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AI-Driven 3D Printed Textile Assistive Devices for Persons with Disabilities

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ABSTRACT

The integration of artificial intelligence (AI) and additive manufacturing creates a design system to create custom, affordable assistive devices based on the specific needs of a person with a disability. This study explains an AI-driven design and manufacture process of a 3D printed textile assistive device prototype using flexible materials, thermoplastic polyurethane (TPU), and Nylon-12. The design utilizes a conditional Generative Adversarial Network (cGAN) to generate individualized textile-inspired assistive-device geometries through multi-objective optimization of anatomical fit, mechanical performance, porosity, and fabrication cost using three-dimensional anatomical scanning data.

This study demonstrates the potential benefits of AI-driven iterative modeling and manufacturing in terms of material utilization, fabrication cost, and user-reported comfort. Experimental results indicate reductions of 40.3% in material use and 41.7% in fabrication cost for the AI-optimized designs, a 65.6% reduction in the overall design-to-fabrication cycle, and improvements of 13.8–25.3% across the evaluated mechanical properties compared with the corresponding conventional designs. Usability feedback from participants yielded an overall mean score of 4.6/5, indicating generally positive user perceptions of comfort, breathability, and flexibility. This research demonstrates an opportunity to shift assistive devices using AI, and 3D textile printing and additive manufacturing for low-cost, inclusive human-centred assistive technologies to improve mobility, accessibility, and quality of life of a person with a disability

1. Introduction:

Individuals with physical disabilities often use assistive devices (e.g., orthotic support, prosthetics, or wearable aids) to recover mobility, independence, or participation in everyday life [9]. However, traditional assistive technology is usually delivered through a rigid, off-the-shelf design, unable to address an individual's specific body shape and comfort. Traditional manufacturing of assistive devices is burdensome and expensive (often requiring multiple manual fittings and adjustments) [2]. There are many people who do not have access to expensive, comfortable and well-fitting assistive devices. This is especially true in developing or low-income countries [3].
Advancements in additive manufacturing (3D printing) have created favorable opportunities for inexpensive, customized, assistive device fabrication [4]. In contrast to traditional subtractive methods: additive manufacturing enables rapid prototyping, light-weight design, and fine geometrical consideration [5]. 3D printing with textiles, using flexible materials, e.g., thermoplastic polyurethane (TPU), nylon, and elastomers, enables wearables that are breathable, stretchable, and soft [6]. Therefore, 3D printed textiles are applicable toward assistive wearables needing prolonged body contact (e.g., joint support, prosthetic liners, or adaptive clothing).

At the same time, artificial intelligence (AI) is now an innovative enabler of design automation and performance optimization. Using generative design algorithms, machine learning, and deep neural networks, AI can analyze data from a body scan, predict the distribution of stresses, and automatically generate optimized geometries specific to the individual user [7]. The intersection of AI and 3D printing enables a shift from manual, trial-and-error production to a data-driven performance adapted production pipeline, with improved accuracy, comfort, and material efficiency [8].

In spite of these advances in technology, there is a knowledge gap related to use of AI- enabled generative design with flexible textile 3D printing that is geared toward assistive devices for individuals with disabilities. Previous studies have primarily focused on the production of rigid prosthetic components rather than the flexible, wearable textile structure molded to the human body. Likewise, the usability and affordability of AI-enabled textile assistive devices have yet to be explored in real- world contexts.

This research proposes an artificially intelligent system for the design and fabrication of 3D printed textile assistive devices for people living with disabilities within the physical domain. The system utilizes machine learning algorithms and body scan databases to produce optimized textile geometries using flexible filaments through the additive manufacturing process. The research evaluates the use of the devices against traditional static assistive technologies with regards to cost, mechanical performance, comfort, and user experience. This research will contribute to the development of low cost, customized and human-centered assistive technologies to help facilitate inclusion and access through the use of artificial intelligence, textile engineering, and additive manufacturing.

2. Related work

Integrating AI-driven technology with 3D printing represents an emerging area of opportunity for textile assistive products for individuals with disabilities. Recent advancements have indicated an opportunity for smart textile technology combined with AI to create fully customized and adaptive designs. Latest trends in adaptive fashion describes developments, in relation to smart textile development and AI customization, toward creating seamless clothing that is a one-piece solution through 3D printing, while increasing ease of use and minimizing production difficulties [9]. This combined capability will provide individuals with garments that not only look better, but will also provide better functionality with fit and use based on the individual's needs.

AI has an important role of promoting accessibility particularly as it relates to adaptive fashion, because AI-driven customization will provide a level of inclusivity and responsiveness to specific disabilities of the clothing and assistive devices for these individuals. The combination of 3D printing with AI has resulted in personalized adaptive clothing options to provide individuals with disabilities a functional and style [10]. Together, these approaches allow for rapid prototyping and iterative design to better ensure the assistive device has all the specific needs of the user. AI has facilitated advancements in prosthetics, primarily through the integration of convolutional neural networks into navigational aids and object manipulation for upper-limb amputees [11]. These devices could potentially utilize the textile component in 3D printing which should further enhance the usability and functionality of prosthetics as well.The development of smart and electronic textiles also contributes to integration in the form of adaptive clothing and wearables for individuals with disabilities and the older adult population [12]. Artificial intelligence technology is also being used not just in the design stage but in the manufacturing stage, where AI algorithms are being utilized for developing smart textiles systems, including enhancing textile performance using powder-based nanomaterials [13]. AI powered devices can even be created to have textiles embedded with sensors and electronic components, meaning that a user could wear a garment embedded with sensors to monitor health indicators or to assist them if they are limited in their mobility. The deployment of additive technology in the production of mobility devices (e.g., 3D printed robotic exoskeletons)

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has improved the diversity of the fabrication of assistive devices by producing them more lightweight, customizable and durable [14].

Soft robotics and powered exoskeletons – often used with textiles produced using 3D printing – are emerging assistive devices to support mobility. These devices focus on treatment such as rehabilitation or supporting daily living activities that the user will engage in, often with AI algorithms to operate in more optimal and adaptable ways [15]. Ultimately, the combination of AI, 3D printed materials, and textiles creates the use of all these technologies in the same platform to create assistive devices tailored to the user that are functional, adaptive and highly personalized to the user in a user- centered design way.
Assistive devices that have been 3D printed, such as those developed by Abilitease Inc. are representative of a tangible representation of these technologies in developing thematic assistive tools for users with disabilities to help mitigate everyday challenges during activities of daily living [16]. These items provide tangible benefits of AI and 3D printed textiles on user independence and quality of life.

