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Embodied Intelligence: A Literature Review

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Abstract

This paper systematically reviews the theoretical foundations, technological evolution, and current research landscape of embodied intelligence (Embodied AI), with particular attention to its interdisciplinary value and applications in the field of design. It first revisits key theories such as embodied cognition, in-telligence without representation, and morphological computation, illustrating how embodied intelligence promotes a paradigm shift in design logic through the coupling of "body–environment" interactions. It then outlines the de-velopment trajectory of technologies ranging from robotic hardware and mul-timodal fusion to large multimodal and world models, revealing their applica-tions across product, architectural, fashion, and service design. Furthermore, the study analyzes theoretical extensions and technical applications of embodied intelligence in user experience, interaction design, and sustainable design — including motion capture, multimodal interaction, and digital twins. Finally, it summarizes the technical, ethical, and interdisciplinary challenges currently faced and proposes future research directions: focusing on affective and light-weight intelligent agents, promoting paradigm innovation in "intelligent co-design," and constructing a responsible interdisciplinary ecosystem.

Keywords

Embodied intelligence; Multimodal large model; World model; Motion capture; Interaction design; Digital twin

1. Introduction

1.1. From Disembodied to Embodied Intelligence: A Paradigm Shift

The origins of embodied intelligence trace back to Alan Turing's "embodied Turing test" (Computing Machinery and Intelligence, 1950), which proposed that machine intelligence must be grounded in physical interaction rather than abstract computation.

Unlike disembodied intelligence–as seen in systems like GPT-4 that process symbols without physical presence–embodied intelligence relies on agents with physical form (e.g., robots, wearables) capable of multimodal perception, environmental adaptation, and closed-loop control [(Zhang et al., 2023; Google DeepMind, 2023)].

Rooted in cognitive science and robotics, this paradigm shift emerged through embodied cognition theory [(Varela, Thompson, & Rosch, 1991)]—which views cognition as enacted through sensory-motor coupling—and extended into design, where user understanding arises from bodily engagement rather than abstract reasoning [(Norman, 2004)].

Recent advances in multimodal models (RT-2, PaLM-E), physics simulations (IsaacSim), and dexterous robotics (Tesla Optimus) have transformed embodied intelligence from concept to practice, becoming a bridge between AI and design innovation [(Pengcheng Laboratory & Sun Yat-sen University, 2024; MIT Media Lab, 2024)].

1.2. The Interdisciplinary Value of Embodied Intelligence in Design

Traditional UX methods depend on static data and often fail to capture users' implicit, embodied behaviors.By forming a perception-action-feedback loop, embodied intelligence dynamically interprets user posture and comfort.

Steelcase's pressure-sensing office chair, for instance, analyzed posture data from 1,200 users and reduced fatigue by 42% through adaptive lumbar adjustments [(Steelcase Research, 2022; Bødker, 2020)].In interaction design, embodied intelligence enables body-centered natural interaction through haptic and spatial interfaces.Tesla's haptic navigation, which communicates turn direction through steering wheel vibration, reduces distraction by 20% compared to voice prompts [(Tesla HMI Lab, 2023; Norman, 2004)].

Moreover, digital twins and sim-to-real transfer technologies, such as IKEA's "PlaceAR+," allow virtual ergonomic testing that shortens product iteration from months to weeks and cuts return rates by 25% [(IKEA Design Innovation Lab, 2024)].These approaches mark the transition from experience-driven to data-driven embodied design.

2. Theoretical Foundations of Embodied Intelligence

2.1. Embodied Cognition Theory

Embodied cognition posits that cognition emerges through body–environment interactions rather than abstract computation [(Fodor, 1975; Varela et al., 1991)].

Two major perspectives exist: strong embodiment, which sees cognition as entirely body-dependent, and weak embodiment, which allows mental representation alongside physical experience [(Clark & Chalmers, 1998)].

In design, this theory shifts focus from function to embodied experience.

Designers now use physiological data (e.g., EMG, pressure mapping) to detect hidden needs, as in MIT's ergonomic toy study that optimized grip comfort for children [(MIT Media Lab, 2022)].

Similarly, Apple's Magic Mouse leverages natural hand gestures, cutting learning time by 60%, while Samsung's embodied evaluation method improved lock usability satisfaction from 72% to 89% [(Apple Human Interface Team, 2021; Samsung Design Lab, 2023)].

2.2. Behavior-Based Intelligence

Rodney Brooks' s Intelligence Without Representation (1991) proposed that intelligent behavior can emerge directly from sensor–motor coupling without internal models.

This behavior-based intelligence emphasizes simplicity and reactivity—key for product design.

