Wearable Device Styling Design Integrating Deep Q-Learning and Morphosemantic Analysis

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ABSTRACT This paper proposes an intelligent styling-design model for wearable devices by integrating Deep Q-Learning reinforcement learning with morphosemantic analysis, aiming to solve the problems of inaccurate user-demand mapping, insufficient design innovation, and weak human–machine interaction adaptability. Based on morphosemantic theory, reinforcement learning principles, and ergonomic guidelines, the core design dimensions of wearable device styling, including morphological features, color schemes, material selection, and interaction layout, are defined together with user-demand evaluation metrics. A multidimensional dataset, WED-2024, is then constructed from mainstream wearable brands, user surveys, and design cases, covering five product categories and eight user satisfaction levels. A technical framework of "requirement semantic mapping-DQN intelligent generation-morphological semantic optimization" is designed. Morphosemantic analysis translates user requirements into design features, while the exploration-exploitation mechanism of DQN generates diverse design proposals. A semantic consistency loss function is introduced to improve the alignment between generated solutions and user needs. Comparative experiments evaluate design satisfaction, innovation, and human–machine adaptability, providing a technical reference for wearable sensing terminals and intelligent interaction design in wireless communication environments.

INDEX TERMS deep q-learning, morphosemantic analysis, wearable devices, styling design, wearable sensing

I. INTRODUCTION

A. RESEARCH BACKGROUND

WITH the deep integration of IoT, biosensing, and smart terminal technologies, wearable devices have evolved from single-function portable tools into multi-scenario terminals characterized by "functional integration, personalized form factors, and intelligent interaction," enabling the textile and apparel industry to seamlessly embed these sophisticated capabilities directly into daily clothing[1,2]. According to IDC's "2024 Global Wearable Devices Market Report," global shipments of wearable devices reached 680 million units by the end of 2024, marking a 12.7% year-over-year increase. Mainstream products such as smartwatches, fitness trackers, and smart glasses accounted for over 85% of the market. Concurrently, user demands for wearables have shifted from "functional fulfillment" to "emotional resonance + experience optimization." 63.7% of consumers cite "aesthetic design" as a core purchasing factor, while 58.2% believe "wearing comfort" directly impacts usage stickiness [3,4].

B. CURRENT STATE OF DOMESTIC AND INTERNATIONAL RESEARCH

As a core method bridging user needs and product form, morphosemantic analysis has been widely applied in sectors like furniture and home appliances[5-7]. Liu et al. [8] from Tsinghua University constructed a "semantic-morphological" mapping matrix for furniture products using the semantic differential method (SD method), translating requirements like 'minimalist' and "warmth" into cabinet forms, resulting in an 18.3% increase in user satisfaction with design proposals. The Park team [9] at Yonsei University, South Korea, combined morphological semantic analysis with genetic algorithms to generate diverse home appliance designs, achieving a 25.7% increase in innovation differentiation compared to traditional methods. In the wearable device domain, existing research primarily focuses on semantic mapping within single morphological dimensions (e.g., watch contours), neglecting the full-dimensional integration of color, material, and interaction. For instance, Zhang et al. [10] conveyed "technological" semantics solely through visual features (color, texture), neglecting the impact of material tactility and interaction logic on user emotional cognition, resulting in incomplete semantic expression of design proposals [11-13]. Currently, research integrating morphological semantic analysis with reinforcement learning remains in its infancy. Existing approaches predominantly follow a sequential workflow of "form-semantic mapping → reinforcement learning optimization," failing to achieve deep synergy between the two. For instance, Chen et al. [14] first generated initial design proposals through form-semantic analysis, then applied DQN for local adjustments. This approach ignored the dynamic semantic constraints during reinforcement learning, resulting in a 12.5% decline in semantic consistency for the optimized proposals. Furthermore, research on design adaptability across multiple wearable device types (watches, bracelets, glasses) and scenarios (sports, healthcare, daily life) remains unexplored, leaving model generalization capabilities unvalidated.

C. RESEARCH QUESTIONS AND INNOVATIONS

1) Core Research Questions

How to construct a comprehensive "semantic-morphological" mapping model for wearable devices (encompassing form, color, material, and interaction) to achieve precise quantitative conversion of user requirements?

How should the state space, action space, and reward function of the DQN algorithm be designed to accommodate the sequential decision-making requirements of wearable device form factor design?

How can the semantic consistency loss function be utilized to achieve synergistic optimization between form-semantic analysis and DQN, thereby enhancing the satisfaction, innovation, and human-machine adaptability of design solutions?

2) Research Innovations

Full-Dimensional Morphological Semantic Mapping Model: Integrates four design dimensions—form, color, material, and interaction—to construct a quantitative mapping matrix using semantic differential methods and multiple linear regression, addressing the partiality of traditional demand mapping models.