The combination of AI, 3D printing and smart textiles technology is revolutionizing the overall environment of assistive device by providing extremely personalized, adaptive and functional textile solutions for individuals with disabilities. AI, 3D printing and smart textiles afford opportunities for inclusive and effective assistive care that were not previously possible.

3. Methodology

This experimental study integrates artificial intelligence, textile engineering, and additive manufacturing to develop and evaluate individualized 3D-printed textile-inspired assistive devices for persons with physical disabilities. The workflow combines three-dimensional anatomical data acquisition, geometric feature extraction, conditional generative design, multi-objective optimization, and additive manufacturing using flexible polymeric materials. The generated designs were evaluated in terms of anatomical fit, mechanical performance, fabrication efficiency, cost, and user-reported usability. The experimental workflow comprised four principal stages: (1) acquisition and preprocessing of anatomical data, (2) AI-driven generation and optimization of assistive-device geometries, (3) fabrication of the optimized geometries using 3D printing, and (4) mechanical and user-based evaluation of the resulting prototypes.

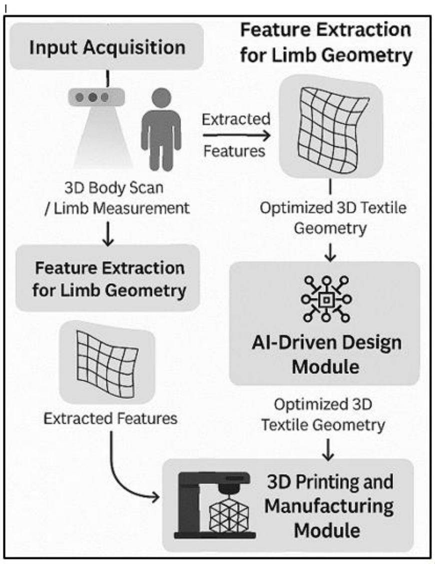

Fig 1: Overview of proposed approach

3.1 Participants and Anatomical Data Acquisition

Ten volunteer participants aged 18–55 years (n = 10) were included in the experimental evaluation. All participants were adults with physical disabilities requiring localized assistive support. The sample comprised 6 males and 4 females, with ages ranging from 18 to 55 years. The participants represented upper- and lower-limb physical disabilities associated with functional limitations affecting the wrist/hand, forearm, and ankle regions.

The anatomical distribution consisted of 4 wrist/hand cases, 3 forearm cases, and 3 ankle cases. Each participant contributed one primary anatomical scan corresponding to the body region for which the assistive-device prototype was designed. Three-dimensional limb scans were obtained from all participants and anonymized before further processing. The same participants subsequently took part in the usability evaluation of the fabricated assistive-device prototypes. The anatomical data were used to generate individualized device geometries based on the geometric characteristics of each participant's limb.

Participants were included if they (1) were aged 18 years or older, (2) had a physical disability or functional limitation affecting the selected limb region, (3) were able to participate in the scanning and prototype-evaluation procedures, (4) were able to provide informed consent, and (5) were able to wear or interact with the prototype during the usability evaluation. Participants were excluded if they had an acute injury or condition that prevented safe participation, were unable to complete the scanning procedure, or were unable to provide informed consent.

The acquired three-dimensional scans were preprocessed to remove background noise and surface irregularities. Laplacian-based smoothing was applied to reduce scanning artifacts, after which the relevant anatomical regions were segmented for subsequent geometric analysis. The processed anatomical representations were then converted into digital models suitable for feature extraction and AI-driven generative design. The resulting representations provided the anatomical input required for generating user-specific lattice geometries.

Written informed consent was obtained from all participants before participation. All participant-related anatomical data were anonymized and handled confidentially.

3.2 AI-Driven Design and Model Development

The AI-driven design module was implemented using a conditional Generative Adversarial Network (cGAN) to generate individualized lattice-based assistive-device geometries from anatomical and geometric conditioning information. The input representation consisted of the extracted anatomical features described in Section 3.1, including curvature and contour characteristics, thickness and cross-sectional profiles, surface-gradient information, stress-related regions, and principal anatomical orientations. These features were normalized and provided to the generative model as conditioning variables.

The cGAN comprised a generator and a discriminator. The generator received the anatomical conditioning vector together with a latent vector and produced candidate textile-inspired lattice geometries. The discriminator was used to distinguish between reference design geometries and generated geometries under the same anatomical conditioning information. Through adversarial optimization, the generator was trained to produce geometries that were consistent with the structural characteristics of the reference design data while remaining responsive to the anatomical conditioning variables.

The generated geometries were subsequently evaluated using the predefined design criteria for anatomical fit, mechanical performance, porosity, fabrication cost, and manufacturability. Five candidate geometries were generated for each participant-specific anatomical input. The candidate with the most suitable combination of predicted fit and manufacturability was selected for subsequent fabrication and experimental evaluation.

3.2.1 cGAN Training Configuration

The conditional Generative Adversarial Network (cGAN) was developed using the anatomical and three-dimensional design data described in Section 4. The model was designed to learn the relationship between anatomical characteristics and textile-inspired assistive-device geometries. The conditioning representation incorporated four principal groups of anatomical and geometric characteristics: (1) curvature and contour topology, (2) thickness and cross-sectional profiles, (3) surface-gradient and stress-zone information, and (4) principal anatomical orientation and limb-symmetry characteristics. These features were normalized before being provided to the generative model as conditioning variables.

The cGAN consisted of a generator and a discriminator. The generator received the anatomical conditioning vector together with a latent vector and produced candidate textile-inspired lattice geometries. The discriminator evaluated whether the generated geometry was consistent with the reference design distribution under the corresponding anatomical condition. Adversarial optimization was then used to improve the ability of the generator to produce anatomically conditioned geometries with structural characteristics consistent with the reference design data.

The publicly available anatomical and three-dimensional design data described in Section 4 were used for model development, whereas the three-dimensional limb scans obtained from the ten participants were reserved as participant-specific anatomical inputs for subsequent design generation and evaluation. Thus, the participant scans were not treated as generic training examples for the generative model. For each participant-specific anatomical input, the trained cGAN generated five candidate assistive-device geometries. The candidate geometries were screened according to the predefined criteria for anatomical fit, mechanical performance, porosity, manufacturability, and fabrication cost. The candidate satisfying the required constraints and providing the most suitable predicted fit and manufacturability characteristics was selected for fabrication and subsequent experimental evaluation.

Because the available study records do not specify the software framework, optimizer, learning rate, batch size, number of training epochs, latent-vector dimensionality, or numerical training/validation/test partition of the reference design dataset, these implementation parameters are not reported as fixed numerical values. Accordingly, the present study describes the cGAN at the workflow and functional level, while the reported participant-specific generation procedure focuses on the application of the trained model to individualized anatomical inputs.

