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Gesture recognition for engaging spatial experiences in healthcare: Co-design of intelligent interactive illuminative textiles

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Abstract

The integration of artificial intelligence (AI) into textile design enhances functionality, automation, and user interaction. While gesture recognition has been explored in smart textiles, contactless interactive systems for healthcare remain underdeveloped. This study presents a human-centered co-design approach to the development of an AI-integrated gesture recognition system embedded in illuminative textile wall panels, aimed at enhancing spatial engagement in healthcare environments. The research was conducted in three key stages. First, a co-design workshop was conducted to explore user preferences in textile materials, graphic design, and gesture interaction. Second, intelligent illuminative textiles were developed by knitting polymeric optical fiber into base wool yarns to enable illumination. A camera was embedded and integrated with a computer vision-based deep learning model for detecting landmarks on the hands, shoulders, and head. The recognized gestures and body movements triggered specific pre-programmed color changes on the textile surface through edge-integrated light-emitting diodes. Finally, a prototype was fabricated and installed in a government-established District Health Centre in Hong Kong to support physical activity and rehabilitation for elderly users. Semi-structured interviews with stakeholders – including co-designers, users, and occupational therapists – were conducted to evaluate usability and inform design refinements. Stakeholders reported high levels of satisfaction, emphasizing the system's ability to enhance community connection, therapeutic engagement, intuitive usability, and compelling visual feedback. These findings suggest that AI-driven interactive textiles present promising opportunities for rehabilitation, therapeutic environments, and the promotion of elderly well-being.

Keywords: Interactive textiles; Illuminative textiles; Gesture recognition; Human-artificial intelligence interaction; Deep learning; Healthcare

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1. Introduction

Artificial intelligence (AI) has significantly influenced modern textile design by promoting "smart fabrics" that adapt to external stimuli and enhance user experiences across domains, such as fashion, sports, and healthcare.[1-4] These AI-driven textiles leverage innovations ranging from bio-signal monitoring and electronic components to contactless control, transforming conventional fabrics into dynamic, interactive platforms.[5] The growth of AI in textile applications is evident in examples, such as temperature-sensitive materials and motion-sensing garments, demonstrating real-time responsiveness in athletic training, safety gear, and medical diagnostics.[5-9] In the area of gesture recognition, most AI-powered textiles rely on wearable sensors (e.g., data gloves) to capture finger and hand movements for sign language translation or rehabilitation exercises.[5] However, limitations remain in fully contactless systems, as many solutions still depend on user touch or close-range sensing, underscoring a gap for more accessible, "touch-free" interfaces in healthcare.[5] As healthcare increasingly shifts toward unobtrusive tools for assisting seniors and individuals with mobility constraints, AI-integrated textiles can offer intuitive, hands-free interaction – an approach further explored in the next section on user-centered co-design. By seamlessly embedding computer vision and deep learning in interior textiles, researchers aim to expand usability from wearable contexts into rehabilitative, clinical, and everyday healthcare settings, thereby enhancing both patient engagement and therapeutic outcomes.[4,10] Proposing innovative healthcare solutions for the elderly is increasingly important, and the integration of AI offers significant potential to enhance well-being through personalized, responsive, and engaging interventions.

As global demographics shift toward an increasingly aging population, healthcare systems worldwide face unprecedented challenges in providing quality elderly care. The World Health Organization projects that by 2030, one in six individuals globally will be aged 60 or older, significantly straining healthcare infrastructure and resources.[11,12] This demographic shift demands transformative changes in elderly healthcare delivery, especially in densely populated urban areas where healthcare facilities already operate at capacity.[13] Older adults typically require up to 4 times more healthcare resources than younger adults due to the prevalence of chronic conditions, such as cardiovascular diseases, diabetes, and dementia, further amplifying pressures on healthcare systems.[13,14] In Asia, countries or regions such as Hong Kong, China, South Korea, and Japan are particularly impacted, with elderly populations projected to surpass 37% by 2050.[15] Specifically, Hong Kong is projected to have 40.6%, South Korea 39.4%, and Japan 37.5% of their populations aged 65 or older by 2050,[16,17] intensifying shortages of specialized healthcare professionals and highlighting the critical urgency for innovative healthcare solutions.[18] In Hong Kong specifically, the elderly population is expected to reach 26% by 2026, further exacerbating demands on local healthcare facilities.[19-21] Responding strategically, the Hong Kong government initiated the establishment of District Health Centres (DHCs) in 2019, aiming to enhance primary healthcare accessibility and effectiveness. By 2023, these centers expanded into comprehensive community-based networks, serving approximately 205,600 (provisional figures as of December 31, 2023) elderly residents.[22] The Wong Tai Sin DHC (WTSDHC), for example, exemplifies this approach by offering specialized services, such as health risk assessments, chronic disease management, and targeted rehabilitation programs delivered through multidisciplinary healthcare teams.[23]

Technological advancements globally illustrate how AI and digital innovations can significantly enhance healthcare efficiency and patient outcomes. International examples include Singapore's widespread adoption of AI initiatives, such as the SELENA+ system, AimSG, and ACE. Other examples include AI in community hospitals and Japan's Cancer Institute Hospital, where AI analyzes extensive clinical datasets annually.[24-27] In contrast, Hong Kong is still in its early stages of AI technology development. Hong Kong's DHCs currently utilize relatively basic technological tools, such as digital health records and standard health screening devices, reflecting limited AI integration.[28,29] Despite the evident potential and global trend toward AI-driven healthcare solutions, adoption remains limited among elderly populations in Hong Kong. Often attributed to technophobia or the grey digital divide, seniors' reluctance toward new technologies commonly stems from internalized ageism – self-imposed beliefs about their inability to learn or master digital tools. However, Köttl *et al.*[30] also highlight that many older adults genuinely desire to learn and can excel in technology use when provided with suitable support and accessible interfaces. Interactive textiles, as intuitive, tactile, and user-friendly platforms, present a valuable starting point for elderly individuals to engage with AI and other emerging technologies. By providing an accessible and reassuring interface, smart textiles offer older users an empowering opportunity to demonstrate their capacity to adopt, learn, and benefit from advanced technological solutions, ultimately bridging the existing digital divide and facilitating wider acceptance of AI-enhanced healthcare interventions.[31-33]

