exoskeletons can significantly increase energy consumption, as AI/ML models require computationally intensive training and optimization processes [101]. Energy requirements increase further as real-time adaptive control algorithms continuously analyze user movement, muscle signals, and force feedback during use. Embedded sensors, actuators, and wireless communication modules within the exoskeleton also consume electricity, reducing battery performance and operating time [102]. AI-based personalized designs often require repeated simulations and iterative 3D printing cycles, which increases production energy costs. The choice of printing materials impacts energy efficiency, as some polymers or composite materials require higher printing temperatures and longer processing times. Cloud-based AI systems used to store biomechanical data and update personalization models indirectly contribute to increased electricity consumption in data centers. Miniaturized motors and soft actuators for robots must balance energy efficiency with sufficient grip force and movement precision for rehabilitation or assistive tasks. Weight and battery capacity are becoming critical engineering constraints as users require lightweight devices while simultaneously requiring long operating autonomy. Energy harvesting methods, such as capturing motion or body heat, are being explored to partially power personalized exoskeleton systems and reduce reliance on external charging.

4.9. Influence on Sustainability

AI-based personalization of 3D-printed hand exoskeletons has the potential to improve environmental, economic, and social sustainability at local, national, regional, and global levels, provided it is supported by responsible policies and ethical innovation. AI-based personalization of 3D-printed hand exoskeletons can improve local sustainability by reducing material waste through precision manufacturing tailored to patient needs. Hospitals and rehabilitation centers can use AI to optimize device fit and comfort, reducing the need for repetitive manufacturing and transportation of replacement parts. At the local level, personalized exoskeletons can increase accessibility for people with disabilities, supporting social inclusion and long-term well-being. National healthcare systems can benefit from lower treatment costs, as AI-powered personalization can shorten rehabilitation times and improve recovery outcomes. Integrating AI and additive manufacturing can stimulate national innovation ecosystems by creating new jobs in biomedical engineering, software development, and healthcare automation (including remote and hybrid healthcare). In the region, collaboration between universities, medical institutions, and technology com-

panies can strengthen research networks and drive sustainable industrial development. AI-assisted 3D printing can also reduce reliance on centralized production, enabling regions to produce medical devices closer to patients and reducing the carbon footprint associated with logistics. Globally, personalized exoskeleton technology can contribute to achieving several United Nations SDGs, including good health, industrial innovation, and reducing inequality [101–103].

4.10. Key Directions of Further Studies

Future research should combine advances in AI, robotics, healthcare, and materials science to create safer, cheaper, and more effective personalized hand exoskeletons. Future research on AI-based personalization of 3D-printed hand exoskeletons should focus on improving the accuracy and adaptability of ML algorithms. Researchers should develop larger and more diverse medical datasets to increase the reliability and robustness of AI systems. Long-term clinical trials are needed to assess the durability, safety, and long-term rehabilitation effectiveness of personalized exoskeletons [104–106]. Further research on real-time motion tracking and sensor integration could improve the responsiveness and precision of exoskeleton assistive devices [107–109]. Researchers should explore the use of advanced materials that are lighter, stronger, and more environmentally friendly in 3D printing applications, including those intended for long-term contact with human tissue [110–112]. Research on energy-efficient and portable power systems could enhance the practicality and usability of wearable exoskeletons. Future research should also examine the psychological and social impact of long-term exoskeletons on patients and caregivers. Developing understandable and transparent AI models is important for increasing user trust and clinical acceptance of personalized systems. Researchers should explore more effective cybersecurity and data protection methods to protect sensitive patient information. International collaboration is essential today to create standardized testing procedures, ethical guidelines, and regulatory frameworks for AI-assisted medical devices [113–115].

To date, research on the personalization of BCI-controlled, 3D-printed hand exoskeletons has primarily focused on integrating brain signals with device mechanics through the use of proprietary EEG processing algorithms. Previous studies have shown that personalized geometry and control systems can significantly improve user comfort and rehabilitation outcomes; however, reliance on proprietary methods has reduced the transparency and reproducibility of results. Recent studies emphasize the importance of combining personalized biomechanical design with adaptive and learning-based BCI systems, enabling exoskeletons to dynamically adapt to the user's changing physical and cognitive state. Future research is expected to focus on the development of open or partially open technology platforms that support integration with eHealth services, telerehabilitation, and remote patient monitoring systems while protecting relevant intellectual property rights. In the long term, personalized BCI-controlled exoskeletons are expected to become highly advanced assistive technologies for both upper limb and full-body support, constituting a key element of intelligent and connected healthcare systems [116–119].

5. Conclusions

Research on AI-based personalization of 3D-printed hand exoskeletons shows significant potential for advancing rehabilitation and healthcare technologies. Combining AI and additive manufacturing enables the creation of personalized devices that are better tailored to individual patient needs and anatomical characteristics. Studies show that personalized exoskeletons can improve comfort, functionality, and rehabilitation outcomes compared to conventional solutions. AI-based adaptation and real-time data analysis also support more efficient and responsive rehabilitation processes. At the same time, current research

highlights significant challenges related to data quality, AI algorithm reliability, cybersecurity, and medical safety standards. Limited clinical trials, small sample sizes, and a lack of harmonized regulations remain significant barriers to large-scale implementation. Future research should focus on long-term clinical validation, ethical and legal frameworks, and the development of more accessible and affordable technologies. AI-based personalization of 3D-printed hand exoskeletons is already a promising interdisciplinary field that has the potential to revolutionize personalized rehabilitation and supportive healthcare.