3.3 Feature Extraction for Limb Geometry

The design process initiates with the initial phase of feature extraction, whereby the three-dimensional body scan of the target limb is translated into a formal representation suitable for an artificial intelligence generative model. The anatomical surface $\mathcal{S} \subset \mathbb{R}$ is reconstructed as a watertight mesh or as a signed-distance-field $d_{\mathcal{S}}: \mathbb{R}^3 \rightarrow \mathbb{R}$. From this surface a complete feature vector is derived that captures the essential geometric and morphological properties of the limb that defines both structure and motion characteristics. These features are given in Table 1.

Table 1: Feature List

Feature	Description
Curvature and Contour Topology	Convexity and concavity measures that provide information on where flexibility or more reinforcement is needed.
Thickness and Cross-Sectional Profiles:	Quantitative measures of local volume distribution for structural support.
Surface Gradient and Stress Zone Mapping	Indicates regions of higher biomechanical stress and repeated movement that will require additional elasticity and comfort.
Principal Orientation and Limb Symmetry Axes	Effective for ensuring the mesh anisotropy is aligned and the optimal orientation of textile for three- dimensional printing.

Extracted features are normalized and embedded as conditioning vectors for the AI generative model, ensuring that textile design generated conforms to the anatomical geometry of the wearer while enabling the limb to function naturally, and maintain mechanical integrity.

3.4 AI-Driven Design Module

The AI-assisted design engine represents the central component of the proposed system and facilitates the automated generation of textile-inspired assistive structures informed by anatomical and geometric data. This component integrates anatomical feature extraction, conditional deep generative modeling, and multi-objective optimization to produce three-dimensional, print-ready geometries for each participant. During the feature-extraction stage, three-dimensional body scans are converted into digital models from which geometric and morphological descriptors, including curvature, surface topology, thickness distribution, and stress-related regions, are derived to characterize individual anatomical variation. These parameters condition the generative process so that regions subject to greater mechanical demand can receive appropriate structural reinforcement while regions associated with movement can retain greater flexibility. The generative design engine uses a conditional Generative Adversarial Network (cGAN) to map latent design variables and anatomical conditioning information to optimized textile-inspired geometries. The cGAN was developed using the reference anatomical and three-dimensional design data described in Section 4, while participant-specific scans were reserved for individualized design generation. The generated geometries were evaluated according to anatomical fit, mechanical performance, porosity, manufacturability, and fabrication cost, and the most suitable candidate was subsequently transferred to the fabrication stage.

Following training, the AI system generated a set of candidate designs conditioned on each participant's anatomical characteristics. Each candidate design was evaluated according to the predefined criteria for mechanical performance, anatomical fit, manufacturability, and material cost. Following this assessment, the selected geometry was transferred to the fabrication module for prototype production.

3.5 3D Printing and Manufacturing Module

Following optimization, the selected assistive-device geometries were fabricated using additive manufacturing with flexible polymeric materials. Two additive-manufacturing techniques, Fused Deposition Modeling (FDM) and Multi-Jet Fusion (MJF), were used to produce the prototypes using thermoplastic polyurethane (TPU) and Nylon 12, respectively.

Printing parameters, including nozzle temperature, print speed, layer height, print orientation, and infill density, were configured according to the requirements of the optimized geometries. These parameters were selected to balance flexibility, mechanical resistance, material utilization, and dimensional stability. The AI-optimized lattice structures provided localized structural support while maintaining flexibility in regions associated with movement.

Following fabrication, the prototypes underwent post-processing procedures, including surface trimming, support removal where applicable, and thermal annealing. The completed prototypes were subsequently subjected to mechanical and usability evaluation to assess tensile and flexural performance, flexibility, comfort, fit, and user-reported usability. The resulting observations were used to evaluate the performance of the proposed AI-driven design and manufacturing workflow.

3.6 Mathematical Model

The proposed model integrates deep generative learning with multi-objective optimization to control the generation of assistive-device geometries, material configuration, and manufacturability of AI-driven 3D-printed textile assistive devices.

Let the anatomical surface be represented by $\mathcal{S} \subset \mathbb{R}^3$, with signed distance function $d_s: \mathbb{R}^3 \to \mathbb{R}$. A feature vector $\boldsymbol{x} \in \mathbb{R}^p$ encodes the anatomical and mechanical characteristics extracted from the three-dimensional limb representation, including curvature, thickness, orientation, and stress-related information. A latent vector $\boldsymbol{z} \sim \mathcal{N}(0, I)$ introduces controlled variation into the generative process. The generator G_φ maps the latent vector and anatomical conditioning vector to a set of textile-geometry parameters $\Theta = \{\psi, U, \lambda\}$, as expressed in Equation (1):

$$G_\varphi: \mathbb{R}^q \times \mathbb{R}^p \to \mathcal{G}, \quad (\boldsymbol{z}, \boldsymbol{x}) \mapsto \Theta. \quad (1)$$

where $\mathcal{G}$ denotes the space of generated assistive-device geometries, φ represents the generator parameters, and Θ represents the resulting geometric design parameters.

Adversarial Optimization

The conditional generative adversarial network (cGAN) consists of a generator G_φ and a discriminator $D\theta$. The discriminator evaluates whether a generated geometry is consistent with the reference design distribution under the corresponding anatomical condition, whereas the generator seeks to produce geometries that satisfy the discriminator while remaining responsive to the conditioning information.

$$L^D = \mathbb{E}[\max(0, 1 - D\theta(Mreal, \boldsymbol{x}))] + \mathbb{E}[\max(0, 1 + D\theta(Mgen, \boldsymbol{x}))]. \quad (2)$$

$$L^G = \mathbb{E}[D\theta(Mgen, \boldsymbol{x})]. \quad (3)$$

where Mreal represents a reference geometry, Mgen represents a generated geometry, $\boldsymbol{x}$ denotes the anatomical conditioning vector, and $D\theta$ denotes the discriminator parameterized by θ.