DQN Design Decision Framework: Transforms wearable device form design into a reinforcement learning task by defining a 12-dimensional state space (morphological parameters) and a 36-class action space (design operations), with a multi-objective reward function integrating semantic matching, ergonomics, and innovation;

Semantic-Reinforcement Collaborative Optimization Mechanism: Introduces a semantic consistency loss function to embed morphological semantic constraints into the DQN training process. This achieves a closed-loop optimization where "needs guide generation, and generation validates needs," preventing design solutions from deviating from user expectations.

Multi-Type Wearable Device Adaptation: Covers 5 mainstream product categories including smartwatches, fitness trackers, and smart glasses. Cross-product training enhances model generalization to meet diverse design demands.

II. THEORETICAL AND TECHNICAL FOUNDATIONS

A. DEEP Q-LEARNING ALGORITHM PRINCIPLES

1) Core Algorithm Framework

DQN is a reinforcement learning algorithm integrating deep learning with Q-Learning. It employs neural networks to approximate Q-value functions, addressing the "curse of dimensionality" in traditional Q-Learning within high-dimensional state spaces. Its core framework comprises five components: Agent, Environment, State, Action, and Reward [15,16], defined as follows:

Agent: Executes design actions (e.g., adjusting contour curvature, changing materials) within the design environment, learning optimal design strategies through interaction with the environment;

Environment: Defines constraints for wearable device form factor design, including user requirement semantics, ergonomic standards (e.g., ISO 9241-210), and manufacturing process limitations;

State: Represents the feature combination of the current design proposal using a 12-dimensional vector, encompassing: visual characteristics (4 dimensions: primary RGB values, material type, texture density), interaction features (3 dimensions: button count, display area ratio, operation mode), and ergonomic intermediate metrics (2 dimensions: wear comfort score, operational ease score);

Actions: Design operations executable by the agent, defined as 36 specific actions categorized into three types: parameter adjustment (e.g., "surface curvature + 0.2 mm^{-1}"), feature combination (e.g., "metallic material + cool color scheme"), and optimization correction (e.g., "reduce display area to enhance wearing comfort");

Reward: Quantifies the effectiveness of design actions, guiding the agent to learn design strategies aligned with user needs.

State: Represents the feature combination of the current design proposal using a 12-dimensional vector, encompassing:

Visual characteristics (4 dimensions): Primary RGB values (0-255), material type (encoded 1-8), texture density (0-1), contour curvature (0-5 mm^{-1});

Interaction features (3 dimensions): Button count (1-10), display area ratio (0.1-0.6), operation mode (encoded 1-3: touch/physical/hybrid);

Ergonomic features (3 dimensions): Wear comfort score (0-1, evaluated via pressure sensor data), operational ease score (0-1, based on finger reach range), skin compatibility score (0-1, referring to ISO 10993 biocompatibility standard);

Semantic matching features (2 dimensions): Core semantic fit (0-1, weight 0.7), secondary semantic fit (0-1, weight 0.3), calculated separately via the semantic consistency formula.

2) Core Formula and Training Mechanism

The DQN algorithm minimizes Q-value prediction error through temporal difference learning. Its core formula is:

$$Q(s,a) = r + \gamma \max_{a'} Q'(s',a') \tag{1}$$

Where: $Q(s,a)$ represents the Q-value (action value) of executing action a in state s, r is the immediate reward, γ is the discount factor (set to 0.95 to balance immediate and long-term rewards), and $Q(s',a')$ is the Q-value for the optimal action a' in the next state s' as output by the target network [17]. To enhance training stability, DQN employs two key mechanisms:

Experience Replay: Stores agent-environment interactions (s,a,r,s') in a buffer (capacity 10,000). During training, 32 samples are randomly sampled to update network parameters, mitigating training oscillations caused by sample correlation;

Target Network: Structurally identical to the evaluation network (used for Q-value prediction), it synchronously updates parameters every 1000 steps to reduce target Q-value fluctuations [18].

B. MORPHOSEMANTIC ANALYSIS THEORY

1) Core Process

Morphosemantic analysis, grounded in product morphology and semantics theory, achieves quantitative transformation from user needs to design features through the process of "semantic requirement extraction $\rightarrow$ morphological feature deconstruction $\rightarrow$ mapping matrix construction" [19,20]. Specific steps are as follows:

Semantic Requirement Extraction: User needs are gathered through mixed research methods (online survey + focus groups). The online survey covered 1,000 wearable device users across different ages and occupations, while the focus group comprised 20 design experts and seasoned users. This process ultimately identified six core semantic dimensions: "minimalism," "tech-savvy," "comfort," fashionable," "durable," and "portable." Each dimension was further divided into five intensity levels (scored 1-5).

Morphological Feature Deconstruction: Wearable device forms were decomposed into three categories: basic morphology, visual characteristics, and interactive features. Each category was refined into quantifiable parameters (e.g., "surface curvature" in basic morphology with a range of 0-5 mm^{-1}).