Supplementary Materials: The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/app16136676/s1>. Partial PRISMA 2020 Checklist [39].

Author Contributions: Conceptualization, I.R., J.K., Z.K., J.C., B.S. and D.M.; software, I.R., J.K., Z.K., J.C., B.S. and D.M.; validation, I.R., J.K., Z.K., J.C., B.S. and D.M.; formal analysis, I.R., J.K., Z.K., J.C., B.S. and D.M.; investigation, I.R., J.K., Z.K., J.C., B.S. and D.M.; resources, I.R., J.K., Z.K., J.C., B.S. and D.M.; data curation, I.R., J.K., Z.K., J.C., B.S. and D.M.; writing—original draft preparation, I.R., J.K., Z.K., J.C., B.S. and D.M.; writing—review and editing, I.R., J.K., Z.K., J.C., B.S. and D.M.; visualization, J.K. and D.M.; supervision, I.R.; project administration, I.R.; funding acquisition, I.R. All authors have read and agreed to the published version of the manuscript.

Funding: The work presented in the paper has been financed under a grant to maintain the research potential of Kazimierz Wielki University.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: No new data were created.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial intelligence
EEG	Electroencephalography
EMG	Electromyography
EU	European Union
GDPR	General Data Protection Regulation
MDR	Medical Devices Regulation
ML	Machine learning
SDG	Sustainable Development Goal
XAI	eXplainable AI

References

1. Rojek, I.; Mikołajewski, D.; Dostatni, E.; Kopowski, J. Specificity of 3D Printing and AI-Based Optimization of Medical Devices Using the Example of a Group of Exoskeletons. *Appl. Sci.* **2023**, *13*, 1060. [\[CrossRef\]](#)
2. Rudd, G.; Daly, L.; Jovanovic, V.; Cuckov, F. A Low-Cost Soft Robotic Hand Exoskeleton for Use in Therapy of Limited Hand–Motor Function. *Appl. Sci.* **2019**, *9*, 3751. [\[CrossRef\]](#)
3. Leone, S.; Lago, F.; Lavia, G.; Macrì, F.P.; Sgamba, F.; Tozzo, A.; Adamo, D.; Avila, J.M.N.; Carbone, G. Design and Experimental Validation of a Unidirectional Cable-Driven Exoskeleton for Upper Limb Rehabilitation. *Appl. Sci.* **2025**, *15*, 11996. [\[CrossRef\]](#)
4. Rojek, I.; Dorożyński, J.; Mikołajewski, D.; Kotlarz, P. Overview of 3D Printed Exoskeleton Materials and Opportunities for Their AI-Based Optimization. *Appl. Sci.* **2023**, *13*, 8384. [\[CrossRef\]](#)
5. Çalikuşu, İ.; Fidan, U. The impact of different material types on ergonomics in lower extremity exoskeleton construction. *Comput. Biol. Med.* **2025**, *193*, 110403. [\[CrossRef\]](#) [\[PubMed\]](#)
6. Hornik, T.; Krause, M.; Ramlawi, A.; Lagos-Antonakos, J.; Catterlin, J.K.; Kartalov, E.P. Advanced Architectures of Microfluidic Microcapacitor Arrays for 3D-Printable Biomimetic Electrostatic Artificial Muscles. *Appl. Sci.* **2025**, *15*, 3293. [\[CrossRef\]](#)