Multi-Objective Design Optimization

In addition to the adversarial objective, the generated geometries are evaluated according to anatomical fit, mechanical performance, porosity, and fabrication cost. For the materials considered in this study, namely thermoplastic polyurethane (TPU) and Nylon 12, the corresponding objective functions are defined in Equations (4)–(7).

$$Lfit = \mathbb{E}[|d_s(\boldsymbol{u})|] + \lambda p\ \mathbb{E}[\max(0, p(\boldsymbol{u}) - psafe)]. \quad (4)$$

where $d_s(\boldsymbol{u})$ represents the signed distance between the generated geometry and the anatomical surface, $p(\boldsymbol{u})$ represents the estimated local pressure, psafe denotes the specified safe-pressure threshold, and λp is the penalty coefficient.

$$Lmech = \hat{C}(M, m) + \lambda\sigma \max(0, \hat{\sigma}max - \sigma allow). \quad (5)$$

where M denotes the generated geometry, m denotes the selected material, $\hat{C}(M, m)$ represents the predicted mechanical-performance cost, $\hat{\sigma}_{max}$ is the predicted maximum stress, σ_{allow} is the allowable stress, and λ_σ is the associated penalty coefficient.

$$L_{por} = |\pi(M) - \pi^*|, \quad \pi(M) = 1 - V_{solid} / V_{box}. \quad (6)$$

where $\pi(M)$ denotes the porosity of the generated geometry, V_{solid} represents the solid volume, V_{box} represents the bounding volume, and π^* denotes the target porosity.

$$L_{cost} = c_m V_{solid} + c_t \hat{T}_{print} \approx L_{toolpath}. \quad (7)$$

where c_m represents the material cost coefficient, V_{solid} is the volume of printed material, c_t represents the time-dependent fabrication cost coefficient, and $\hat{T}_{print}$ denotes the estimated printing time.

Total Optimization Objective

The individual objectives are combined into a weighted total objective function:

$$L_{total} = L_{adv} + \beta_1 L_{fit} + \beta_2 L_{mech} + \beta_3 L_{por} + \beta_4 L_{cost}. \quad (8)$$

where β_1, β_2, β_3, and β_4 are weighting coefficients controlling the relative contribution of anatomical fit, mechanical performance, porosity, and fabrication cost, respectively.

The optimized candidate geometries $\{M_i, \lambda_i\}$ are subsequently evaluated according to their mechanical, anatomical-fit, and cost-related performance:

$$F(M_i) = [F_{mech}, F_{fit}, F_{cost}].$$

The optimal configuration is selected according to the weighted multi-objective criterion:

$$(M^*, \lambda^*) = \arg\min \, [\omega_{mech} F_{mech} + \omega_{fit} F_{fit} + \omega_{cost} F_{cost}]. \quad (9)$$

where M^* and λ^* denote the selected optimal geometry and associated design parameters, respectively, while ω_{mech}, ω_{fit}, and ω_{cost} are the weights assigned to mechanical performance, anatomical fit, and fabrication cost.

Overall, Equations (1)–(9) describe a generative-design framework in which anatomical information conditions the generation of candidate geometries, while multi-objective optimization is used to balance anatomical conformity, mechanical performance, porosity, and fabrication cost. The resulting optimal geometry is then transferred to the additive-manufacturing stage for fabrication and subsequent mechanical and usability evaluation.

4 Dataset

The study incorporated publicly available anatomical, three-dimensional design, and material-property data together with participant-specific anatomical scan data. These data sources supported the development and evaluation of the AI-driven design workflow by providing anatomical representations, assistive-device and lattice geometries, and material-property information for the design and optimization stages. Participant-specific three-dimensional limb scans were used as individualized anatomical inputs to generate customized assistive-device geometries.

4.1 Anatomical Data

The BodyParts3D dataset from the University of Tokyo [17] and the SenseNet 3D Hand Dataset were used as sources of three-dimensional anatomical representations. These data provided reference geometries for representing anatomical variation and supporting the development of the geometric feature-extraction and AI-driven design workflow.

4.2 Textile and Orthotic Design Data

Three-dimensional design files available through public repositories, including GrabCAD and Thingiverse [18], were used as sources of assistive-device, orthotic-support, and textile-inspired geometries. These design data provided examples of geometric configurations and structural parameters relevant to lattice density, filament thickness, contouring, and other characteristics considered during the generative design process.

4.3 Material-Property Data

Material-property data for polymeric materials were incorporated into the design-optimization process, including properties such as elastic modulus, tensile strength, elongation at break, and Poisson's ratio. These parameters were used to inform the mechanical evaluation and optimization of the assistive-device geometries fabricated using TPU and Nylon 12.

4.4 Dataset Partitioning and Data Usage

The data sources were used according to their respective roles within the AI-driven design workflow. Publicly available anatomical and three-dimensional design data were used to establish the geometric and structural representations required for development of the conditional generative model. Material-property data were

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incorporated into the optimization stage to support mechanical and fabrication-related constraints. The three-dimensional limb scans obtained from the ten participants were subsequently used as individualized anatomical inputs to the trained cGAN for generation of user-specific assistive-device geometries. For each participant, five candidate geometries were generated, and the candidate satisfying the predefined manufacturability constraints and predicted fit requirements was selected for fabrication.

The participant-specific anatomical scans were therefore treated as individualized evaluation inputs rather than as generic design examples. This separation was intended to reduce direct dependence of the generated participant-specific geometries on the corresponding evaluation cases and to assess the ability of the trained generative model to adapt its output to previously acquired anatomical configurations.

Algorithm 1 AI-Driven 3D Printed Textile Assistive Device Framework

Inputs: B: 3D body scan, G_ϕ: Generator (cGAN/cVAE), D_θ: Discriminator, $\hat{S}(M,m)$: Surrogate model, $m \in \{TPU, Nylon12\}$

Outputs: Optimized geometry M^*, configuration λ^*, prototype P_{out}

1: **Acquire Geometry:** Capture and preprocess scan $S = Smooth(Segment(Scan(B)))$, then export mesh M_0.

2: **Feature Extraction:** Compute shape descriptors $\{\kappa, \tau, \sigma_z, a\}$ and form vector $x = f(\kappa, \tau, \sigma_z, a)$.

3: **Generative Design:** Sample $z \sim \mathcal{N}(0, I)$, generate $\Theta = G_\phi(z, x)$, decode $M = Decode(\Theta)$.

4: **Evaluate Manufacturability:** $\hat{S}(M,m) = \{\hat{C}, \hat{\sigma}_{max}, \hat{T}_{print}\}$; refine if constraints violated.

5: **Optimization:**

$$L_{total} = L_{adv/VAE} + \beta_1 L_{fit} + \beta_2 L_{mech} + \beta_3 L_{cost}$$

$$\lambda^* = \arg\min_{\lambda}(c_m V_{solid}(M) + c_t \hat{T}_{print}(M, \lambda))$$

6: **Fabrication:** Select (m, P), generate G-code, print $P_{out} = 3DPrint(M, \lambda^*, m)$.

7: **Testing:** Evaluate mechanical and user metrics; compute $U_{score} = \frac{1}{n}\sum u_i$.

8: **Feedback:** Update dataset $D_{new} = \{x, M, m, \lambda^*, U_{score}\}$ and retrain G_ϕ, $\hat{S}$.