This study proposes an AI-driven gesture recognition textile-based system, developed through a co-design approach, to create interactive illuminative wall panels that integrate smart textiles and user-centered design principles for healthcare applications. As outlined in

Figure 1A, the research followed a structured process comprising three main stages: (i) a workshop (co-design session A) was conducted with the staff and elderly members in WTSDHC to explore preferences in soft textile materials, visually engaging and memorable imagery, and gesture-based interactions aimed at enhancing user engagement, (ii) development of intelligent textiles using knitted polymeric optical fiber (POF), integrated with a microcomputer running a deep learning-based model for real-time hand, shoulder, and head landmark detection, and (iii) prototype fabrication and installation at the WTSDHC, where semi-structured interviews (co-design session B and C) with stakeholders, including co-designers, users, and occupational therapists (OT), were conducted to assess overall satisfaction and gather feedback for system improvement. Figure 1B illustrates the workflow of the textile-based gesture and posture recognition system, from real-time gesture capture to visual output on the fabric's surface. The process begins with a user standing in front of the textile panel, where a

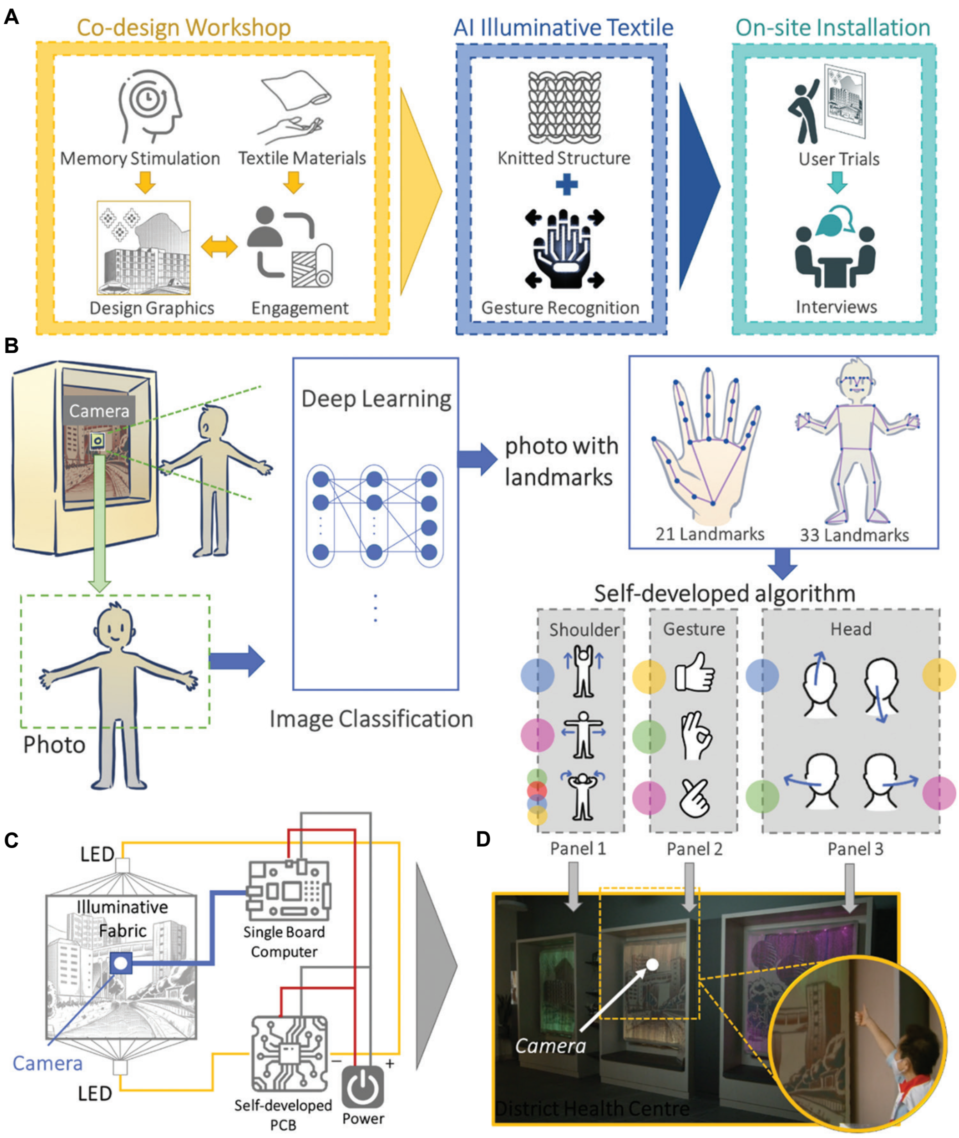

Figure 1. Overview of the co-design development process and artificial intelligence-based gesture recognition system for the interactive illuminative textile. (A) Structured research process, including a co-design workshop, intelligent textile development, and system deployment. (B) Computer vision-based deep learning model for gesture and posture recognition through landmark detection on hands, shoulders, and head. (C) Integration of polymeric optical fibers, edge-connected light-emitting diodes, camera, power supply, single-board computer, and custom printed circuit board to enable real-time color feedback on textile surfaces. (D) Installed prototype of three interactive textile wall panels at Wong Tai Sin District Health Centre, designed to enhance elderly engagement and spatial interaction.

camera captures a live image (photo) without storing it in memory. This image is passed to a deep learning model for image classification, which detects 21 hand landmarks or 33 body landmarks, depending on the type of input (e.g., hand gesture or full-body posture). The output of the deep learning model is a photo annotated with landmark points in (x, y) coordinate format. These landmarks are then processed by a self-developed algorithm, which interprets the spatial relationships between the landmarks to classify the user's physical position or gesture. Different gestures and body positions triggered distinct color responses on the surface of the illuminative fabric. These colors were activated through light-emitting diodes (LEDs) connected to the textile's edges, which were optically linked through the integrated POFs (Figure 1C). A camera was embedded within the textile system, and a single-board computer and a custom-designed printed circuit board (PCB) were connected to support real-time interaction. Figure 1D shows the installed prototype, consisting of three illuminative fabric wall panels in WTSDHC, designed to enhance engagement and promote well-being among elderly users.