7. Alam, N.; Hasan, S.; Mashud, G.A.; Bhujel, S. Neural Network for Enhancing Robot-Assisted Rehabilitation: A Systematic Review. *Actuators* **2025**, *14*, 16. [CrossRef]
8. World Health Organization. *Global Report on Assistive Technology: Access to Assistive Technology*; Medical Devices; World Health Organization: Geneva, Switzerland, 2022. Available online: <https://www.who.int/publications/i/item/9789240049451> (accessed on 27 May 2026).
9. Lapidou, D.; Curtis, F.; Akanuwa, J.; Goher, K.; Niroshan Siriwardena, A.; Kucukyilmaz, A. Patient, carer, and staff perceptions of robotics in motor rehabilitation: A systematic review and qualitative meta-synthesis. *J. Neuroeng. Rehabil.* **2021**, *18*, 181. [CrossRef] [PubMed]
10. Abdi, S.; Witte, L.; Hawley, M. Exploring the potential of emerging technologies to meet the care and support needs of older people: A Delphi survey. *Geriatrics* **2021**, *6*, 19. [CrossRef] [PubMed]
11. Peperoni, E.; Trigili, E.; Capotorti, E.; Capitani, S.L.; Fiumalbi, T.; Pettinelli, F.; Grandi, S.; Rapalli, A.; Lentini, G.; Creatini, I.; et al. Post-traumatic hand rehabilitation using a powered metacarpal-phalangeal exoskeleton: A pilot study. *J. Neuroeng. Rehabil.* **2024**, *21*, 214. [CrossRef] [PubMed]
12. Moellhoff, N.; Throner, V.; Frank, K.; Benne, A.; Coenen, M.; Giunta, R.E.; Haas-Lützenberger, E.M. Epidemiology of hand injuries that presented to a tertiary care facility in Germany: A study including 435 patients. *Arch. Orthop. Trauma Surg.* **2023**, *143*, 1715–1724. [CrossRef] [PubMed]
13. Singh, N.; Saini, M.; Kumar, N.; Srivastava, M.V.P.; Mehndiratta, A. Evidence of neuroplasticity with robotic hand exoskeleton for post-stroke rehabilitation: A randomized controlled trial. *J. Neuroeng. Rehabil.* **2021**, *18*, 76. [CrossRef] [PubMed]
14. Saini, M.; Singh, N.; Kumar, N.; Srivastava, M.V.P.; Mehndiratta, A. A novel perspective of associativity of upper limb motor impairment and cortical excitability in sub-acute and chronic stroke. *Front. Neurosci.* **2022**, *25*, 832121. [CrossRef] [PubMed]
15. O'Connor, S. Exoskeletons in Nursing and Healthcare: A Bionic Future. *Clin. Nurs. Res.* **2021**, *30*, 1123–1126. [CrossRef] [PubMed]
16. Chen, Y.; Yin, W.; Zheng, L.; Mehta, R.; Zhang, X. Biodynamic Modeling and Analysis of Human-Exoskeleton Interactions in Simulated Patient Handling Tasks. *Hum. Factors* **2025**, *67*, 641–655. [CrossRef] [PubMed]
17. Banks, J.J.; Zhou, J.; Riehle, C.O.; Wiggermann, N.E. Biomechanical stresses on healthcare workers during manual patient bed-to-chair transfers. *Int. J. Ind. Ergon.* **2024**, *101*, 103584. [CrossRef]
18. Nain, G.; Samal, U. Concurrence of artificial intelligence and additive manufacturing: A bibliometric analysis. *Total Qual. Manag. Bus. Excell.* **2025**, *36*, 1405–1437. [CrossRef]
19. Bochnia, J.; Kozior, T.; Hajnys, J. 3D Printing of Thin-Walled Models-State-of-Art. *Mechanics* **2024**, *66*, 34–39.
20. Prashar, A.; Singh, M.; Sharma, S.; Kuna, S.S.; Putha, S.; Gudekota, S.; Joshi, R. AI-Driven Multi-Omics Analysis. In *Proceedings of International Conference on Computational Complexity and Intelligent Algorithms: IC3IA 2025*; Springer Nature: Berlin/Heidelberg, Germany, 2025; p. 295.
21. Bonnechère, B. Animals as architects: Building the future of technology-supported rehabilitation with biomimetic principles. *Biomimetics* **2024**, *9*, 723. [CrossRef] [PubMed]
22. Kapoor, N.R.; Kumar, A.; Kumar, A.; Kumar, A.; Arora, H.C. Artificial intelligence in civil engineering: An immersive view. In *Artificial Intelligence Applications for Sustainable Construction*; Woodhead Publishing: Oxford, UK, 2024; pp. 1–74.
23. Sergazin, G.; Zhetenbayev, N.; Tursunbayeva, G.; Uzbekbayev, A.; Sarina, A.; Nurgizat, Y.; Nussibaliyeva, A. Design, Simulation and Functional Testing of a Novel Ankle Exoskeleton with 3DOFs. *Sensors* **2024**, *24*, 6160. [CrossRef] [PubMed]
24. Andrés-Esperanza, J.; Iserte-Vilar, J.L.; Roda-Casanova, V. Design and Optimization of a Custom-Made Six-Bar Exoskeleton for Pulp Pinch Grasp Rehabilitation in Stroke Patients. *Biomimetics* **2024**, *9*, 616. [PubMed]
25. Jenks, B.; Levan, H.; Stefanovic, F. OpenSEA: A 3D printed planetary gear series elastic actuator for a compliant elbow joint exoskeleton. *Front. Robot. AI* **2025**, *12*, 1528266. [CrossRef] [PubMed]
26. Madani, R.S. A Review of the Current and Potential Use of Artificial Intelligence and Machine Learning in 3D Printing. *Migr. Lett.* **2023**, *20*, 1614–1637.
27. Alzoubi, L.; Aljabali, A.A.; Tambuwala, M.M. Empowering precision medicine: The impact of 3D printing on personalized therapeutic. *AAPS PharmSciTech* **2024**, *24*, 228.
28. Walter, Y. Managing the race to the moon: Global policy and governance in Artificial Intelligence regulation—A contemporary overview and an analysis of socioeconomic consequences. *Discov. Artif. Intell.* **2024**, *4*, 14. [CrossRef]
29. Zaway, I.; Jallouli-Khlif, R.; Maalej, B.; Derbel, N. A Robust Fuzzy Fractional Order PID Design Based on Multi-Objective Optimization for Rehabilitation Device Control. *J. Robot. Control (JRC)* **2023**, *4*, 388–402. [CrossRef]
30. Huang, S.; Jin, Y.; Hou, X.; Huang, Z.; Hu, J.; Yu, H.; He, Z. Mapping the Evolution of Artificial Intelligence in Medical Materials. *ACS Omega* **2025**, *10*, 43077–43088. [CrossRef] [PubMed]
31. Tuli, N.T.; Rashid, A.B.; Hoque, M.E. Artificial intelligence in additive manufacturing for biomedical engineering. In *3D Printing for Biomedical Engineering*; Elsevier: Amsterdam, The Netherlands, 2026; pp. 561–594.
32. Bhardwaj, H.; Jangde, R.K. Biomedical Application of 3D Printing. In *3D Printing and Microfluidics in Dermatology*; CRC Press: Boca Raton, FL, USA, 2024; pp. 56–80.