9: **Final Optimization:**

$$(M^*, \lambda^*, m^*) = \arg\min_{M,\lambda,m}(w_1 F_{mech} + w_2 F_{fit} + w_3 F_{cost})$$

Ensure $\hat{\sigma}_{max} \le \sigma_{allow}$ and $t(s) \ge t_{min}$.

“Because the available study records do not provide complete counts for the individual public datasets or design files used during model development, dataset sizes are not reported as fixed numerical values.”

5 User Evaluation

To evaluate the usability, comfort, and functional acceptability of the fabricated assistive-device prototypes, the ten participants who provided the anatomical scan data also participated in the user evaluation. Following fabrication and post-processing, participants evaluated the prototypes during controlled motion and activity sessions lasting approximately one hour. User-reported outcomes were collected using a five-point Likert-scale questionnaire addressing comfort and fit, breathability, flexibility during movement, and ease of wearing and removal, together with an overall satisfaction assessment. Participants also provided qualitative feedback regarding their experience with the prototypes, including perceived comfort, freedom of movement, and areas requiring further improvement. The quantitative responses were summarized using mean scores and standard deviations, while the qualitative comments were reviewed to identify recurring aspects of user experience that could inform subsequent iterations of the AI-generated designs.

6 Evaluation Metrics

The performance of the proposed framework was evaluated using quantitative and qualitative metrics covering fabrication cost, anatomical conformity, mechanical performance, printing efficiency, and user-reported usability. These metrics were selected to assess the principal technical and user-centered outcomes of the AI-driven assistive-device development process.

6.1 Cost Savings:

The total fabrication cost of the AI-optimized 3D-printed assistive device was compared with the corresponding cost of the conventional design. The percentage cost reduction was calculated using Equation (10):

$$\text{Cost Reduction (\%)} = \frac{C_{\text{traditional}} - C_{\text{AI-3D}}}{C_{\text{traditional}}} \times 100 \quad (10)$$

where Ctraditional represents the cost of the conventional assistive-device design and CAI-3D represents the total fabrication cost of the AI-optimized 3D-printed textile assistive device.

6.2 Anatomical Fit Evaluation

Anatomical fit was evaluated using the model-derived fit score obtained for each generated assistive-device geometry. The score was based on the correspondence between the generated device geometry and the anatomical characteristics extracted from the corresponding three-dimensional limb scan, with consideration of surface conformity and regions subject to pressure or mechanical loading. The same fit-evaluation procedure was applied to the AI-generated designs and the conventional CAD-based comparator designs to permit a consistent comparison between the two approaches. The resulting fit scores were expressed as percentages, with higher values indicating greater conformity between the device geometry and the corresponding anatomical input.

6.2.1 Fit-Score Validation

The fit scores obtained from the AI-generated designs were compared with the corresponding scores obtained for the conventional CAD-based designs. The comparison was performed using the same anatomical input and the same fit-evaluation criterion for both design approaches. The resulting scores were used to quantify the relative performance of the AI-generated geometries in adapting to the participant-specific anatomical characteristics.

The anatomical fit score was treated as a model-derived conformity measure rather than as a classification accuracy measure. The score represented the degree of correspondence between the generated assistive-device geometry and the anatomical characteristics extracted from the corresponding three-dimensional limb scan. Higher scores indicated greater geometric conformity between the device and the anatomical input. The same fit-evaluation criterion was applied to both the AI-generated and conventional CAD-based designs to ensure comparability between the two design approaches. The reported values of 98.2% for the AI-generated designs and 93.4% for the conventional CAD-based designs therefore represent comparative anatomical-conformity scores under the model-defined evaluation criterion.

Because the present evaluation was based on a model-derived fit measure, the scores should not be interpreted as conventional predictive or classification accuracy. Independent physical validation using surface-deviation measurements, pressure mapping, or other objective fitting procedures would provide additional validation of anatomical conformity in future studies.

6.3 Mechanical Performance:

Physical mechanical performance was evaluated in terms of tensile strength, flexural strength, elastic modulus, and elongation at break. Tensile testing was conducted in accordance with ASTM D638, while flexural testing was conducted in accordance with ASTM D790. The measured properties of the AI-optimized TPU and Nylon 12 prototypes were compared with those obtained from the corresponding conventional designs. The comparison was used to quantify the relative differences in tensile and flexural performance associated with the AI-generated lattice geometries.

6.4 Finite Element Analysis (FEA)

Finite Element Analysis (FEA) was used as a supplementary numerical assessment to examine the distribution of mechanical stress within the AI-optimized and conventional assistive-device geometries. The analysis focused on the regions of the structures exposed to localized mechanical loading and was used to assess whether the AI-generated lattice configuration provided a more uniform distribution of stress than the corresponding conventional design.

The AI-optimized and conventional geometries were evaluated under comparable loading and geometric conditions to facilitate a direct comparison of their predicted mechanical responses. The principal outcome considered in the analysis was the maximum stress concentration within the device geometry. The percentage reduction in peak stress concentration was calculated by comparing the maximum predicted stress in the AI-optimized design with that of the corresponding conventional design.

The FEA results were used as supplementary evidence to support the experimental mechanical-testing results. In particular, the analysis provided an indication of how changes in lattice geometry influenced the distribution of mechanical stress in motion-critical regions. Because the present study does not report the specific FEA software, mesh characteristics, material constitutive model, boundary conditions, or solver settings, these implementation details are not specified here and should not be inferred. Accordingly, the FEA findings are interpreted as supplementary numerical evidence rather than as an independently validated prediction of long-term device performance.

6.5 Usability Rating:

User experience data obtained from the participant surveys were analyzed descriptively to determine mean satisfaction scores and standard deviations for comfort and fit, breathability, flexibility during movement, ease of wearing and removal, and overall satisfaction. Responses from the ten participants were summarized to provide an overall indication of user-reported usability and consistency across the evaluated prototypes.

6.6 Printing Efficiency:

Printing efficiency was evaluated using printing time and material consumption as the principal indicators. These measures were compared between the conventional and AI-optimized designs to assess differences in fabrication efficiency and material utilization. The resulting values were also incorporated into the cost analysis and used to evaluate the efficiency of the proposed AI-driven manufacturing workflow.

7 Results and Discussion

The experimental evaluation was conducted to assess the proposed AI-based 3D textile printing framework against its premise of producing anatomically accurate, cost-effective, and strong assistive devices. The experimental design consisted of three major components: (1) generating AI based design (2) 3D fabrication and (3) performance assessment.