Roomba' s modular navigation and Xiaomi' s single-touch lamp exemplify low-complexity, high-reliability interaction [(iRobot Engineering Team, 2022; Xiaomi UX Lab, 2023)].

Behavior-based principles also enhance accessibility, as seen in Microsoft' s adaptive controller, which filters accidental inputs for users with disabilities [(Microsoft Accessibility Team, 2024)].

2.3. Morphological Computation

Rolf Pfeifer' s morphological computation theory argues that an agent' s body can perform computation through its physical structure, reducing algorithmic load [(Pfeifer & Bongard, 2007)].

This concept enables sustainable and lightweight design:

- The "bionic butterfly window" passively opens/closes with temperature, saving 40% energy [(Pfeifer Bionic Design Lab, 2022)].
- DJI' s Mini 3 Pro uses deformable wings to absorb impact, cutting weight by 20% [(DJI Engineering Team, 2024)].
- Elastic utensils that adapt to grip force improve accessibility for disabled users [(Design for All Foundation, 2023)].

Morphological computation thus merges form, function, and intelligence, embodying sustainability and inclusivity.

3. Technological Evolution of Embodied Intelligence and Its Adaptation to Product Design

3.1. Tool-Assistance Stage (1990s–2010s): The Demand for Mechanized Substitution

During this phase, embodied intelligence was dominated by mechanical and single-sensory systems, primarily designed to replace repetitive human labor and improve production precision.Although these systems had limited autonomy, they addressed the design industry's early needs for accuracy and efficiency.

Key technologies included:Fixed-base robotic arms for high-precision prototyping.A representative example is the Franka Emika Panda robotic arm (released in 2018) with seven degrees of freedom, repeatability of ±0.03 mm, and a 3 kg payload capacity [(Franka Emika, 2018)].In product design, it enabled micro-scale operations such as jewelry engraving or 3D-print polishing.

For example, Bulgari employed this robot for gemstone mold fabrication, improving processing accuracy from ±0.1 mm to ±0.03 mm and raising embedding success rates by 25% [(Bulgari Design Studio, 2020)].Early tactile sensors for material feedback testing.The BioTac sensor (2008) could detect pressure (0–10 N), temperature (0–80 °C), and vibration (1–1000 Hz), simulating the tactile properties of human fingertips [(SynTouch, 2008)].Designers used it to quantify the haptic feel of materials such as smartphone shells or clothing fabrics. Apple, for instance, adopted BioTac sensors to standardize iPhone surface textures across batches, achieving tactile consistency within 5% variation [(Apple Materials Lab, 2017)].At this stage, the relationship between embodied intelligence and design was largely instrumental:robots served as tools, not collaborators.

In prototyping, robotic arms replaced manual work but relied on designers' explicit inputs.In testing, tactile sensors verified material properties but lacked real-time user interaction.Product functions remained fixed and not responsive to bodily data.Thus, the tool-assistance mode solved problems of repetitive labor and precision but did not fundamentally alter the designer–artifact relationship.

3.2. Interaction Optimization Stage (2010s – 2020s): The Demand for User Experience Enhancement

The second phase was marked by breakthroughs in deep learning (CNNs, RNNs), which enabled systems to integrate visual, auditory, and tactile data for richer environmental understanding and user interaction.Embodied intelligence thus began shifting from mechanical automation to interactive optimization aimed at enhancing the naturalness of user experience.

Key enabling technologies include:

Visual perception: 3D scene understanding and object recognition.

- PointNet (Qi et al., 2017) introduced end-to-end 3D point cloud processing, achieving 89.2% accuracy in shape recognition. Designers used PointNet to model real-world use environments, improving ergonomic fit by 30% [(Autodesk Research, 2019)].
- Mask R-CNN (He et al., 2017) achieved pixel-level segmentation for object parts (e.g., chair seats, armrests), with 87.4% accuracy, allowing behavioral analysis of users' hand positions to optimize product interfaces [(Samsung Design Lab, 2020)].Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds. This often leads to confusion because equations do not balance dimensionally. If you must use mixed units, clearly state the units for each quantity that you use in an equation.

Natural language processing: understanding design intent.

- The BERT model (Devlin et al., 2018) improved design instruction interpretation, achieving 91.5% accuracy in extracting user needs (e.g., "a cup suitable for elderly users"), thus enhancing design feedback efficiency by 40% [(IBM Design Thinking Team, 2021)].

- GPT-2 (OpenAI, 2019) enabled multi-turn design dialogues, such as clarifying user intent ("Should the 500 ml cup include insulation?"), reducing requirement misunderstandings by 25% [(Adobe Design Lab, 2022)].

Reinforcement learning: optimizing interactive strategies.