2. Literature review

This research focused on achieving a user-centered design for intelligent interactive illuminative textiles to enhance spatial experiences through gesture recognition. The study was reviewed from three key aspects: (i) the co-design process, (ii) the design and development of interactive illuminative textiles, and (iii) the application of AI technology in gesture recognition. Finally, the research identified existing gaps in the literature.

2.1. Co-design

Design thinking is commonly applied within co-design processes, facilitating collaboration through structured, iterative methods. Popularized by IDEO and Stanford University's Hasso Plattner Institute of Design (also known as the Stanford d.school), design thinking integrates human needs, technological possibilities, and business viability through empathizing, defining, ideating, prototyping, and testing phases.[34] Specifically, when applied to designing solutions for older adults, design thinking bridges potential gaps between designers' assumptions and the actual needs and preferences of elderly users.[35] Co-design, representing the collective creativity of designers and non-designers collaborating in the development process, has become essential in creating user-centered solutions. This approach harnesses diverse expertise, benefiting from interdisciplinary contributions, which can lead to innovative and contextually appropriate designs.[36] For instance, Sanders and Stappers[35] highlight how co-design facilitates a richer understanding of user requirements and fosters a sense of ownership among end-users, ultimately leading to higher adoption rates and user satisfaction.[35] While co-design and design thinking often share overlapping tools and values – such as empathy, iteration, and participation – design thinking typically provides the structured methodology, whereas co-design emphasizes deeper user involvement as co-creators throughout the process. Distinguishing between them helps to clarify the specific roles of facilitated creativity and participatory engagement in the project context.

Experience-based co-design (EBCD) specifically applies co-design principles within healthcare service improvement contexts, systematically capturing and utilizing the lived experiences of service users and providers to enhance service quality.[37] For example, studies have shown EBCD's effectiveness in improving elderly care services by deeply engaging elderly individuals and caregivers in the design process, thereby ensuring solutions resonate with users' personal experiences and emotional needs.[38] Actively involving older adults through co-design processes, such as EBCD has demonstrated notable benefits, including improved service outcomes, increased user empowerment, and enhanced social connectedness.[39] Human-centered design further emphasizes placing human needs, capabilities, and behaviors at the forefront, making systems usable, accessible, and effective through ergonomic and usability principles.[40]

In designing for elderly users, methodologies, such as co-design, EBCD, and human-centered design are especially valuable, particularly when addressing cognitive or emotional connections to personal history and memory.[41] Research indicates that reminiscence therapy, commonly employed in dementia care and elderly mental health interventions, effectively utilizes personal memories and past experiences to improve psychological well-being and social engagement among elderly individuals.[42] Integrating reminiscence therapy principles within co-design methodologies has shown potential in creating solutions that significantly enhance elderly users' emotional health, autonomy, and dignity by actively involving them in crafting personalized and meaningful interventions.[43]

2.2. Interactive illuminative textiles

Interactive textiles, also known as e-textiles, are textiles designed to dynamically respond to external stimuli or user interactions through integrated electronic components and embedded technologies.[44-48] Illuminative interactive textiles specifically utilize lighting elements, such as POFs, to offer visual feedback and facilitate sensory stimulation.[49-52] POF textiles integrate flexible polymer-based fibers, such as polymethyl methacrylate, into fabric structures to enable uniform side illumination. Light is transmitted through the fiber and emitted laterally through engineered surface modifications, allowing flexible, efficient, and interactive lighting within textiles.[53] Tan *et al*.[54] designed a gesture-controlled illuminated textile utilizing computer vision to recognize mid-air hand gestures, triggering corresponding color changes in the fabric. Prior research has primarily examined woven illuminative textiles designed for creating engaging sensory environments. However, recent innovations have begun exploring knitted textiles. Lam *et al*.,[55] investigated various knitted structures to optimize the illuminative effects of POFs, demonstrating the feasibility of integrating such technologies into wearable and interior applications, favored for their superior flexibility and user comfort, thereby enhancing interaction potential and application versatility, particularly in healthcare environments.[55,56] Data presented at the Hong Kong Geriatrics Society Annual Scientific Meeting showed that the use of knitted illuminative textiles, in the form of touch-and-proximity responsive cushions, substantially improved engagement in individuals with dementia.[57] Notably, 90% of participants with late-stage dementia demonstrated active participation during sensory interventions, and all participants (100%) reported positive experiences, providing strong empirical support for prior anecdotal observations. These findings affirm the potential effectiveness of interactive illuminative textiles in supporting elderly sensory therapies.

Nevertheless, a notable research gap persists regarding the comprehensive integration of advanced AI capabilities into knitted textile systems for wider healthcare applications. To address this gap, future research could emphasize AI integration to enhance user interactions and usability, especially among elderly populations who may experience reluctance due to perceptions of complexity or internalized ageism. Continued collaborative co-design efforts involving multidisciplinary teams and end-user participation are critical to developing solutions that closely align with user needs and enhance overall acceptance and effectiveness in healthcare applications.