Mapping Matrix Construction: Selecting 100 mainstream wearable devices as samples, 50 users employed the Semantic Differential Method (SD Method) to score each sample across the six semantic dimensions. Multivariate linear regression analysis calculated the influence coefficients of each morphological parameter on semantic dimensions, constructing a 12×6 "Semantic - Morphology" mapping matrix W, enabling the transformation from the requirement vector S to the morphological feature vector F: $F = W^T \times S$ (where W^T denotes the pseudo-inverse matrix of W).

Mapping Matrix Construction:

Nonlinear Dimensionality Reduction: Apply Kernel Principal Component Analysis (KPCA) to high-dimensional morphological features (kernel function: RBF) to retain core semantic-related features (variance contribution rate $\geq$95%);

Nonlinear Mapping Modeling: Use Gradient Boosting Regression (GBR) to construct the semantic-morphological mapping relationship, capturing nonlinear correlations between complex semantics and morphological features. The mapping formula is:

$$F = \phi(W^T \times S) + \epsilon \tag{2}$$

Where $\phi(\cdot)$ is the nonlinear kernel function, ϵ is the error correction term (≤ 0.03), and W^T is the optimized weight matrix.

Matrix Validation: The 12×6 "Semantic-Morphology" mapping matrix W is validated via 5-fold cross-validation, with an average prediction error of 4.2%.

2) Semantic Consistency Evaluation

To quantify the alignment between design proposals and user requirements, the Semantic Consistency Index (SCI) is defined with the following formula:

$$SCI = \cos\theta = \frac{S_{pred} \cdot S_{true}}{\|S_{pred}\| \times \|S_{true}\|} \tag{3}$$

where S_{pred} is the predicted semantic vector of the design proposal (calculated via the morphological-semantic mapping model), S_{true} is the actual user requirement vector, and SCI ranges from 0 to 1, with higher values indicating greater semantic alignment [21].

C. ERGONOMIC EVALUATION SYSTEM FOR WEARABLE DEVICES

Combining the wearing characteristics of wearable devices with ergonomic standards (ISO 13407, ISO 9241-210), an evaluation system comprising 3 primary indicators and 8 secondary indicators was established. The Analytic Hierarchy Process (AHP) was employed to determine indicator weights, as detailed in Table 1:

TABLE 1. Ergonomic evaluation system for wearable devices

First-level Indicator	Weight	Second-level Indicator	Weight	Evaluation Method
Wearing Comfort	0.4	Pressure Distribution Uniformity	0.45	Measured by pressure sensor, uniformity >85% is excellent
		Weight Distribution Rationality	0.35	Center of gravity offset <2mm is excellent
		Fit Degree	0.2	Compared with human body scanning data, fit degree >90% is excellent
Operational Convenience	0.35	Finger Reach Range	0.4	95% of the operation area within finger reach range is excellent
		Key Trigger Difficulty	0.3	Trigger force 50-150g is excellent
		Display Information Readability	0.3	Viewing angle >120°, brightness adapted to ambient light is excellent
Physiological Adaptability	0.25	Skin Breathability	0.5	Breathability rate >500g/(m^2·24h) is excellent
		Material Biocompatibility	0.5	No adverse reaction in skin irritation test is excellent

The comprehensive ergonomic score E is calculated using the fuzzy comprehensive evaluation method:

$$E = \sum_{i=1}^{8} w_i \times e_i \tag{4}$$

where w_i is the weight of the i secondary indicator and e_i is the score of the i-th indicator (in the range 0–1). E ranges from 0 to 1 [22].

III. DESIGN AND IMPLEMENTATION OF THE INTELLIGENT STYLING DESIGN MODEL

A. OVERALL MODEL ARCHITECTURE

The intelligent design model for wearable devices, integrating DQN with morphological semantic analysis, comprises four modules: requirement parsing layer, morphological semantic mapping layer, DQN intelligent generation layer, and optimization evaluation layer. This architecture enables end-to-end intelligent processing from user requirements to optimal design solutions. The requirement parsing layer inputs user needs and outputs structured semantic vectors; the morphological semantic mapping layer generates initial design proposals based on a mapping matrix; The DQN intelligent generation layer iteratively optimizes solutions through reinforcement learning. The optimization evaluation layer calculates semantic consistency and ergonomics scores to determine whether to output a solution.

B. MORPHOLOGICAL-SEMANTIC MAPPING LAYER IMPLEMENTATION

1) Structuring Semantic Requirements

Natural Language Processing (NLP) techniques are employed to parse unstructured user requirements, following these steps:

Word segmentation and part-of-speech tagging: The jieba segmentation tool processes user requirement text, tagging nouns and adjectives (e.g., "tech-savvy," "athletic").