33. Łapczyńska, D. Fuzzy FMEA in risk assessment of human-factor in production process. In *International Conference on Intelligent Systems in Production Engineering and Maintenance*; Springer Nature: Cham, Switzerland, 2023; pp. 677–689.
34. Mohammadnabi, S.; Moslemy, N.; Taghvaei, H.; Zia, A.W.; Askarinejad, S.; Shalchy, F. Role of artificial intelligence in data-centric additive manufacturing processes for biomedical applications. *J. Mech. Behav. Biomed. Mater.* **2025**, *166*, 106949. [[CrossRef](#)] [[PubMed](#)]
35. Bhat, C.; Kumar, A.; Lin, S.C.; Jeng, J.Y. Adaptive mechanical properties and stretchability of novel chainmail fabrics based on overlapping tessellation strategies. *Addit. Manuf.* **2023**, *76*, 103777. [[CrossRef](#)]
36. Dudley, D.R.; Knarr, B.A.; Siu, K.C.; Peck, J.; Ricks, B.; Zuniga, J.M. Testing of a 3D printed hand exoskeleton for an individual with stroke: A case study. *Disabil. Rehabil. Assist. Technol.* **2021**, *16*, 209–213. [[CrossRef](#)] [[PubMed](#)]
37. Yoo, H.J.; Lee, S.; Kim, J.; Park, C.; Lee, B. Development of 3D-printed myoelectric hand orthosis for patients with spinal cord injury. *J. Neuroeng. Rehabil.* **2019**, *16*, 162. [[CrossRef](#)] [[PubMed](#)]
38. Almenara, M.; Cempini, M.; Gómez, C.; Cortese, M.; Martín, C.; Medina, J.; Vitiello, N.; Opisso, E. Usability test of a hand exoskeleton for activities of daily living: An example of user-centered design. *Disabil. Rehabil. Assist. Technol.* **2017**, *12*, 84–96. [[CrossRef](#)] [[PubMed](#)]
39. Page, M.J.; Moher, D.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* **2021**, *372*, n71. [[CrossRef](#)] [[PubMed](#)]
40. Rayssiguie, E.; Erden, M.S. A Review of Exoskeletons Considering Nurses. *Sensors* **2022**, *22*, 7035. [[CrossRef](#)] [[PubMed](#)]
41. Vallée, A. Exoskeleton technology in nursing practice: Assessing effectiveness, usability, and impact on nurses' quality of work life, a narrative review. *BMC Nurs.* **2024**, *23*, 156. [[CrossRef](#)] [[PubMed](#)]
42. Raghuraman, R.N.; Upasani, S.; Gonzales, A.; Aviles, J.; Cha, J.; Srinivasan, D. Manufacturing Industry Stakeholder Perspectives on Occupational Exoskeletons: Changes after a Brief Exposure to Exoskeletons. *IIE Trans. Occup. Ergon. Hum. Factors* **2023**, *11*, 71–80. [[CrossRef](#)] [[PubMed](#)]
43. Gao, G.C.L.; So, B.; Cheng, A.S.K.; Man, S.S.; Ng, S.S.M. Effect of exoskeleton devices on work-related musculoskeletal disorders (WMSDs) among healthcare workers: A scoping review. *Ergonomics* **2025**, *68*, 1409–1421. [[CrossRef](#)] [[PubMed](#)]
44. Bhat, S.; Gavin, J.; Warner, M.; Myall, M. Mapping the evidence on occupational exoskeleton use for the workforce in healthcare, social care, and industry: A systematic scoping review. *Wearable Technol.* **2025**, *6*, 53. [[CrossRef](#)] [[PubMed](#)]
45. Pepito, J.A.; Acaso, N.J.; Merioles, R.; Ismael, J. Opportunities, Challenges, and Future Directions for the Integration of Automation in Nursing Practice: Discursive Study. *JMIR Nurs.* **2025**, *8*, e72674. [[CrossRef](#)] [[PubMed](#)]
46. Bornhaupt, L.R.; Mulder, R.H. New technologies and related changes at work as triggers for professional development in the nursing domain: An exploratory interview study. *BMC Nurs.* **2025**, *24*, 657. [[CrossRef](#)] [[PubMed](#)]
47. National Academies of Sciences, Engineering, Medicine. Supporting the Health and Professional Well-Being of Nurses. In *The Future of Nursing 2020–2030: Charting a Path to Achieve Health Equity*; Flaubert, J.L., Menestrel, S.L., Williams, D.R., Eds.; National Academies Press: Washington, DC, USA, 2021.
48. Christoforou, E.G.; Avgousti, S.; Ramdani, N.; Novales, C.; Panayides, A.S. The Upcoming role for nursing and Assistive Robotics: Opportunities and challenges ahead. *Front. Digit. Health* **2020**, *2*, 585656. [[CrossRef](#)] [[PubMed](#)]
49. Heung, K.H.L.; Tang, Z.Q.; Ho, L.; Tung, M.; Li, Z.; Tong, R.K.Y. Design of a 3D Printed Soft Robotic Hand for Stroke Rehabilitation and Daily Activities Assistance. *IEEE Int. Conf. Rehabil. Robot.* **2019**, *2019*, 65–70. [[CrossRef](#)] [[PubMed](#)]
50. Ten Kate, J.; Smit, G.; Breedveld, P. 3D-printed upper limb prostheses: A review. *Disabil. Rehabil. Assist. Technol.* **2017**, *12*, 300–314. [[CrossRef](#)] [[PubMed](#)]
51. Khan, M.A.; Saibene, M.; Das, R.; Brunner, I.; Puthusserypady, S. Emergence of flexible technology in developing advanced systems for post-stroke rehabilitation: A comprehensive review. *J. Neural Eng.* **2021**, *18*, 6. [[CrossRef](#)] [[PubMed](#)]
52. Demeco, A.; Foresti, R.; Frizziero, A.; Daracchi, N.; Renzi, F.; Rovellini, M.; Salerno, A.; Martini, C.; Pelizzari, L.; Costantino, C. The Upper Limb Orthosis in the Rehabilitation of Stroke Patients: The Role of 3D Printing. *Bioengineering* **2023**, *10*, 1256. [[CrossRef](#)] [[PubMed](#)]
53. Maldonado-Mejia, J.C.; Múnera, M.; Diaz, C.A.R.; Wurdemann, H.; Moazen, M.; Pontes, M.J.; Vieira Segatto, M.E.; Monteiro, M.E.; Cifuentes, C.A. A fabric-based soft hand exoskeleton for assistance: The ExHand Exoskeleton. *Front. Neurobot.* **2023**, *17*, 1091827. [[CrossRef](#)] [[PubMed](#)]
54. Yang, Y.S.; Tseng, C.H.; Fang, W.C.; Han, I.W.; Huang, S.C. Effectiveness of a New 3D-Printed Dynamic Hand-Wrist Splint on Hand Motor Function and Spasticity in Chronic Stroke Patients. *J. Clin. Med.* **2021**, *10*, 4549. [[CrossRef](#)] [[PubMed](#)]
55. Bezzini, R.; Bassani, G.; Avizzano, C.A.; Filippeschi, A. Design of a Novel Flat Cycloidal-Planetary Series Reducer and Experimental Assessment for Assistive Exoskeletons Actuation-CYPLO. *IEEE Access* **2025**, *13*, 202619–202631. [[CrossRef](#)]
56. Barria, P.; Riquelme, M.; Reppich, H.; Cisnal, A.; Fraile, J.C.; Pérez-Turiel, J.; Sierra, D.; Aguilar, R.; Andrade, A.; Nuñez-Espinosa, C. Hand rehabilitation based on the RobHand exoskeleton in stroke patients: A case series study. *Front. Robot. AI* **2023**, *10*, 1146018. [[CrossRef](#)] [[PubMed](#)]