2.3. Gesture recognition

Recent developments in smart textile research have opened new possibilities for gesture recognition interfaces within healthcare. By embedding sensor networks or computer-vision modules directly into fabrics, researchers aim to create seamless, intuitive systems that detect hand and finger movements with minimal user discomfort.[5] Early studies typically integrated wearable sensors – such as stretchable gloves or multiple inertial measurement units – for real-time motion capture[58,59]; however, the field still recognizes the potential of more ambient or contactless gesture solutions, particularly in clinical contexts.[10] A key impetus for pursuing AI-based gesture recognition in textiles is its potential application in rehabilitation and elderly care. With aging populations growing globally, there is an urgent need for unobtrusive monitoring technologies and interactive support for seniors.[60,61] Traditional camera-based systems may achieve high accuracy in controlled environments, but often face issues related to occlusion, lighting conditions, and perceived intrusiveness among older adults.[62] Consequently, intelligent textiles – integrated with conductive yarns, POFs, or advanced "smart glove" sensors – offer more user-friendly alternatives, minimizing external hardware and seamlessly blending into healthcare environments.[4]

2.3.1. Wearable and contactless frameworks

Early gesture-recognition textiles frequently relied on wearable forms, such as sensor-equipped gloves, to track finger angles or subtle hand movements.[10,61] These gloves typically embed pressure sensors or strain gauges in conductive yarns along finger segments, capturing real-time flexion–extension data. Complementary approaches integrate surface electromyography (sEMG) signals or multiple inertial measurement units to enhance motion capture accuracy, especially for dynamic tasks, such as stroke rehabilitation. Such gloves excel in precision and support personalized rehabilitation by offering biofeedback on gesture performance. However, some older patients or those with physical constraints may find gloves cumbersome or difficult to put on and remove daily, thus limiting practical adoption.

Recent studies acknowledge the potential of "contactless" gesture detection textiles, where embedded optical or capacitive sensors track mid-air hand movements. Tan *et al*.[54] propose an illuminative textile system using computer vision to detect mid-air number gestures without direct physical contact. This approach points toward fabric-based "wall panels" or "ambient curtains" capable of sensing gestures in healthcare environments where cleanliness and infection control are paramount. In addition, contactless designs can enhance accessibility for patients with limited dexterity or object-avoidance requirements.

2.3.2. AI and machine learning integration

Gesture recognition systems commonly integrate multiple stages: data collection from sensors or vision modules, preprocessing for noise reduction and feature extraction, classification using machine learning models, and real-time feedback or database storage. Databases containing gesture data – either from annotated video streams or sensor readings – are vital for training robust AI models.

Alternative gesture-tracking models comparable to popular hand landmark solutions include OpenPose, Leap Motion, and other proprietary landmark detection frameworks that similarly leverage neural networks for real-time gesture tracking.[63,64]

Raw data from e-textiles, such as pressure signals, optical signals, or electromyography, benefit from robust classification algorithms capable of interpreting complex spatiotemporal patterns.[5,59] Neural architectures, such as convolutional neural networks or attention-based transformers, interpret subtle gesture variations and adapt to user-specific differences. Guo *et al.*,[61] demonstrated that a one-dimensional convolutional neural network trained on sEMG signals could classify 10 distinct hand poses relevant to stroke therapy, achieving accuracy exceeding 90%. Such data-driven modeling is critical for real-time feedback, flagging suboptimal movements or guiding corrective steps during rehabilitation. Nevertheless, deep learning's power consumption and computational overhead pose challenges for embedded textile platforms with limited battery or hardware resources.[5] Researchers are thus exploring lightweight or optimized neural models deployable on microcontrollers. Edge computing can minimize reliance on cloud connectivity, which is advantageous for remote or resource-limited clinical environments.[60] Prototypes also employ data fusion techniques, combining optical gesture tracking with sEMG signals, refining gesture accuracy without significantly increasing hardware complexity.[61]

2.3.3. Healthcare applications and user acceptance

Gesture-driven textiles hold substantial promise in healthcare, including telemedicine, physical therapy, and elderly care.[54,62] A textile-based gesture interface could enable older adults to call for help using simple hand signs rather than navigating small buttons. In stroke recovery, interactive textiles or gloves could monitor progress during range-of-motion exercises, providing real-time feedback and gamified incentives. Practical deployment, however, demands attention to usability, washability, and robustness.[5,6] E-textiles integrated into hospital curtains or seat covers must withstand repeated cleaning cycles, and wearable gloves must maintain accurate sensor functions despite mechanical stresses.

User acceptance among older adults remains critical. Oudah *et al.*,[62] noted seniors' skepticism toward unfamiliar technologies as a potential barrier to adoption. Co-design strategies involving healthcare staff, caregivers, and older patients can yield intuitive gestures and esthetically pleasing fabrics. Studies like Tan *et al.*[54] emphasize visual feedback – illuminative textiles can confirm correct gesture detection by changing color or brightness, enhancing user confidence.[54] Future research could further explore these user-centered design approaches to ensure gesture recognition technologies feel neither intrusive nor burdensome.

3. Methodology

3.1. Interviews

This research adopted a multi-phase participatory design approach over a 37-month period. The study commenced with a workshop (co-design session A; December 22, 2021) at SKH Calvary Church in Wong Tin Sin, establishing the foundation for community-driven design principles. Subsequent semi-structured interviews (co-design session B) with the research lead and the OT lead (February 7, 2023) at the Core Centre at WTSDHC provided institutional perspectives on implementation requirements and healthcare objectives. User experience evaluation (co-design session C) was conducted through structured interviews with co-designers and end-users (March 25, 2024) at the same place. The study received ethical approval from the Institutional Review Board at the authors' affiliated university. All participants provided informed consent before the commencement of the interviews.

This methodological sequence allowed for iterative development while maintaining alignment with both community needs and healthcare requirements. The technical development phase implemented these insights through a gesture recognition illuminative knitted textile system, comprising three interactive interfaces. Each interface was developed using specific interaction modalities: hand gesture recognition, shoulder movement detection, and head movement recognition, with corresponding visual feedback mechanisms. The final evaluation phase employed qualitative user feedback, enabling systematic refinement of the system's technical parameters while maintaining therapeutic efficacy and user engagement objectives.