Semantic Dimension Matching: Construct a semantic dictionary to map tokenized results to 6 core semantic dimensions (e.g., "tech-savvy" matches "tech-savvy" dimension, "sporty" matches 'durable' and "portable" dimensions);

Intensity Level Quantification: Based on semantic sentiment dictionaries (e.g., HowNet) and modifiers in user requests (e.g., "very," "strong"), quantify semantic intensity on a 1-5 scale to generate structured semantic vectors [23].

2) Initial Design Proposal Generation

Based on the 12×6 "semantic-morphological" mapping matrix W, initial morphological feature vectors F are computed via pseudoinverse matrix calculation: $F = W^+ \times S$ where S is the 6-dimensional semantic vector and W is the Moore-Penrose pseudoinverse of W (computed using Python's numpy library). For example, if the user requirement vector $S = [3, 5, 4, 2, 5, 4]$ ("Tech-inspired" 5 points, 'Durability' 5 points), the initial morphological feature vector F contains: * "Primary Color RGB Values": [50,60,80] (cool tones), "material type" is metal, and "surface curvature" is 3.5 mm^{-1}, aligning with the "tech-inspired" semantic requirement [24]. To guide the agent toward generating design solutions that are "semantically matched, ergonomically adapted, and innovatively diverse," a multi-objective reward function r is designed with the following calculation formula:

$$r = \alpha \times r_{sem} + \beta \times r_{erg} + \delta \times r_{inn} \times I(r_{erg} \geq 6) \tag{5}$$

Where: $\alpha = 0.4$, $\beta = 0.35$, $\delta = 0.25$ (dynamic adjustment: δ increases to 0.3 in the late training stage); $I(r_{erg} \geq 6)$ is an indicator function: $I = 1$ when $r_{erg} \geq 6$ (ergonomic score ≥ 0.6), otherwise $I = 0.5$; r_{sem}, r_{erg}, r_{inn} represent semantic matching reward, ergonomics reward, and innovation reward, respectively.

C. DQN INTELLIGENT GENERATION LAYER IMPLEMENTATION

1) Network Architecture Design

The DQN network adopts a hybrid structure of "convolution layers + fully connected layers" to accommodate multidimensional morphological feature inputs. The specific architecture is as follows:

Input Layer: Receives a 12-dimensional state vector (morphological features + ergonomic intermediate indicators);

Convolution Layers: 3 convolution layers with 3×3 kernel size, stride 1, and ReLU activation function to extract local correlations in morphological features;

Fully Connected Layers: Two fully connected layers with 128 and 64 neurons respectively, using ReLU activation to fit the state-action mapping relationship;

Output Layer: Outputs Q-values for 36 actions using Linear activation (no activation function) [25]. The target network shares the same architecture as the evaluation network. Network parameters are synchronously evaluated every 1000 steps to mitigate training oscillations.

2) Reward Function Design

To guide the agent toward generating design solutions that are "semantically matched, ergonomically adapted, and innovatively diverse," a multi-objective reward function r is designed with the following calculation formula:

$$r = \alpha \times r_{sem} + \beta \times r_{erg} + \gamma \times r_{inn} \tag{6}$$

where $\alpha = 0.4$, $\beta = 0.35$, $\gamma = 0.25$ are weight coefficients (optimized via grid search), while r_{sem}, r_{erg}, and r_{inn} represent semantic matching reward, ergonomics reward, and innovation reward, respectively. Detailed calculations are as follows:

Semantic matching reward: $r_{sem} = SCI \times 10$ (SCI denotes semantic consistency index, with r_{sem} ranging from 0 to 10);

Ergonomic reward: $r_{erg} = E \times 10$ (E is the comprehensive ergonomic score, with r_{erg} ranging from 0 to 10);

Innovation reward: $r_{inn} = Sim \times 10$, where Sim is the feature divergence between the current proposal and training set cases (calculated via cosine similarity: $Sim = 1 - \cos\theta$, with Sim ranging from 0 to 1 and r_{inn} from 0 to 10) [26].

Innovation-Practical Balance Mechanism: In the late training stage ($\epsilon \leq 0.1$), the innovation-practical balance coefficient δ increases from 0.25 to 0.3;

Set a lower limit for ergonomic reward: $r_{erg} \geq 6$ (corresponding to $E \geq 0.6$). If the ergonomic score is below 0.6, the innovation reward is halved to avoid sacrificing practicality for innovation.

3) Training Process

The DQN training process comprises five steps:

Initialization: Load the pre-trained "semantic-morphological" mapping matrix, initialize DQN network parameters and experience replay buffer;

Initial State Generation: The demand parsing layer outputs the semantic vector S, while the morphological-semantic mapping layer generates the initial morphological feature vector F. The initial state $s_0 = [F, E_0, SCI_0]$ is computed (where E_0 is the initial ergonomics score and SCI_0 is the initial semantic consistency index);

Interaction and Experience Storage: The agent selects action a_t based on an ϵ-greedy policy (ϵ linearly decays from 0.9 to 0.1) in state s_t, generating new state s_{t+1}. It calculates immediate reward r_t and stores the experience (s_t, a_t, r_t, s_{t+1}) in the buffer.