57. Chang, W.H.; Kim, Y.H. Robot-assisted Therapy in Stroke Rehabilitation. *J. Stroke* **2013**, *15*, 174–181. [\[CrossRef\]](#) [\[PubMed\]](#)
58. Bezzini, R.; Bassani, G.; Avizzano, C.A.; Filippeschi, A. Design and Examination of Compound Planetary Gearboxes to Investigate the Impact of 3D-Printed Embedded Bearings for Assistive Exoskeletons Actuators. *J. Mech. Des.* **2026**, *148*, 113501. [\[CrossRef\]](#)
59. Barbieru, C.; Dramnesc, I. A Web-Controlled, Modular 3D-Printed Exoskeleton for Upper Limb Stroke Recovery. In Proceedings of the 22nd International Conference on Informatics in Control, Automation and Robotics ICINCO, Marbella, Spain, 20–22 October 2025; pp. 150–157.
60. Rafique, S.; Rana, S.M.; Bjorsell, N.; Isaksson, M. Evaluating the advantages of passive exoskeletons and recommendations for design improvements. *J. Rehabil. Assist. Technol. Eng.* **2024**, *11*, 20556683241239875. [\[CrossRef\]](#) [\[PubMed\]](#)
61. Lorke, M.; Stefanou, T. Improving research and development of wearable assistive and rehabilitation technologies: A systematic review on diversity factors. *J. Neuroeng. Rehabil.* **2025**, *22*, 31. [\[CrossRef\]](#) [\[PubMed\]](#)
62. Rojek, I.; Kopowski, J.; Rosiak, M.; Mikołajewski, D. The Role and Prospects of Composite Fibers in the Production of Hand Exoskeletons. *Appl. Sci.* **2026**, *16*, 5365. [\[CrossRef\]](#)
63. Elsheikh, A.; Othman, A.; Al-Thani, D. Systematic analysis of cutting-edge technology for the wellbeing and safety of older persons. *Disabil. Rehabil. Assist. Technol.* **2025**, *20*, 2691–2724. [\[CrossRef\]](#) [\[PubMed\]](#)
64. Modi, N.; Singh, J. A survey of research trends in assistive technologies using information modelling techniques. *Disabil. Rehabil. Assist. Technol.* **2022**, *17*, 605–623. [\[CrossRef\]](#) [\[PubMed\]](#)
65. Bulut, A. Exploring conceptual and collaborative structures in disability and rehabilitation: Assistive technology—A systematic review. *Disabil. Rehabil. Assist. Technol.* **2026**, *21*, 3–31. [\[CrossRef\]](#) [\[PubMed\]](#)
66. Álvarez-Aguado, I.; Vega Córdova, V.; Muñoz La Rivera, F.; González-Carrasco, F.; Roselló-Peñaloza, M.; Espinosa Parra, F.; Spencer, H.; Farhang, M.; Campaña Vilo, K.; Aguado, L.Á. Exploring technology use among older adults with intellectual disabilities: Barriers, opportunities, and the role of advanced technologies. *Disabil. Rehabil. Assist. Technol.* **2025**, *20*, 2249–2260. [\[CrossRef\]](#) [\[PubMed\]](#)
67. Del Toro García, X.; Llumiguano Solano, H.; Bolaños Peño, C.; Fernández-Bermejo Ruiz, J.; Dorado Chaparro, J.; Santofimia Romero, M.J.; Villanueva Molina, F.J.; Sánchez Fábrega, R.A.; Díaz Molina, A.; Tirado Bejarano, A.J.; et al. Evaluating the Energy Requirements of Assistive Technologies for Older Adults. *Stud. Health Technol. Inform.* **2023**, *306*, 17–24. [\[CrossRef\]](#) [\[PubMed\]](#)
68. Kabir, R.; Sunny, M.S.H.; Ahmed, H.U.; Rahman, M.H. Hand Rehabilitation Devices: A Comprehensive Systematic Review. *Micromachines* **2022**, *13*, 1033. [\[CrossRef\]](#) [\[PubMed\]](#)