During the first experimental component, the anonymized three-dimensional limb scans obtained from the ten participants were preprocessed by removing background noise, applying Laplacian-based smoothing, and segmenting the scans into relevant anatomical regions. The processed scans were then used as inputs to the trained conditional generative adversarial network (cGAN), which generated customized lattice geometries conditioned on anatomical features including curvature, limb thickness, and regions associated with mechanical stress. Five candidate designs were generated for each participant, and the most promising candidate was selected according to manufacturability constraints and the predicted fit score.

The second component consisted of fabricating the optimized geometries using fused deposition modeling (FDM) and Multi-Jet Fusion (MJF) technologies. The materials selected for 3D printing were thermoplastic polyurethane (TPU) and Nylon 12 because of their flexibility, durability, and suitability for the intended assistive-device applications. Printing parameters, including infill density, layer height, nozzle temperature, and print orientation, were configured according to the optimized design requirements. Each printed prototype subsequently underwent post-processing, including surface trimming, support removal where applicable, and thermal annealing before mechanical and usability evaluation.

The last component of the study indicated each device was administered mechanical, usability, and cost assessment to evaluate performance. Mechanical testing was conducted in accordance with ASTM D638 (i.e., tensile) and ASTM D790 (i.e., flexural). Usability was tested with the same ten participants through controlled motion and activity sessions lasting one hour, where participants self-reported their feedback using Likert-scale surveys assessing comfort, breathability, flexibility, and ease of motion for every prototype.

For comparative evaluation, the AI-generated prototypes were compared with conventional CAD-based orthotic designs using the performance criteria defined in the study, including anatomical fit, fabrication efficiency, material use, mechanical properties, and fabrication cost. The conventional CAD designs served as the comparator condition for evaluating the relative performance of the AI-driven workflow.

“The AI generative model produced adaptive, user-targeted textile geometries. The AI-generated designs achieved a mean predicted anatomical fit score of 98.2%, compared with 93.4% for the conventional CAD-based orthotic designs. The higher score indicates greater conformity between the generated device geometry and the corresponding anatomical characteristics according to the model-based fit criterion.”

Because the fit measure was derived from the model-based anatomical conformity assessment, the reported percentage should be interpreted as a fit score rather than as a conventional classification accuracy. Independent validation using physical surface-deviation measurements, pressure mapping, or other objective fit-assessment techniques would provide additional evidence of anatomical conformity in future studies.

In addition to the improvement in predicted anatomical fit, the AI-assisted workflow reduced the overall design-to-fabrication time compared with the conventional CAD-based workflow. The comparative analysis showed a reduction in the total design-to-fabrication cycle from 3.2 hours for the conventional approach to 1.1 hours for the AI-optimized approach, corresponding to a 65.6% reduction. Printing time alone decreased from 184 to 112 minutes, corresponding to a 39.1% reduction. These results indicate that the principal time-saving effect was associated with the combined reduction in design and fabrication stages rather than printing time alone.

Table 2. Cost–Benefit and Fabrication Efficiency Analysis

Parameter	Conventional Design	AI-Optimized Design	Reduction (%)
Material Usage (g)	115.4	68.9	40.3
Print Time (min)	184	112	39.1
Energy Consumption (Wh)	143.5	96.8	32.5
Total Fabrication Cost (USD)	18.7	10.9	41.7
Design-to-Fabrication Cycle (hours)	3.2	1.1	65.6

The findings show that AI-optimized designs resulted in 40–42% reductions in material and cost, while achieving a 65% reduction in total production time associated with adaptive lattice density and AI-guided print-parameter tuning. A usability assessment was completed to evaluate end-user satisfaction and ergonomic comfort. Mean scores and standard deviations from ten participants who ranked devices on a 5-point Likert scale are presented in Table 3.

Table 3. Usability Evaluation Results (n = 10)

Criterion	Mean Score	Standard Deviation
Comfort and Fit	4.7	0.3
Breathability	4.5	0.4
Flexibility in Movement	4.6	0.5
Ease of Wearing and Removal	4.4	0.6
Overall Satisfaction	4.8	0.2

The usability outcomes indicated high participant-reported satisfaction, particularly with respect to comfort and fit, breathability, and flexibility during movement. The mean scores ranged from 4.4 to 4.8 on the five-point Likert scale, indicating generally positive user perceptions of the fabricated prototypes. These findings provide preliminary evidence that the textile-inspired lattice configuration may support comfortable and flexible use. However, thermal regulation and physiological changes were not directly measured in the present study; therefore, no direct conclusion regarding thermal-regulation performance can be drawn from the usability questionnaire.

Table 4. Mechanical Property Comparison Between AI-Optimized and Conventional Designs

Property	**TPU (AI-Optimized)**	**TPU (Conventional)**	**TPU Improvement (%)**	**Nylon 12 (AI-Optimized)**	**Nylon 12 (Conventional)**	**Nylon 12 Improvement (%)**
Tensile Strength (MPa)	22.6	18.9	19.6	31.3	27.5	13.8
Elastic Modulus (MPa)	68.4	54.6	25.3	92.1	80.3	14.7
Elongation at Break (%)	320	270	18.5	265	230	15.2
Flexural Strength (MPa)	28.1	23.7	18.6	36.8	32.1	14.6

Note. Improvement percentages were calculated separately for each material using the following equation:

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$$\text{Improvement }(\%) = \frac{X_{\text{AI}} - X_{\text{Conventional}}}{X_{\text{Conventional}}} \times 100$$

where XAI represents the measured property of the AI-optimized design and XConventional represents the corresponding property of the conventional design.

The AI-optimized structures exhibited higher mechanical-property values than the corresponding conventional designs for both TPU and Nylon 12. For TPU, tensile strength increased by 19.6%, elastic modulus by 25.3%, elongation at break by 18.5%, and flexural strength by 18.6%. For Nylon 12, the corresponding improvements were 13.8%, 14.7%, 15.2%, and 14.6%, respectively. These results indicate that the AI-generated lattice configurations were associated with improved tensile, elastic, and flexural performance relative to the corresponding conventional geometries. The magnitude of improvement varied according to the material and mechanical property evaluated. Finite Element Analysis (FEA) provided supplementary numerical evidence regarding the mechanical behavior of the assistive-device geometries. Under the comparative simulation conditions, the AI-optimized geometry exhibited a 22.4% reduction in peak stress concentration compared with the corresponding conventional geometry. This finding suggests that the AI-generated lattice configuration may provide a more uniform distribution of mechanical stress in motion-critical regions.
Mechanical testing provided quantitative evidence of the tensile, elastic, elongation, and flexural properties of the fabricated prototypes.