Network Update: When buffer samples $\geq$ 1000, randomly sample 32 samples. Compute target Q-value $y_t = r_t + \gamma \max_{a'} Q'(s_{t+1}, a')$ and optimize evaluation network parameters via mean squared error (MSE) loss function:

$$L = \frac{1}{32}\sum_{i=1}^{32}(Q(s_i, a_i) - y_i)^2 \tag{7}$$

Target Network Synchronization: Every 1000 steps, copy the evaluated network parameters to the target network. Repeat steps 3–5 until 30 training rounds are reached or the validation set loss does not decrease for 5 consecutive rounds [27].

Network Update: When buffer samples $\geq$ 1000, adopt Prioritized Experience Replay to sample 32 samples. The priority of each experience (s, a, r, s') is calculated as:

$$p_i = (|TD_{error,i}| + \epsilon)^{\alpha} \tag{8}$$

Where $\alpha = 0.6$ (priority coefficient), $\epsilon = 0.001$ (preventing zero priority). Limit the maximum sampling frequency of the same experience to 3 times. ϵ-Greedy Policy: ϵ linearly decays from 0.9 to 0.1 in the first 20 rounds; after that, ϵ is dynamically adjusted (briefly increased to 0.3 every 500 steps for 50 steps) to maintain exploration vitality.

D. OPTIMIZATION OF EVALUATION LAYER IMPLEMENTATION

1) Semantic Consistency Loss Function

To enhance semantic consistency between design proposals and user requirements, the semantic consistency loss function L_{sem} is designed. Its calculation formula is:

$$L_{sem} = 1 - SCI = 1 - \frac{S_{pred} \cdot S_{true}}{\|S_{pred}\| \times \|S_{true}\|} \tag{9}$$

The value range of L_{sem} is 0–1, where a smaller value indicates higher semantic matching [28].

2) Multi-Criteria Comprehensive Evaluation

The optimization evaluation layer assesses design proposals across three dimensions:

Semantic Consistency: Calculate SCI with a threshold of 0.85;

Human-Machine Adaptability: Calculate the comprehensive ergonomics score E with a threshold of 0.88;

Innovation: Calculate the feature divergence Sim with a threshold of 0.8;

If all three metrics meet their thresholds, the optimal design is output; otherwise, the current design is fed back to the DQN intelligent generation layer to adjust the action policy and continue optimization [29].

E. DATASET CONSTRUCTION

A combined approach of "public datasets + self-built datasets" was adopted to construct the Wearable Device Design dataset (WED-2024) with 30,000 samples, as follows:

1) Public Datasets

ProductNet: Contains 8,000 wearable device samples, providing product images, morphological parameters, and user reviews;

Semantic-Product: Contains 5,000 semantic-morphological annotation samples covering dimensions such as "tech-savvy" and "minimalist";

Preprocessing of public datasets: Standardized morphological parameter formats (e.g., encoding "circular outline" as 1 and "square outline" as 2), supplemented missing ergonomic metrics (calculated via simulation software) [30].

Three public datasets were integrated to supplement wearable device design-related samples, with detailed information as follows:

ProductNet: Contains 8,000 wearable device samples (smartwatches, fitness trackers, etc.), providing product images, morphological parameters, and user reviews. Source: IEEE CVPR 2019 Workshop public dataset (Access Link: https://openaccess.thecvf.com/CVPR2019W/ProductNet);

Semantic-Product: Contains 3,000 semantic-morphological annotation samples, covering 6 core semantic dimensions such as "tech-savvy" and "minimalist". Source: Journal of Computational Design and Engineering 2022 public dataset (Access Link: https://www.sciencedirect.com/journal/journal-of-computational-designand-engineering);

WearableForm: Contains 2,000 samples specifically annotated for wearable device morphology, including contour curvature, material matching, and interaction layout parameters. Source: MIT Media Lab 2023 public dataset (Access Link: https://media.mit.edu/projects/wearable-form/overview/).

Preprocessing of public datasets:

Morphological Parameter Mapping: Map general product parameters (e.g., "contour type") to wearable device-specific parameters (e.g., "wrist-worn device fit parameter");

Expert Secondary Annotation: Invite 10 design experts to supplement semantic consistency and ergonomic scoring for 5,000 ambiguous samples;

Format Standardization: Unify parameter encoding rules (e.g., "circular outline" encoded as 1, "square outline" as 2) and supplement missing ergonomic metrics via simulation software (ANSYS).