3.1.1. Co-design workshop

This study adopted a systematic participatory action research framework, comprising three distinct yet interconnected phases. The initial phase employed a participatory design methodology to engage members of the WTSDHC in a 3-h co-design workshop (co-design session A). A total of 11 participants, including five staff members and OTs and six center members, took part in the session. The workshop was divided into two parts. The first part consisted of a presentation introducing the concept and applications of intelligent illuminative textiles, aiming to provide participants with foundational knowledge (Figure 2A). The second part focused on collecting participants' opinions regarding the design and development of an AI-enhanced, textile-based gesture recognition system tailored for use at WTSDHC. Structured activities and semi-structured discussions were utilized to elicit feedback on contextual needs, design esthetics, and relevant local cultural elements. This approach aimed to ensure that both user preferences and community values were reflected in the design process. A semi-structured interview guide was used during the co-design workshop

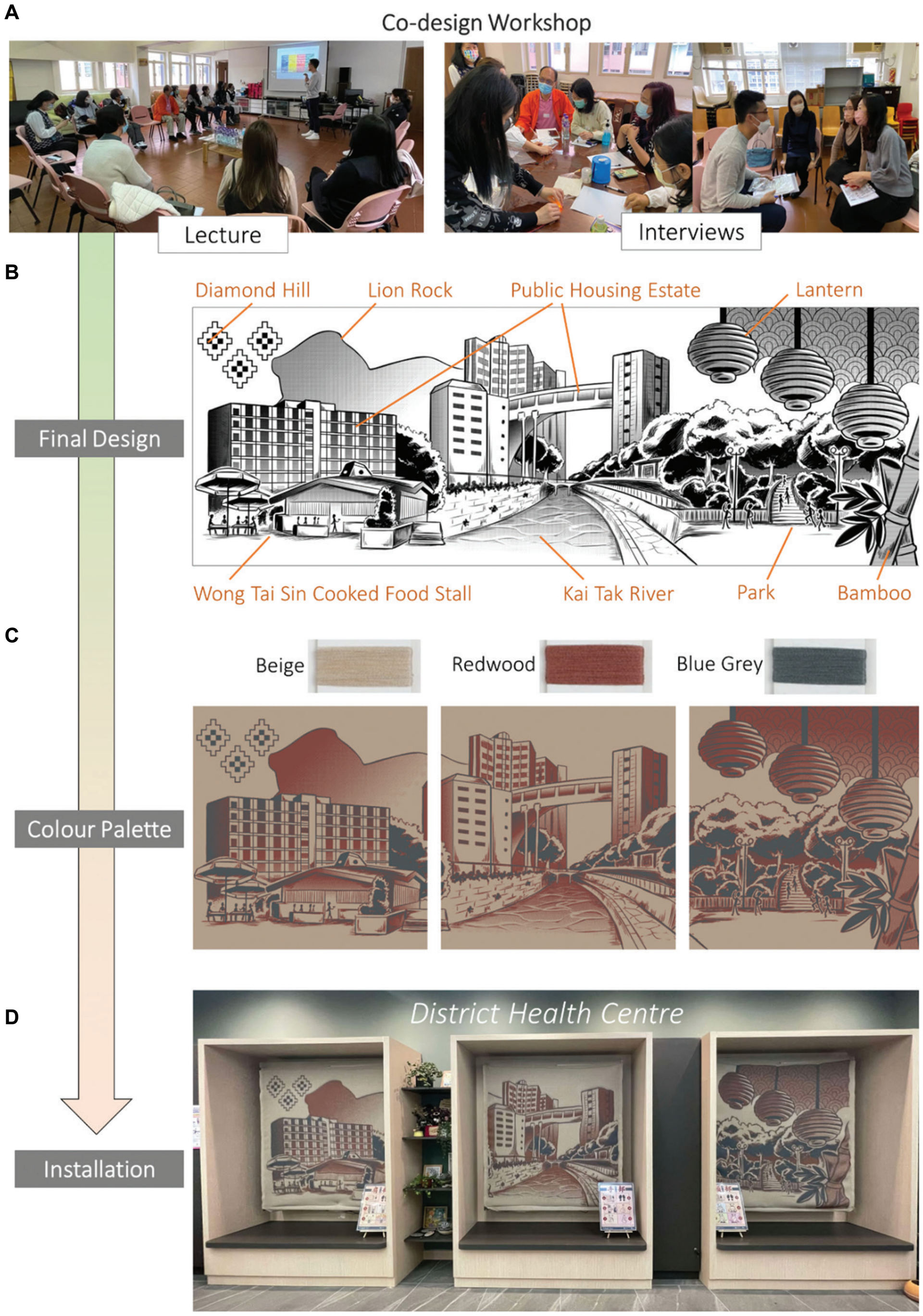

Figure 2. Co-design process. Photos from the co-design workshop showing (A) the lecture session and (B) interviews and group discussions. (C) Final illustration and design of the wall panels featuring several landmarks from the Wong Tai Sin district. (D) Color palette selected by co-designers for fabric development. (E) Installed wall panels in the Wong Tai Sin District Health Centre.

discussions, focusing on two main areas: (i) participants' background and experience with the social center, and (ii) their preferences regarding textile design. The first section explored general usage and engagement with the center through the following questions:

(i) Question 1: Have you visited a similar social center before?
(ii) Question 2: Approximately how long do you usually stay at the center during each visit?
(iii) Question 3: How frequently do you attend the center?
(iv) Question 4: Do you usually visit the center alone?
(v) Question 5: What activities are typically available to you?
(vi) Question 6: Which activities do you enjoy the most?
(vii) Question 7: Which activities do you think could be improved?
(viii) Question 8: What is your primary reason for visiting the center?
(ix) Question 9: Outside of the center, where do you usually spend your time, and what are your hobbies?