7. Discussion

The results of this study indicate that the proposed AI-based 3D textile printing system represents a promising approach to personalized assistive technology. For example, this system combines characteristics of deep generative design, adaptive lattice modeling, and responsive material printing to establish an effective pathway between user-specific customization and prototype-level manufacturing with reduced fabrication time and cost. The discussion that follows articulates the main implications of these results in terms of comfort, adaptability, cost, material properties, and design impact. The most apparent improvement achieved by the proposed system is in user comfort and adaptability. Conventional rigid orthotic and prosthetic devices typically hinder mobility and can cause pressure points as a result of their uniform structural stiffness and poor air flow. The adapted design of the fabric is generated by AI in the lattice construction to create localized flexibility and breathability that adapts to the body's natural motions. The density of the adaptive lattice has also been tailored automatically through the AI model to dynamically respond to the anatomy and stress on each individual. This model promotes better weight distribution and pressure relief in critical loading zones. The textile-inspired lattice geometry may facilitate ventilation because of its open structure; however, airflow, heat retention, skin temperature, and skin irritation were not directly measured in the present study. Therefore, these potential benefits should be considered hypotheses for future investigation rather than demonstrated outcomes. The user-evaluation results indicated high reported levels of comfort and breathability for the AI-generated devices. These findings provide preliminary evidence that the textile-inspired lattice configuration may support comfortable and flexible use; however, direct comparative conclusions regarding conventional orthotic devices should be interpreted cautiously because the comparative evaluation protocol was not independently detailed.
"In terms of flexibility and customization, the proposed framework integrates anatomical data, generative design, and additive manufacturing within a single digital workflow. The participant-specific anatomical inputs were processed through the trained cGAN to generate multiple candidate geometries, after which the candidates were screened according to the predefined fit and manufacturability criteria. This workflow reduced the time required for design generation compared with the conventional CAD-based approach and enabled the production of geometries adapted to the anatomical characteristics of individual participants. The cGAN framework therefore provides a basis for further development of individualized assistive-device design as additional validated anatomical and performance data become available."
The investigation also demonstrated reductions in material use, fabrication cost, and overall design-to-fabrication time. The AI-optimized workflow reduced material consumption by 40.3%, fabrication cost by 41.7%, and the overall design-to-fabrication cycle by 65.6% compared with the conventional design. These findings indicate potential efficiency advantages at the prototype-development level. However, scalability, workforce requirements, and performance in routine clinical or industrial production were not evaluated in the present study and require further investigation.
When compared to traditional rigid assistive devices, the use of a textile approach offers structural and functional

advantages. Rigid orthoses are built from solid thermoplastics and composites that are very strong and stable for high load-bearing use. While stability is a benefit, rigidity is not, as rigid devices tend to be uncomfortable, may irritate soft tissue, and limit range of motion. This textile-enabled 3D printed devices embrace some of the compliant properties and mechanical support of a woven fabric. Another physical added feature includes the AI optimized lattice structure (softness and strength) that creates a hybrid system with shock-load absorption (pre-determined) deformation and stabilization of movement, improving usability without compromising balance or support. When the physical weight of a device is reduced (with textile based assistive devices), this contributes to improved user compliance and less user fatigue, particularly, if the other featured improvements include minimizing impairments in user's biomechanics. These characteristics may contribute to user comfort and functional support; however, their effects on movement biomechanics were not directly measured in the present study.

There are some limitations associated with existing studies and those limitations would open opportunities for further study. The first limitation is related to the long- term durability, and potential fatigue and pre-mature softening of the material (flexible polymers; TPU and Nylon 12) when evaluate in a cyclic mechanical load situation. Participant's testing the devices regularly could put stress on the device beyond its limits and therefore change the inherent performance characteristics over time based on the use of the textiles. As we evoke cycled loading on flexible polymers (i.e TPU and Nylon 12), essentially we may induce micro-crack development in the struts of the lattice; with extended repeated load that could also decrease the load- bearing lifespan. Future studies can examine the use of composite filaments (to increase durability) and/or reinforced fibers in the lattice for potential improvements.

A second limitation concerns printer precision and resolution. Differences in layer thickness, dimensional accuracy, and surface resolution may affect the consistency and comfort of the fabricated lattice structures. Future studies could investigate higher-resolution and multi-material printing approaches, including variable-density or micro-extrusion methods, to improve dimensional fidelity and surface quality. A further limitation is inter-individual anatomical variability. Limb morphology, skin sensitivity, and movement patterns may differ substantially across users. Future research should therefore include larger and more diverse datasets and evaluate the robustness of the AI-generated designs across a broader range of anatomical and functional characteristics.

In terms of sustainability, the observed reduction in polymer use may provide potential environmental benefits. However, carbon emissions and life-cycle impacts were not directly quantified in the present study; therefore, the environmental implications of the material reduction should be interpreted as potential rather than demonstrated effects.

The discussion indicates that through the advent of an AI-driven 3D textile printing paradigm, there is a new holistic approach to assistive design. The framework enhances both functionality and accessibility through considerations of ergonomics, affordability, and sustainable manufacturing processes. Although challenges remain in regards to material longevity and printer resolution, the advances with respect to comfort, adaptability, and affordability provides an excellent foundation for future studies of AI-accessible human centered design assistive technology.

The framework provides a basis for further research into AI-assisted, human-centered assistive-device design and localized digital manufacturing, particularly through larger participant samples, longer-term mechanical testing, and more comprehensive validation of anatomical fit.

8. Conclusion

This study developed and experimentally evaluated an AI-driven framework that integrates conditional generative design, textile-inspired lattice structures, and additive manufacturing for individualized assistive-device prototypes. The framework used participant-specific three-dimensional anatomical inputs to generate candidate geometries that were evaluated according to anatomical conformity, mechanical performance, fabrication efficiency, material utilization, cost, and user-reported usability.

The experimental findings indicated that the AI-optimized designs achieved higher model-derived anatomical fit scores, reduced material consumption and fabrication cost, shortened the overall design-to-fabrication cycle, and demonstrated improved mechanical properties compared with the corresponding conventional designs. The usability evaluation also indicated generally positive participant perceptions of comfort, breathability, flexibility, and overall satisfaction.

These findings suggest that AI-assisted generative design combined with additive manufacturing may provide a promising approach for developing individualized textile-inspired assistive devices. However, the results should be interpreted within the limitations of the present study, including the small participant sample, the model-derived nature of the anatomical fit score, the absence of independent physical fit validation, and the lack of long-term fatigue and clinical performance assessment. In addition, environmental impacts were not directly quantified.

Future research should therefore examine larger and more diverse participant populations, standardized objective fit-validation procedures, long-term mechanical durability, clinical usability, and environmental impacts. Such studies would help establish the generalizability and practical applicability of AI-assisted additive manufacturing for personalized assistive-device development.