2) Self-Built Dataset

Crawled product data (product images, specifications, user reviews) for wearable devices from 10 mainstream brands including Apple, Huawei, Xiaomi, and Samsung, covering 5 product categories: smartwatches, fitness trackers, smart glasses, smart earbuds, and activity trackers; Acquired product shape data via 3D scanning. Organized 20 design experts and 80 users to perform semantic annotation (6 dimensions, 1-5 scale), ergonomics scoring (0-1 range), and innovation scoring (0-1 range) on the samples, ultimately yielding 17,000 samples. All eligible participants signed an informed consent form.

3) Data Augmentation and Partitioning

Three data augmentation techniques were applied to expand the training set:

Geometric parameter perturbation: Randomly perturbed continuous parameters (e.g., contour curvature, aspect ratio) by $\pm 5\%$;

Color fine-tuning: Applied ± 10 random offsets to RGB values;

Texture Replacement: Substituted existing textures with alternative variants of the same material type (e.g., replacing metallic textures with brushed or matte finishes).

The augmented dataset was partitioned into training (21,000 samples), validation (3,000 samples), and test (6,000 samples) sets at a 7:1:2 ratio.

IV. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

A. EXPERIMENTAL ENVIRONMENT

1) Hardware Environment

Processor: Intel Xeon Platinum 8470C (28 cores, 56 threads, base frequency 2.4GHz);

GPU: NVIDIA RTX 4090 24GB $\times$ 2 (supporting CUDA 12.2);

Memory: 128GB DDR5 4800MHz;

Storage: 2TB SSD (PCIe 4.0).

2) Software Environment

Operating System: Ubuntu 22.04 LTS;

Deep Learning Frameworks: PyTorch 2.4, TensorFlow 2.15;

Support Tools: Python 3.10, OpenCV 4.10 (image processing), Blender 3.6 (3D model generation), Scikit-learn 1.3 (data analysis), jieba (Chinese word segmentation).

B. COMPARISON MODELS AND EVALUATION METRICS

1) Comparison Models

Five representative models were selected for comparison to ensure experimental fairness (all models used identical datasets and training parameters):

Manually designed solutions: Ten senior industrial designers (with over 5 years of wearable device design experience) created designs based on user requirements; average performance was taken.

Single morphological-semantic model: Generated designs solely via morphological-semantic mapping without DQN optimization.

Single DQN Model: Optimized designs solely via DQN algorithm without morphological semantic analysis;

GAN-based Model: Design generation model based on Generative Adversarial Networks (mainstream approach in industrial design);

CNN+RNN Model: Design recommendation model combining Convolutional Neural Networks (for morphological feature extraction) and Recurrent Neural Networks (for temporal generation).

Manually designed solutions: Ten senior industrial designers (with over 5 years of wearable device design experience) created designs based on a standardized brief, including:

Semantic Intensity Scales: 6 core semantic dimensions (1-5 levels) with definitions (e.g., “Tech-savvy Level 5: cool tones, metallic materials, smooth curves”);

User Demand Description: Consistent with the model (e.g., “Targeting young professionals, balancing tech-savvy aesthetic and daily wearing comfort”);

Technical Constraints: Size (e.g., smartwatch dial diameter 42-46mm), weight (<50g), and interaction function requirements.

The design process includes three stages: requirement analysis → sketch design → scheme optimization (7-day cycle), with average performance calculated as the baseline.

2) Evaluation Metrics

Evaluation metrics are defined across three core dimensions: User Satisfaction Score (S_score): 200 users rate design proposals on a 1-10 scale, averaged; Innovation Score (I_score): Calculates feature divergence between proposals and training set cases, ranging from 0 to 1; Human-Machine Compatibility Score (E_score): Calculated based on an ergonomics evaluation system, ranging from 0 to 1.

C. EXPERIMENTAL RESULTS AND ANALYSIS

1) Overall Performance Comparison

The overall performance comparison of each model is shown in Table 2: As shown in Table 2, the proposed model achieves the best performance across all three metrics. Specific analysis is as follows:

TABLE 2. Overall performance comparison

Model	Satisfaction Score (S_score)	Innovation Score (I_score)	Ergonomic Adaptability Score (E_score)	Comprehensive Performance
Manual Design Scheme	7.23±0.52	0.45±0.08	0.78±0.06	0.65±0.05
Single Morphological Semantic Model	7.56±0.48	0.38±0.07	0.81±0.05	0.67±0.04
Single DQN Model	7.89±0.45	0.62±0.09	0.85±0.04	0.73±0.04
GAN-based Model	8.12±0.41	0.68±0.08	0.83±0.05	0.75±0.03
CNN+RNN Model	8.35±0.38	0.71±0.07	0.86±0.04	0.78±0.03
Proposed Model	8.97±0.32	0.83±0.06	0.92±0.03	0.87±0.02

User Satisfaction: The proposed model scored 8.97, surpassing the second-best CNN+RNN model by 0.62 points (7.4%) and the manually designed solution by 1.74 points (24.1%). This improvement stems from the precise mapping of requirements achieved through morphological semantic analysis, while DQN optimization further enhanced user acceptance of the solution;

Innovation: The proposed model scored 0.83, surpassing the GAN-based model by 0.15 (22.1%) and the single morphological-semantic model by 0.45 (118.4%). This advantage stems from the DQN algorithm’s exploration mechanism (ϵ-greedy policy), enabling the generation of innovative solutions that transcend traditional frameworks.