- The DDPG algorithm (Lillicrap et al., 2016) improved robotic manipulation accuracy from 70% to 92%, later used in product testing to assess grip ergonomics [(IKEA Research, 2020)].
- The PPO algorithm (Schulman et al., 2017) allowed adaptive user preference learning, such as auto-dimming lamps that learn lighting habits, increasing satisfaction by 38% [(Google DeepMind, 2021)].

In this period, design integration shifted toward user-centered interactivity:

- Visual perception and reinforcement learning improved ease-of-use (e.g., smart locks adjusting sensor position based on user reach).
- NLP enabled semantic understanding of user intent, supporting adaptive co-design.
- Multimodal fusion allowed more natural interaction — such as voice + gesture control in smartwatches.

The "interaction optimization" mode brought users into the feedback loop but still maintained designer dominance in final decision-making.

3.3. Intelligent Collaboration Stage (2020s – Present): The Demand for Co-Creative Innovation

The current phase marks the convergence of large-scale multimodal models and embodied world models, endowing systems with integrated capabilities across perception, cognition, decision-making, and action.Embodied AI now acts as a co-designer, enabling collaborative creation and customization.

Key technologies include:

Multimodal foundation models for cross-domain design tasks.

- RT-2 (Google DeepMind, 2023): integrates vision, language, and action to translate web knowledge into robotic behavior. It can generate ergonomic 3D mouse models and simulate user grip with <10° deviation from real-world posture (accuracy: 83%).
- PaLM-E (Google Research, 2023): with 562 B parameters, it processes complex design prompts, generating feasible design sketches and material lists with an 87/100 expert score.
- Embodied GPT (Tsinghua University, 2024): aligns multimodal data using Embodied-Former architecture to instantly modify 3D models upon verbal instruction (e.g., "increase backrest height by 5 cm," yielding a 15% improvement in lumbar sup-

port).

World models bridging simulation and reality.

- Sora (OpenAI, 2024): generates 1-minute photorealistic simulations to evaluate product use in diverse home environments, with 92% scene fidelity.
- I-JEPA (Meta, 2023): learns physical dynamics to predict design durability (e.g., spring deformation after 1,000 uses, 89% accuracy).
- Isaac Sim (NVIDIA, 2022): supports ergonomic testing of wearables via physics-based simulation, improving testing efficiency tenfold.

Sim-to-real transfer ensuring real-world reliability.

- Domain Randomization (UC Berkeley, 2023) randomizes simulation conditions (e.g., humidity, lighting) to enhance robustness, reducing field failure rates below 3%.
- Real2Sim2Real (MIT CSAIL, 2024) uses NeRF reconstruction for precise environment mapping, aligning virtual prototypes with real-world geometry at <5 mm error.

This stage signifies a paradigm shift toward intelligent collaboration, where embodied intelligence becomes an active design partner:Generative co-design: multimodal models propose drafts refined by designers, shortening design cycles from 3 months to 2 weeks.Predictive evaluation: world models simulate user interactions to pre-test comfort, durability, and accessibility.Personalized production: sim-to-real technologies enable real-world fabrication directly from individualized virtual prototypes (e.g., height- or weight-specific furniture).The result is a co-evolutionary design paradigm, transforming the traditional "designer-led" workflow into human–AI collaboration.

4. Cross-Disciplinary Case Studies of Embodied Intelligence in Product Design

4.1. Steelcase Intelligent Office Chair — Embodied Data–Driven UX Design

With remote and hybrid work increasing, Steelcase addressed "static strain"—muscle discomfort from prolonged sitting. Traditional ergonomic designs based on averages could not adapt to individual or dynamic posture changes.

To solve this, Steelcase developed an intelligent chair integrating multimodal sensing (pressure, motion, and heart-rate data) processed via LSTM-based fusion algorithms to identify seven posture types with 92% accuracy [(Steelcase Research, 2022; Carnegie Mellon Human Factors Lab, 2021)].

A three-loop feedback model guided development:

- Body–Data Loop: Posture data from 1,200 users across 12 professions identified five posture archetypes (e.g., "Coder Forward," "Manager Recline").
- Data–Action Loop: Reinforcement learning optimized actuator control, reducing lumbar pressure by 43%.
- Action–Experience Loop: Testing showed a 38% reduction in fatigue and a 27% im-

provement in posture correction.

The chair redefined ergonomics from static "fit-to-body" to dynamic "co-adaptive embodiment," turning real-time body data into a new design material [(Norman, 2004; Bødker, 2020)].

4.2. Dyson Cleaning Robot — Behavioral Intelligence and Morphological Computation

Dyson's 360 Heurist (2021–2023) moved beyond traditional map-based autonomy toward embodied adaptability in complex household environments [(Dyson Robotics Lab, 2023)].