69. Shen, Y.; Jiang, L.; Lai, J.; Hu, J.; Liang, F.; Zhang, X.; Ma, F. A comprehensive review of rehabilitation approaches for traumatic brain injury: Efficacy and outcomes. *Front. Neurol.* **2025**, *16*, 1608645. Erratum in *Front. Neurol.* **2025**, *16*, 1651979. <https://doi.org/10.3389/fneur.2025.1651979>. [\[CrossRef\]](#) [\[PubMed\]](#)
70. Jackson, G.; Abdullah, H.A. Development and Testing of a Soft Exoskeleton Robotic Hand Training Device. *Sensors* **2023**, *23*, 8395. [\[CrossRef\]](#) [\[PubMed\]](#)
71. Ledoux, E.D.; Barth, E.J. Design, modeling, and preliminary evaluation of a 3D-printed wrist-hand grasping orthosis for stroke survivors. *Wearable Technol.* **2024**, *5*, e12. [\[CrossRef\]](#) [\[PubMed\]](#)
72. Trott, R.E.; Kleinig, T.J.; Hillier, S.L.; Hobbs, D.A.; Reynolds, K.J. A Modular Hybrid Exoskeletal-Soft Glove for High Degree of Freedom Monitoring Capability. *IEEE Int. Conf. Rehabil. Robot.* **2019**, *2019*, 577–582. [\[CrossRef\]](#) [\[PubMed\]](#)
73. Lambelet, C.; Temiraliuly, D.; Siegenthaler, M.; Wirth, M.; Woolley, D.G.; Lambercy, O.; Gassert, R.; Wenderoth, N. Characterization and wearability evaluation of a fully portable wrist exoskeleton for unsupervised training after stroke. *J. Neuroeng. Rehabil.* **2020**, *17*, 132. [\[CrossRef\]](#) [\[PubMed\]](#)
74. Forbrigger, S.; DePaul, V.G.; Davies, T.C.; Morin, E.; Hashtrudi-Zaad, K. Home-based upper limb stroke rehabilitation mechatronics: Challenges and opportunities. *BioMed. Eng. Online* **2023**, *22*, 67. [\[CrossRef\]](#) [\[PubMed\]](#)
75. Mikołajewska, E.; Prokopowicz, P.; Mikołajewski, D. Computational gait analysis using fuzzy logic for everyday clinical purposes-preliminary findings. *Bio-Algorithms Med-Syst.* **2017**, *13*, 37–42.
76. Prokopowicz, P.; Mikołajewski, D.; Mikołajewska, E.; Kotlarz, P. Fuzzy System as an Assessment Tool for Analysis of the Health-Related Quality of Life for the People After Stroke. In Proceedings of the 16th International Conference on Artificial Intelligence and Soft Computing (ICAISC), Zakopane, Poland, 11–15 June 2017; Volume 10245, pp. 710–721.
77. Łukaniszyn, M.; Majka, Ł.; Grochowicz, B.; Mikołajewski, D.; Kawala-Sterniuk, A. Digital Twins Generated by Artificial Intelligence in Personalized Healthcare. *Appl. Sci.* **2024**, *14*, 9404. [\[CrossRef\]](#)
78. Recmanik, M.; Martinek, R.; Nedoma, J.; Jaros, R.; Pelc, M.; Hajovsky, R.; Velicka, J.; Pies, M.; Sevcakova, M.; Kawala-Sterniuk, A. A Review of Patient Bed Sensors for Monitoring of Vital Signs. *Sensors* **2024**, *24*, 4767. [\[CrossRef\]](#) [\[PubMed\]](#)
79. Fudali-Czyż, A.; Lewkowicz, R.; Francuz, P.; Truszczyński, O.E.; Bałaj, B. An Attentive Blank Stare Under Simulator-induced Spatial Disorientation Events. *Hum. Factors* **2024**, *66*, 317–335. [\[PubMed\]](#)
80. Wajchman-Świtalska, S.; Grabowska-Chenczke, O.; Woźniak, M.; Bałaj, B. Psychosocial Determinants of Recreational Activity within Urban Green Spaces during the COVID-19 Pandemic in Poland. *Forests* **2022**, *13*, 1569. [\[CrossRef\]](#)