The second section addressed textile and design preferences:

(i) Question 1: What are your impressions of the sample illuminative textiles?
(ii) Question 2: Are you familiar with the concept of a sensory wall?
(iii) Question 3: Do you have suggestions for the design of the wall panels – for example, preferred themes, colors, or functional features?

3.1.2. Stakeholders' interviews after on-site installation

A systematic evaluation of the installation's efficacy was conducted through two methodologically distinct phases: expert interviews with the research lead and the OT lead (co-design session B) on February 7, 2023, followed by interviews with two co-designers and two end-user representatives (co-design session C) on March 25, 2024. This multi-phase assessment provided meaningful insights into the long-term impact of implementing co-designed, workshop-derived principles within a healthcare setting.

The expert interviews consisted of a series of structured questions aimed at understanding both conceptual foundations and practical applications of the intelligent textile system. Questions for the research lead included:

(i) Question 1: Could you share the background of this research study?
(ii) Question 2: Why do we need to use multisensory stimulation tools to treat or respond to this problem?
(iii) Question 3: What is the innovation or novelty of using intelligent textiles as a multisensory tool?
(iv) Question 4: Why is it important for the system to be contactless?
(v) Question 5: What is special about the fact that textile is soft or tactile, and how could that benefit this purpose?
(vi) Question 6: For this project with the WTSDHC, can you share the background – how did the collaboration come about?
(vii) Question 7: How much room is there for future improvement of this product or innovation?
(viii) Question 8: Can you describe the co-design process involved in developing these wall panels?

Questions for the OT lead focused on therapeutic impact, rehabilitation value, and real-world application. These included:

(i) Question 1: How have the intelligent textiles contributed to the multisensory experiences of users in your center?
(ii) Question 2: Is it important for visitors at your center to move around?
(iii) Question 3: Do you think the changing colors and AI-driven interactions on the wall provide an effective way to stimulate or engage users?
(iv) Question 4: What are the main benefits of using this new material in a rehabilitation context?
(v) Question 5: Why do you believe this AI textile system is unique?
(vi) Question 6: From your observation, how has this design engaged users?
(vii) Question 7: In your opinion, is there a need for intelligent materials in rehabilitation practices?
(viii) Question 8: Can you describe the effects of the AI wall and the benefits it has brought to your center?

Interviews with co-designers and end-users focused on their personal engagement in the co-design process and their perceptions of usability, esthetics, and experiential value after installation. Questions for the co-designers included:

(i) Question 1: How did participating in the co-design process make you feel?
(ii) Question 2: What are your thoughts on the final design, particularly considering it incorporates features inspired by the Wong Tai Sin District?
(iii) Question 3: How do you feel about seeing your ideas manifest in the design of the illuminative panels?
(iv) Question 4: What is your impression of the installed panels in the health center, particularly regarding texture and color change?
(v) Question 5: What do you think about the gestures selected for the gesture recognition technology integrated into the panels?

(vi) Question 6: How do you feel about the customized gesture design aligning with the center's slogan?
(vii) Question 7: In what ways did you feel engaged or connected to the community through the co-design process?
(viii) Question 8: Do you believe the panels will be adopted widely? Do you think elderly users will enjoy and regularly engage with them?
(ix) Question 9: Overall, how has participating in the co-design process influenced your sense of belonging to the center and the broader community?

Questions for the end-users focused on interaction experience, intuitiveness, comfort, and social aspects of engagement with the panels and included:
(i) Question 1: How was your overall experience interacting with the illuminative panels? Did you find the activity enjoyable and the instructions clear? Was the exercise easy or difficult to follow?
(ii) Question 2: Was interaction with the panels intuitive or challenging? How did your peers respond?
(iii) Question 3: Do you anticipate regularly using the panels and engaging with them socially alongside others?
(iv) Question 4: How do you feel about the color change feature that confirms your posture or gesture is correct?
(v) Question 5: What do you think of the visual esthetics of the panels, given that they were designed based on the features of the Wong Tai Sin District?
(vi) Question 6: Have you interacted with similar technologies or used AI-driven systems before?

3.2. Design and development of a textile-based gesture recognition system

3.2.1. Illuminative fabric development

Optical fiber made with polymethyl methacrylate, whose fiber diameter is 0.25 mm, was knitted with textile-based yarns to create the illuminative fabrics. Wool yarn was chosen to provide the users a soft and comfortable hand feel when touching the fabrics. A transparent yarn made with nylon and polyester was added in the second version to improve the illuminated effect. Table 1 shows the details of the POF and yarns used for the fabric development. The knitting process was conducted on a 14-gauge computerized v-bed knitting machine, which is an industrial machine and is able to realize scalable production. To knit out the design graphics, a knit structure of doubled jacquard in three colors was utilized. The design graphics were separated into three panels. Three fabric panels were knitted, each with a size of 123 cm in width and 139 cm in height. In the first version, the jacquard structure was only knitted with wool yarns. However, the illuminated area was not apparent, so the illuminative effect of the fabric panels was not satisfactory. Therefore, a transparent yarn was added when developing the second version to highlight the illuminated area.

3.2.2. Integration of illuminative fabrics and a gesture recognition system

The gesture recognition system consists of several key components working in an integrated pipeline. An embedded camera captured real-time images of the user's hand, arm, or head in front of the textile panel. The visual input was processed by a single-board computer, which runs a deep learning model to detect 21 landmarks on the hand, as well as 33 landmarks on the shoulder and head. A self-developed algorithm interpreted these landmark data coordinates to classify specific gestures. The recognized gestures were then converted into encoded serial data, which was transmitted to a self-developed PCB incorporating an ESP32 microcontroller (Espressif Systems, China). The PCB decoded the serial signal and transformed it into a pulse width modulation (PWM) signal that controls the illumination effect of RGB LEDs embedded in the illuminative textile panel. In addition, POFs were integrated into the fabric to emit the LED light, enabling gesture-driven color changes directly on the textile surface.