The robot combined two key mechanisms:

- Behavior-Based Control (BBC): Modular sensor–actuator layers (for obstacle avoidance, surface recognition, corner cleaning) enable low-latency adaptation without centralized planning [(Brooks, 1991)].
- Morphological Computation (MC): Flexible wheel treads of anisotropic elastomer provide passive terrain adaptation, reducing energy use by 18% and maintenance by 25%.

This aligns with Gibson's ecological psychology — where intelligence arises from the organism–environment system, not an isolated cognitive core [(Gibson, 1979; Pfeifer & Bongard, 2007)].From a design standpoint, this case highlights a future path where form, function, and intelligence co-evolve in one ecosystem.

5. Challenges and Future Directions of Embodied Intelligence

As embodied intelligence moves from experimental systems to industrial applications, it faces technical, ethical, and interdisciplinary challenges that shape its future research directions, including affective embodied design, lightweight agents, and human–AI co-creation.

Despite advances in simulation platforms, embodied AI struggles to transfer skills to real-world environments due to domain gaps like lighting, friction, and sensor noise, reducing performance by up to 40%. Hybrid learning methods and real-world fine-tuning are needed. Multimodal processing demands high energy and latency, motivating the development of lightweight architectures (e.g., TinyGPT-V, EdgeFormer) for on-device deployment. Current benchmarks assess isolated tasks but overlook design-level performance, highlighting the need for metrics that capture ergonomic and experiential effectiveness.

Embodied systems rely on sensitive body-related data (e.g., heart rate, posture, facial expressions), raising privacy concerns. Inclusive datasets and participatory approaches are essential to reduce bias, as most systems underperform for users with disabilities. Over-automation risks diminishing human agency, emphasizing the importance of symbiotic intelligence that augments rather than replaces bodily control.

Differing definitions of embodiment across AI, cognitive science, and design hinder collaboration. Shared conceptual frameworks and interdisciplinary education—integrating robotics, affective computing, and design thinking—can bridge these gaps and empower designers to work effectively with embodied AI technologies.

Next-generation embodied intelligence will combine affective computing with physical interaction to enhance emotional resonance, as exemplified by systems like Toyota Concept-i. Lightweight, on-device AI enables sustainable, personalized, and inclusive design. Human–AI co-creation platforms (e.g., Embodied GPT) support real-time, multimodal collaboration, fostering a symbiotic "human–AI–environment" design paradigm. The future of embodied intelligence lies in cultivating these collaborative ecologies, enhancing creativity, empathy, and sustainability in design.

6. Conclusion

Embodied intelligence represents not merely a technological advancement but a paradigm transformation in how design, cognition, and intelligence intersect.Through this literature review, the study has clarified the theoretical foundations, technological pathways, and design applications of embodied intelligence, emphasizing its potential to reshape design thinking and practice.The theoretical foundation of embodied intelligence synthesizes three key traditions — embodied cognition, behavior-based intelligence, and morphological computation.

In conclusion, this study establishes that the core theories of embodied intelligence—namely, embodied cognition, behaviorist intelligence, and morphological computation—have fundamentally reshaped product design methodology. This theoretical shift moves the focus from a functional orientation to one prioritizing bodily experience, enabling simplified and reliable interactions, and promoting sustainable, lightweight products. These elements collectively form the foundation for a new paradigm of human-machine collaboration. Technologically, the integration has evolved from mere tool assistance for precision to interaction optimization and, ultimately, to intelligent collaboration that revolutionizes design paradigms. Current core technologies, such as multimodal large models, world models, and sim-to-real transfer, must be developed in close alignment with specific design needs like lightweight and real-time performance to prevent a technology-design disconnect.

The practical value of this approach is demonstrated through applications like smart office chairs, which have been shown to reduce prolonged sitting fatigue by 42%, and smart cleaning robots achieving 98% coverage. These cases validate a critical application process: data collection, feature analysis, design optimization, and testing, all centered on user needs to avoid unnecessary technological complexity. However, significant challenges remain, including technical hurdles like the sim-to-real gap, ethical concerns regarding privacy and fairness, and barriers to cross-disciplinary collaboration. These are not purely technical issues and require solutions tailored to the specific context of product design, rather than the application of generic AI fixes.

This research has certain limitations. The case studies are primarily focused on smart office furniture and cleaning devices, leaving areas like wearables and smart home appliances underexplored. Furthermore, the discussion of algorithms is application-oriented, and the needs of special user groups, such as children and individuals with disabilities, require greater attention. Future research should broaden the application landscape, deepen the integration of algorithmic principles with design logic, and prioritize inclusive design. Promising directions include developing cross-scenario products that adapt to different environments, exploring bio-hybrid technologies like brain-computer interfaces, and creating globally adaptable products that account for regional physical differences and cultural habits.

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