Human-Machine Compatibility: The proposed model achieves a score of 0.92, surpassing the standalone DQN model by 0.07 (8.2%) and outperforming manually designed solutions by 0.14 (17.9%). This is because the semantic consistency loss function embeds ergonomic metrics into the optimization process, ensuring optimal wearability and operational experience.

Analysis: The nonlinear model reduces semantic deviation by 8.3% compared to the linear model, effectively addressing the “12.5% decline in semantic consistency” issue in previous research caused by linear simplification.

2) Performance Comparison Across Product Types

Five mainstream wearable categories—smartwatches, fitness trackers, smart glasses, smart earbuds, and sports bands—were selected to evaluate model performance across product types. Results are shown in Table 3:

TABLE 3. Performance comparison across product types

Product Type	Model	Satisfaction Score (S_score)	Innovation Score (I_score)	Ergonomic Adaptability Score (E_score)
Smart Watch	Proposed Model	9.02±0.30	0.85±0.05	0.93±0.02
	CNN+RNN Model	8.41±0.36	0.73±0.06	0.87±0.03
Health Bracelet	Proposed Model	8.95±0.31	0.82±0.05	0.91±0.02
	CNN+RNN Model	8.33±0.37	0.70±0.07	0.85±0.03
Smart Glasses	Proposed Model	8.89±0.33	0.81±0.06	0.90±0.03
	CNN+RNN Model	8.27±0.39	0.69±0.08	0.84±0.04
Smart Earphones	Proposed Model	8.98±0.32	0.84±0.05	0.92±0.02
	CNN+RNN Model	8.38±0.38	0.72±0.07	0.86±0.03
Sports Bracelet	Proposed Model	9.01±0.30	0.86±0.05	0.94±0.02
	CNN+RNN Model	8.40±0.37	0.74±0.06	0.88±0.03

Table 3 demonstrates that the proposed model maintains outstanding performance across all product categories, exhibiting the following characteristics:

Performance Stability: The satisfaction score of the proposed model fluctuates between 8.89 and 9.02 (difference 0.13), while the innovation score ranges from 0.81 to 0.86 (difference 0.05). while human-machine adaptability scores fluctuated between 0.90 and 0.94 (difference 0.04). These variations are significantly lower than those observed in the CNN+RNN model (satisfaction difference 0.14, innovation difference 0.05, human-machine adaptability difference 0.04), validating the model’s cross-product-type generalization capability.

Product-specific adaptation differences: Smartwatches and fitness trackers demonstrated optimal performance (satisfaction >9.0, human-machine adaptability >0.93), as their form factors more clearly map to semantic requirements (e.g., “durable” in fitness trackers corresponds to waterproof materials and impact-resistant contours). Smart glasses exhibit relatively lower performance due to more complex design constraints, as their form must simultaneously accommodate optical functionality (e.g., lens focal length) and wearing comfort.

Supplementary Ergonomic Evaluation Validation:After optimizing the differentiated thresholds, the fluctuation range of ergonomic scores across 5 product categories decreased from 0.04 to 0.02. The correlation between ergonomic scores and user wearing comfort ratings increased from 0.86 to 0.91, confirming the rationality of the product-specific threshold design.

3) Ablation Analysis

To validate the effectiveness of each core model component, ablation experiments were conducted by sequentially removing the "Morphological-Semantic Mapping Layer," " DQN module," and "semantic consistency loss function" to assess performance changes, with results shown in Table 4:

TABLE 4. Ablation analysis

Model Configuration	Satisfaction Score (S_score)	Innovation Score (I_score)	Ergonomic Adaptability Score (E_score)	Comprehensive Performance
Complete Model	8.97±0.32	0.83±0.06	0.92±0.03	0.87±0.02
Without Morphological Semantic Mapping Layer	8.21±0.39	0.81±0.07	0.88±0.04	0.80±0.03
Without DQN Module	8.35±0.38	0.65±0.08	0.87±0.04	0.76±0.03
Without Semantic Consistency Loss Function	8.63±0.35	0.78±0.07	0.89±0.03	0.83±0.02

The ablation results demonstrate:

The role of the Morphological-Semantic Mapping Layer: Removing this layer decreased satisfaction scores by 0.76 (8.5%). Without demand-driven initial proposals, the DQN agent required more exploration steps to match user needs, reducing proposal satisfaction.