To clarify and expand upon the implementation of the gesture recognition system, the system leveraged Google's MediaPipe framework, specifically the MediaPipe Hand landmarks detection and Pose landmarks detection, which are pre-trained using over 30,000 real-world labeled images covering diverse hand and body postures.[65] These models enabled the detection of 21 hand landmarks and

Table 1. Polymeric optical fiber and yarn used for the illuminative fabric development

Materials	Details
Polymethyl methacrylate polymeric optical fiber	Fiber diameter: 0.25 mm, transmission loss: 350 dB/km, temperature range: −55°C to 70°C
Wool yarn	Count: Nm 2/48; composition: 100% extra fine merino wool; care label: machine wash cold or 40°C; do not bleach; dry flat; iron at low heat
Transparent yarn	Count: Nm 1/80; composition: 55% nylon, 45% polyester; care label: machine wash cold or 30°C; do not bleach; do not tumble dry; iron at low heat

33 pose landmarks (including head and shoulder) in real time without requiring additional custom training. The system operated on a Python-based software pipeline (version 3.12) deployed on a single-board computer (Raspberry Pi 4), achieving a processing rate of approximately 5 – 7 frames per second. This frame rate satisfied the application requirement.

Regarding algorithmic transparency, gesture classification was performed through a custom rule-based algorithm that interprets the relative x- and y-coordinates of the detected landmarks. Specific gestures were classified based on thresholds of angular relationships, spatial distances between relevant anatomical points (e.g., distance from index fingertip to thumb), and limb orientation. A finite state machine governed the gesture-to-command mapping, enhancing robustness by tolerating minor variations in gesture and posture.

Concerning AI model transparency and performance evaluation, the system utilized MediaPipe's pre-trained models without additional architectural modification or retraining. Detailed information regarding network architecture, training datasets, accuracy metrics, and optimization techniques is publicly available through official MediaPipe documentation.[65] Since the study focuses on real-time system integration and user interaction rather than novel model development, quantitative benchmarking (e.g., accuracy and latency) was not the primary evaluation method. Instead, performance was assessed qualitatively through stakeholder feedback collected during co-design workshops and prototype trials conducted in actual healthcare-related contexts. This approach facilitated iterative refinement of the system based on practical usability and user-centered design principles.

4. Results and discussion

4.1. User preferences in textile materials, design graphics, and gestures

Analysis of the co-design session A revealed critical insights into how interactive textile installations can effectively engage elderly users through visual, tactile, and interactive elements. The associated interview transcript is presented in Table S1. Through systematic examination of participant responses, four distinct themes emerged that significantly influenced the final design implementation:

(i) Incorporating local landmarks for memory stimulation and therapeutic engagement: The integration of local landmarks in graphic elements emerged as a powerful catalyst for memory stimulation and therapeutic engagement. Workshop participants emphasized that "remembering the past" was "helpful to the condition," specifically highlighting the significance of incorporating familiar elements like "Lion Rock plus Lion Pavilion. plus flowers and green grass." The strategic use of "eye-catching red, yellow, colorful" elements created visually comfortable environments that facilitated connections with past experiences and community identity.

(ii) Enhancing interaction through visual recognition: Visual recognition processes emerged as a crucial factor in ensuring effective user interaction with the installation. Participant feedback revealed that "simple things, let them associate them, and they can recognize them faster by looking at pictures than by reading words." This insight demonstrated the importance of developing intuitive visual elements that users could readily identify, emphasizing how graphic recognition served as a primary pathway for engagement.

(iii) The role of material tactility in user comfort and interaction: Material tactility emerged as a fundamental consideration that shaped the physical design and user comfort levels. Workshop participants explicitly articulated that "hard objects will make you nervous," while "touch and hearing, flow and sound" elicited "strong responses." Their emphasis on the need for "relaxing" elements and "soft music" underscored how material choices directly influenced user willingness to engage with the installation.

(iv) Gamification as a strategy for sustained engagement: Interactive engagement through gamification emerged as an essential strategy for sustained user participation. Participants observed that when users "press it, find it fun," indicating that "game elements attract the elderly" and should be "interesting, not preachy." This emphasis on playful interaction revealed how carefully designed interactive elements could overcome initial hesitation and encourage active participation among elderly users.

The graphic illustration was created using Clip Studio Paint EX (version 2.0) and Adobe Photoshop CS6 (version 13), with Drafts 1 and 2 presented in Figure S1. Both drafts featured signature landmarks from the Diamond Hill and Lion Rock areas, including the Wong Tai Sin Temple, a lantern representing Lok Fu Plaza, and bamboo symbolizing nature. Draft 1 included imagery of the Wong Tai Sin Temple and a dragon, symbolizing Kowloon. However, because SKH is a Christian organization, the depiction of the Wong Tai Sin Temple was replaced in Draft 2 with representations of public housing estates, sports elements, and parks. The final design, shown in Figure 2B, emphasizes local neighborhood landmarks, including the Wong Tai Sin Cooked Food Stall and Kai Tak River. In addition, four color palettes composed of three yarn colors each were proposed for the fabric knitting process (Figure S2). The combination of beige, redwood, and blue-grey was selected by stakeholders and is shown in Figure 2C. Using this palette, three knitted fabric wall panels were fabricated and subsequently installed at the WTSDHC, as shown in Figure 2D.