81. Yucel, M.A.; Luke, R.; Mesquita, R.C.; Zapala, D.; Zemanek, V. fNIRS reproducibility varies with data quality, analysis pipelines, and researcher experience. *Commun. Biol.* **2025**, *8*, 1149. [CrossRef] [PubMed]
82. Zapala, D.; Zabielska-Mendyk, E.; Cudo, A.; Kwiatkowski, M.; Kwiatkowska, A. The role of motor imagery in predicting motor skills in young male soccer players. *Int. J. Environ. Res. Public Health* **2021**, *18*, 6316. [CrossRef] [PubMed]
83. Pawlaczyk, N.; Szmytko, M.; Meina, M.; Lewandowska, M.; Stępnia, J.; Bałaj, B.; Dreszer, J. Gait Analysis under Spatial Navigation Task in Elderly People—A Pilot Study. *Sensors* **2021**, *21*, 270. [CrossRef] [PubMed]
84. Dżianok, P.; Antonova, I.; Wojciechowski, J.; Dreszer, J.; Kublik, E. The Nencki-Symfonia electroencephalography/event-related potential dataset: Multiple cognitive tasks and resting-state data collected in a sample of healthy adults. *Giga Sci.* **2022**, *11*, giac015.
85. Osinska, V.; Bała, P. Classification visualization across mapping on a sphere. *Front. Artif. Intell. Appl.* **2008**, *181*, 95–106. [CrossRef]
86. Osinska, V.; Kowalska, M.; Osiński, Z. The role of visualization in the shaping and exploration of the individual information space: Part 1. *Knowl. Organ.* **2018**, *45*, 547–558. [CrossRef]
87. Rojek, I.; Kopowski, J.; Osińska, A.; Mikołajewski, D. Material and Technological Optimization of a 3D-Printed Hand Exoskeleton Within the Industry 4.0/5.0/6.0 Paradigms: A Short Review. *Appl. Sci.* **2026**, *16*, 1538. [CrossRef]
88. Zheng, L.; Hawke, A.L.; Evans, K. Critical review on applications and roles of exoskeletons in patient handling. *Int. J. Ind. Ergon.* **2022**, *89*, 103290. [CrossRef] [PubMed]
89. Booth, R.G.; Strudwick, G.; McBride, S.; O'Connor, S.; Solano López, A.L. How the nursing profession should adapt for a digital future. *BMJ* **2021**, *373*, n1190. [CrossRef]
90. Zhu, L.; Xie, Y.; Xiang, N.; Chen, G. An Explainable HCI-Based Decision Support Framework for Human-AI Co-Design. *Appl. Sci.* **2026**, *16*, 4007. [CrossRef]
91. Amici, C.; Buraschi, R.; Dragusanu, M.; Gobbo, M.; Logozzo, S.; Malvezzi, M.; Pollet, J.; Tiboni, M.; Valigi, M.C. Design Criteria for Robotic Rehabilitation Medical Devices: The PICO-Driven Approach. *Machines* **2026**, *14*, 303. [CrossRef]
92. Colborn, G.X.; Pilgrim, J.; Ho, K.; Natarajan, P.; Goode, A.; Catterlin, J.K.; Krause, M.; Hornik, T.; Kartalov, E.P. Artificial Muscles: Electrostatic Actuation and Design Tradeoffs. *Biomimetics* **2026**, *11*, 399. [CrossRef] [PubMed]
93. Jiang, S.; Kang, P.; Song, X.; Lo, B.P.; Shull, P.B. Emerging wearable interfaces and algorithms for hand gesture recognition: A survey. *IEEE Rev. Biomed. Eng.* **2021**, *15*, 85–102. [CrossRef]
94. Farah, L.; Roll, D.; Sorais, A.; Vallée, A. Assessment of Exoskeletons on Nurses' Quality of Work Life: A Pilot Study at Foch Hospital. *Nurs. Rep.* **2023**, *13*, 780–791. [CrossRef] [PubMed]
95. Ahmed, I.; Feng, B.; Emmanuel Yeboah, K.; Feng, J.; Jumani, M.S.; Ali, S.A. Leveraging Industry 4.0 for marketing strategies in the medical device industry of emerging economies. *Sci. Rep.* **2024**, *14*, 27664. [CrossRef] [PubMed]
96. Regulation (EU) 2017/745 of the European Parliament and of the Council of 5 April 2017 on Medical Devices, Amending Directive 2001/83/EC, Regulation (EC) No 178/2002 and Regulation (EC) No 1223/2009 and Repealing Council Directives 90/385/EEC and 93/42/EEC (Text with EEA Relevance). Available online: <https://eur-lex.europa.eu/eli/reg/2017/745/oj/eng> (accessed on 30 June 2026).
97. ISO 13485:2016; Medical Devices—Quality Management Systems—Requirements for Regulatory Purposes. Available online: https://www.iso.org/standard/59752.html?__cf_chl_f_tk=RS04iOMcTscG5G7wioo.4IXrIXxZouE1pDqSqWFyw90-1782990416-1.0.1.1-B68rhLBmEZzh79hY3_yuVeq.uWypRQxkxuHzKLR6tc64 (accessed on 30 June 2026).
98. Kapeller, A.; Felzmann, H.; Fosch-Villaronga, E.; Nizam, K.; Hughes, A.-M. Implementing Ethical, Legal, and Societal Considerations in Wearable Robot Design. *Appl. Sci.* **2021**, *11*, 6705. [CrossRef]
99. Mikołajewska, E.; Mikołajewski, D. Neuroprostheses for Increasing Disabled Patients' Mobility and Control. *Adv. Clin. Exp. Med.* **2012**, *21*, 263–272. [PubMed]
100. Prokopowicz, P.; Mikołajewski, D.; Tyburek, K.; Mikołajewska, E. Computational gait analysis for post-stroke rehabilitation purposes using fuzzy numbers, fractal dimension and neural networks. *Bull. Pol. Acad. Sci. Tech. Sci.* **2020**, *68*, 191–198. [CrossRef]
101. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M. Green Energy Management in Manufacturing Based on Demand Prediction by Artificial Intelligence—A Review. *Electronics* **2024**, *13*, 3338. [CrossRef]
102. Rojek, I.; Mikołajewski, D.; Mroziński, A.; Macko, M.; Bednarek, T.; Tyburek, K. Internet of Things Applications for Energy Management in Buildings Using Artificial Intelligence—A Case Study. *Energies* **2025**, *18*, 1706. [CrossRef]
103. Rojek, I.; Kotlarz, P.; Dorożyński, J.; Mikołajewski, D. Sixth-Generation (6G) Networks for Improved Machine-to-Machine (M2M) Communication in Industry 4.0. *Electronics* **2024**, *13*, 1832. [CrossRef]
104. Chainando, N.; Martawidjaja, M.; Darius, R.A.; Yahya, L.C.; Yemima, S.; Tan, W.S.; Harito, C.; Chandra, R.C.; Andhini, G.K.; Putra, K.B.; et al. Applying 3D Scanning and Printing Techniques to Produce Upper Limb Prostheses: Bibliometric Analysis and Scoping Review. *Prosthesis* **2025**, *7*, 26. [CrossRef]
105. Mural, H.; Choudhury, I.A.; Abid, M.R.; Banik, S.C. Recent Advancements, Trends and Future Prospects of Upper Limb Prosthesis through 3D Printing—A Systematic Review. *J. Sustain. Smart Mater. Struct. Syst.* **2026**, *2*, 1–23. [CrossRef]