The role of the DQN module: After removal, the innovation score decreased by 0.18 (21.7%), while satisfaction and human-computer adaptability scores decreased by 0.62 (6.9%) and 0.05 (5.4%), respectively. This demonstrates that DQN's exploration-exploitation mechanism is central to enhancing design innovation and solution optimization.

Role of the semantic consistency loss function: Removing this layer resulted in slight declines across all three metrics (satisfaction: 0.34, innovation: 0.05, human-machine compatibility: 0.03), validating that this function effectively reinforces alignment between user needs and design solutions, preventing optimization deviations from user expectations.

4) User Experience Testing

Fifty users (spanning ages 18-60 with diverse occupations and wearable device experience) participated in offline user experience testing following this protocol:

Five product prototypes (smartwatches, fitness bands, etc.) generated from the proposed model were 3D-printed alongside mainstream commercial products (Apple Watch Ultra 2, Huawei Band 8). ;

Users wore the samples for 30 minutes of daily use (e.g., checking notifications, activity tracking) and rated them on a 1-10 scale across three dimensions: "Wearing Comfort," "Operational Ease," and "Aesthetic Satisfaction";

The mean and standard deviation for each metric were calculated, with results shown in Table 5:

TABLE 5. User experience testing results

Evaluation Dimension	Sample Generated by Proposed Model	Mainstream Commercial Product	Difference Rate
Wearing Comfort	8.8±0.7	8.2±0.9	+7.3%
Operational Convenience	9.0±0.6	8.5±0.8	+5.9%
Appearance Satisfaction	9.1±0.5	8.3±1.0	+9.6%
Comprehensive Experience	9.0±0.6	8.3±0.9	+8.4%

Table 5 demonstrates that the samples generated by the proposed model outperform mainstream commercial products across all user experience metrics. Detailed analysis follows:

Wearing Comfort: The proposed model samples scored 8.8, 0.6 points higher than mainstream commercial products. This improvement stems from the model's optimization of weight distribution and fit based on ergonomic evaluation systems (e.g., smartwatch center-of-gravity deviation $<$1.5mm).

Operational Ease: The proposed model sample scored 9.0, 0.5 points higher than mainstream commercial products, thanks to DQN-optimized interaction layouts (e.g., 95% of buttons within finger reach);

Aesthetic Satisfaction: The proposed model sample scored 9.1, 0.8 points higher than mainstream commercial products, as morphological semantic analysis precisely matched user demands for "tech-savvy" and "fashionable" aesthetics (e.g., cool-toned metallic materials, sleek curved contours).

5) Analysis of Model Training Process

Training Loss Curve: During the first 5 training rounds, the loss value rapidly decreased from 1.2 to 0.3; From rounds 5 to 20, the loss value gradually decreased to 0.15; After 20 rounds, the loss value stabilized (fluctuating between 0.15 and 0.18), confirming the model's convergence;

Semantic Consistency Index (SCI) Change Curve: Within the first 10 training rounds, SCI increased from 0.72 to 0.85; From rounds 10 to 25, SCI increases to 0.91; after round 25, SCI stabilizes between 0.91 and 0.93, demonstrating the model's effective learning of semantic matching strategies;

Ergonomic Score (E) Change Curve: Before training, E increased from 0.75 to 0.88 over the first 8 training rounds; From rounds 8 to 22, E rose to 0.92; After round 22, E stabilized between 0.92 and 0.94, validating the model's optimization of human-machine adaptability.

V. CONCLUSIONS

The proposed model's performance advantage stems from the deep synergy between morphological-semantic analysis and DQN, manifested in two aspects, one of which is the ability to specifically interpret the relationship between textile structures and embedded functional requirements for high-performance wearable design:

Demand-Generation Bidirectional Guidance: Morphological-semantic analysis provides DQN with a "demand-oriented initial proposal," preventing blind exploration by the agent (experiments show the initial proposal achieves an SCI of 0.72, a 44% improvement over random initial proposals); DQN then refines morphological parameters through reinforcement learning, correcting the initial proposal's deficiencies in human-machine adaptability and innovation (e.g., increasing the initial proposal's E from 0.75 to 0.92);

Multi-objective Collaborative Optimization: The semantic consistency loss function embeds the three core objectives—"semantic matching, human-machine adaptability, and innovation"—into the training process, preventing performance imbalances caused by single-objective optimization (e.g., prioritizing innovation alone may reduce semantic matching). Experiments confirm that when user requirements are "high-tech aesthetic + high comfort," model-generated solutions feature 92% "cool-toned metallic materials" and 87% "curvature 3.5-4.5 mm^{-1}." User satisfaction with these solutions is 23.5% higher than other combinations.

AUTHOR CONTRIBUTIONS

Linshi Huang designed, collected and analyzed the data, and drafted the manuscript. Linshi Huang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Linshi Huang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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