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The conditional Generative Adversarial Network (cGAN) described in this study was used for assistive-device design generation and multi-objective optimization. The author reviewed and verified the resulting computational outputs and takes full responsibility for the content and conclusions of this manuscript.
Conflicts of Interest:
The authors declare no conflicts of interest.
Ethics Statement
"The study involved human participants who voluntarily participated in the usability evaluation of the 3D-printed assistive-device prototypes. Written informed consent was obtained from all participants before participation. According to the applicable institutional requirements, formal institutional ethics committee approval was not sought for this study. The study procedures were conducted in accordance with applicable ethical requirements and the principles of the Declaration of Helsinki. All participant data, including three-dimensional anatomical scan data, were anonymized and handled confidentially."

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أجهزة مساعدة نسيجية مطبوعة ثلاثية الأبعاد مدفوعة بالذكاء الاصطناعي للأشخاص ذوي الإعاقة

رندا السبحي[1]

الملخص

يؤدي التكامل بين الذكاء الاصطناعي والتصنيع بالإضافة إلى تطوير نظام تصميم يتيح إنشاء أجهزة مساعدة مخصصة ومنخفضة التكلفة، تستند إلى الاحتياجات الفردية الخاصة بالأشخاص ذوي الإعاقة. توضح هذه الدراسة عملية لتصميم وتصنيع نموذج أولي لجهاز مساعد نسيجي مطبوع ثلاثي الأبعاد ومدعوم بالذكاء الاصطناعي، باستخدام مواد مرنة تشمل البولي يوريثان الحراري باللدونة (TPU) والنايلون-12. ويعتمد التصميم على شبكة توليدية تنافسية مشروطة (cGAN) لتوليد أشكال هندسية فردية لأجهزة مساعدة مستوحاة من المنسوجات، من خلال التحسين متعدد الأهداف الذي يراعي الملاءمة التشريحية، والأداء الميكانيكي، والمسامية، وتكلفة التصنيع، بالاعتماد على بيانات المسح التشريحي ثلاثي الأبعاد.

وأظهرت الدراسة الفوائد المحتملة للنمذجة والتصنيع التكراري المدعومين بالذكاء الاصطناعي من حيث كفاءة استخدام المواد، وخفض تكلفة التصنيع، وتحسين الراحة التي أبلغ عنها المستخدمون. وأشارت النتائج التجريبية إلى انخفاض بنسبة **40.3%** في استخدام المواد، وانخفاض بنسبة **41.7%** في تكلفة التصنيع بالنسبة إلى التصميمات المحسّنة باستخدام الذكاء الاصطناعي، إلى جانب انخفاض بنسبة **65.6%** في إجمالي دورة التصميم إلى التصنيع. كما تحسنت الخصائص الميكانيكية التي جرى تقييمها بنسب تراوحت بين **13.8%** و**25.3%** مقارنة بالتصميمات التقليدية المناظرة. وأظهرت تغذية المشاركين الراجعة بشأن قابلية الاستخدام متوسطًا كليًا بلغ **4.6 من 5**، مما يشير إلى اتجاهات إيجابية بوجه عام نحو الراحة، والتهوية، والمرونة. وتبرز هذه النتائج إمكانية توظيف الذكاء الاصطناعي والطباعة النسيجية ثلاثية الأبعاد والتصنيع بالإضافة في تطوير أجهزة مساعدة منخفضة التكلفة وشاملة تتمحور حول الإنسان، بما يسهم في دعم الحركة وإتاحة الوصول وتحسين جودة الحياة للأشخاص ذوي الإعاقة.

الكلمات المفتاحية: الذكاء الاصطناعي؛ الطباعة ثلاثية الأبعاد؛ المنسوجات الذكية؛ الأجهزة المساعدة؛ دمج الأشخاص ذوي الإعاقة؛ التصميم التوليدي؛ التكنولوجيا القابلة للارتداء.

الاستنتاجات

خلصت الدراسة إلى أن دمج الذكاء الاصطناعي مع الطباعة ثلاثية الأبعاد والتصنيع بالإضافة يمكن أن يوفر نهجًا فعالًا لتطوير أجهزة مساعدة نسيجية مخصصة تستجيب بصورة أفضل للاحتياجات الفردية للأشخاص ذوي الإعاقة. وأظهر استخدام نموذج الشبكة التوليدية التنافسية المشروطة(cGAN) ، إلى جانب التحسين متعدد الأهداف، قدرة على دعم تصميم أشكال هندسية تراعي في الوقت نفسه الملاءمة التشريحية والأداء الميكانيكي والمسامية وتكلفة التصنيع.

كما بينت النتائج أن التصميمات المحسّنة باستخدام الذكاء الاصطناعي حققت كفاءة أعلى في استخدام المواد، حيث انخفض استهلاك المواد بنسبة **40.3%**، وانخفضت تكلفة التصنيع بنسبة **41.7%**، في حين انخفضت دورة التصميم والتصنيع الكلية بنسبة **65.6%**.كذلك أظهرت التصميمات المحسّنة تحسنًا في الخصائص الميكانيكية التي تم تقييمها، تراوح بين **13.8%** و**25.3 %**مقارنة بالتصميمات التقليدية.

ومن ناحية أخرى، أظهر تقييم المستخدمين مستوى مرتفعًا نسبيًا من القبول، بمتوسط كلي بلغ **4.6من 5**، ولا سيما فيما يتعلق بالراحة والتهوية والمرونة. وتشير هذه النتيجة إلى أن الجمع بين المرونة المستوحاة من المنسوجات وإمكانات التصنيع الرقمي يمكن أن يسهم في تطوير أجهزة مساعدة أكثر ملاءمة للاستخدام الشخصي.

وبناءً على ذلك، تؤكد الدراسة أن توظيف الذكاء الاصطناعي في عمليات التصميم التوليدي والطباعة ثلاثية الأبعاد يمثل اتجاهًا واعدًا نحو تطوير تقنيات مساعدة منخفضة التكلفة وقابلة للتخصيص وشاملة، تتمحور حول احتياجات المستخدم. ويمكن لهذا النهج أن يدعم تحسين الحركة وإمكانية الوصول وجودة الحياة للأشخاص ذوي الإعاقة، مع تقليل الوقت والموارد اللازمة لتطوير وتصنيع الأجهزة المساعدة. كما تبرز النتائج أهمية مواصلة تطوير هذه التقنيات والتحقق منها من خلال تطبيقات وتجارب أوسع تشمل مستخدمين مختلفين واحتياجات وظيفية متنوعة.

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