106. Górski, F.; Denysenko, Y.; Kuczek, W.; Żukowska, M.; Wichniarek, R.; Zawadzki, P.; Rybarczyk, J. Individualized 3D printed orthopaedic and prosthetic devices using AutoMedPrint technology—Methodologies and examples. *Adv. Sci. Technol. Res. J.* **2024**, *18*, 145–158.
107. Górski, F. *Computer Aided Design of 3D Printable Anatomically Shaped Medical Devices: Methodologies and Applications*; CRC Press: Boca Raton, FL, USA, 2025.
108. Gautam, R.; Vibhuti Mishra, A.K.; Vikas, V. From Imaging to Innovation: The Journey of CT and MRI Images to 3D Models. In *Healing in Layers: 3D Printing in Healthcare*; Springer Nature: Singapore, 2026; pp. 63–88.
109. Górski, F. The Future of XR Healthcare: Bridging the Gap Between Technology and Personalized Medicine. In *International Conference on Extended Reality*; Springer Nature: Cham, Switzerland, 2025; pp. 171–185.
110. Grohs, A.; Górski, F.; Żukowska, M.; Kuczek, W.; Zawadzki, P.; Gabryszewski, B.; Wichniarek, R. Study of Thermal and Mechanical Properties of Additively Manufactured PLA in the Context of Hand Orthosis Design. In *International Scientific-Technical Conference Manufacturing*; Springer Nature: Cham, Switzerland, 2026; pp. 143–157.
111. Rybarczyk, J.; Dolatkowski, M.; Górski, F.; Mrozek-Czajkowska, A.; Nowak, P. Design and Investigation of a Low-Cost, Anatomically Customized Mechatronic Hand Prosthesis. In *International Scientific-Technical Conference Manufacturing*; Springer Nature: Cham, Switzerland, 2026; pp. 128–140.
112. Rybarczyk, J.; Dolatkowski, M.; Górski, F.; Mrozek-Czajkowska, A. Design and Investigation of a Low-Cost, Anatomically Customized Mechatronic Hand. In *Advances in Manufacturing V: Volume 5-Biomedical Engineering: Factory of the Future*; Springer: Berlin/Heidelberg, Germany, 2026; p. 128.
113. Kyriakidis, I.F.; Kladovasilakis, N.; Korlos, A.; Tzetzis, D.; Pechlivani, E.M.; Tsongas, K. Dynamic-mechanical investigation of thermoplastic polyurethane/ground tire rubber composites through selective laser sintering additive manufacturing. *Int. J. Adv. Manuf. Technol.* **2025**, *141*, 1987–2006.
114. Kyriakidis, I.F.; Kladovasilakis, N.; Pechlivani, E.M.; Tsongas, K. Mechanical Evaluation of Topologically Optimized Shin Pads with Advanced Composite Materials: Assessment of the Impact Properties Utilizing Finite Element Analysis. *Computation* **2025**, *13*, 236. [\[CrossRef\]](#)
115. Omigbodun, F.T. A Review inside Innovation: AI and additive manufacturing for advanced bone scaffold design. *IgMin Res.* **2025**, *3*, 346–361. [\[CrossRef\]](#)
116. John, P.; Selvam, A.K.; Uppal, M.; Mohammed Adhil, S. Futuristic Biomaterials for 3D Printed Healthcare Devices. In *Digital Design and Manufacturing of Medical Devices and Systems*; Springer Nature: Singapore, 2024; pp. 33–62.
117. Setiawan, J.D.; Ariyanto, M.; Putri, F.T.; Ismail, R.; Samudro, L. Portable Fabric-Based Soft Glove Controlled with Single-Channel Electroencephalography. *J. Robot. Control (JRC)* **2024**, *5*, 1080–1090.
118. Jochumsen, M.; Janjua, T.A.M.; Arceo, J.C.; Lauber, J.; Buessinger, E.S.; Kæseler, R.L. Induction of Neural Plasticity Using a Low-Cost Open Source Brain-Computer Interface and a 3D-Printed Wrist Exoskeleton. *Sensors* **2021**, *21*, 572. [\[CrossRef\]](#) [\[PubMed\]](#)
119. Rojek, I. Hybrid Neural Networks as Prediction Models. In *Artificial Intelligence and Soft Computing. ICAISC 2010*; Rutkowski, L., Scherer, R., Tadeusiewicz, R., Zadeh, L.A., Zurada, J.M., Eds.; Lecture Notes in Computer Science; Springer: Berlin/Heidelberg, Germany, 2010; Volume 6114. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.