4.2. Integration of illuminative fabrics into an AI-based system

Figure 3A presents a block diagram outlining the overall workflow of the gesture recognition pipeline used to drive the LED-based illumination of the textile surface. The process began with an integrated camera capturing real-time BGR images, which are sent directly to a deep learning model without being stored. The model included pre-trained hand-tracking and body pose detection networks capable of identifying 21 hand landmarks and 33 body landmarks (e.g., hands, shoulders, head) in each frame. The output is a set of landmark coordinates (x, y), which was processed by a self-developed algorithm to classify specific gestures and postures. The classified result was then converted into encoded serial data, later decoded by a custom-made PCB and transformed into PWM signals that controlled the RGB LED-based textile illumination. Figure 3B illustrates a specific example of this interaction workflow. When a user performs a "thumbs up" gesture, the camera captures the hand image, and the deep learning model identifies 21 corresponding landmark points. These landmarks – represented by their (x, y) coordinates – are analyzed by the self-developed algorithm, which identifies the gesture as "good" based on the relative positions and angles between landmark points. This classification is processed using simple state machine logic and converted into encoded serial data. The data are transmitted to the control unit, a self-developed PCB, where it is decoded and output as a PWM signal. This signal activates the appropriate LED channel, resulting in a yellow illumination on the textile surface, providing immediate visual feedback to the user. Figure 3C demonstrates the hand gesture, body, and head movement recognition.

4.3. Refinement in the textile-based gesture recognition system

The textile-based gesture recognition system was first installed at WTSDHC on June 29, 2021. After the initial installation, refinements were made to both the gesture recognition system and the three fabric wall panels to enhance the illuminative effect and expand the variation of color selection. The improved system and updated panels were reinstalled on January 22, 2025, as part of the system optimization and technical refinement phase. Transparent

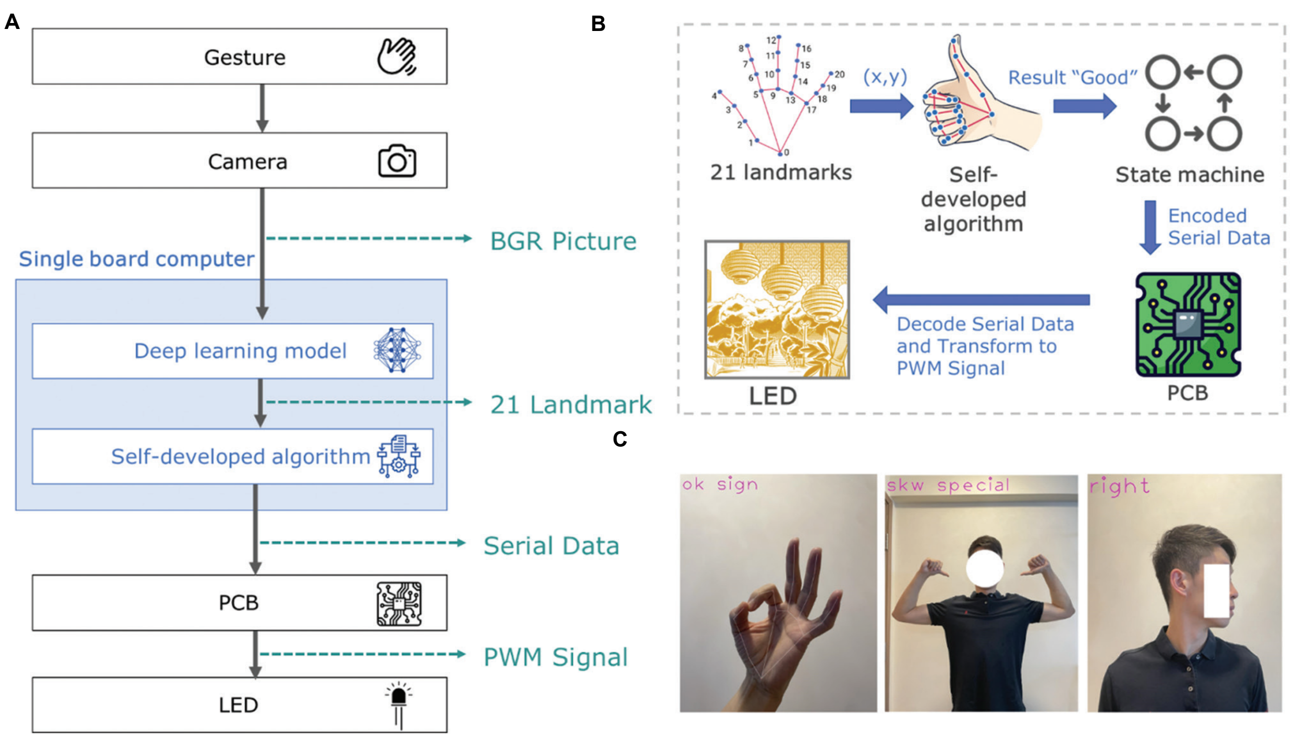

Figure 3. System architecture and workflow of the gesture recognition system. (A) Block diagram and (B) flowchart illustrating the process of the gesture recognition system. (C) Hand gesture, body, and head movement recognition.
Abbreviations: BGR: Blue, green, red; LED: Light-emitting diode; PCB: Printed circuit board; PWM: Pulse width modulation.

yarns were incorporated into the knitted structure to enhance the illuminative effect by better diffusing the emitted light across the textile surface (Figure 4A). Figure 4A shows the fabric in version A without transparent yarn, and the illuminative effect is not obvious, while the fabric in version B has transparent yarn, and the illuminative effect is apparent in the transparent parts. Furthermore, the upgraded configuration allows for a wider selection of color responses, enabling finer-tuned visual feedback in response to various gesture inputs. In Version 1, color output was restricted to basic RGB channels supporting only seven pre-defined colors (combinations of red, green, and blue at either 0 or 255 nm), as shown in Figure 4B. In contrast, Version 2 enables full-spectrum color control by allowing each RGB channel to range from 0 to 255 nm, resulting in up to 16,777,215 possible color combinations (Figure 4C).

In both the initial and advanced prototypes, the gesture recognition system was integrated into textile

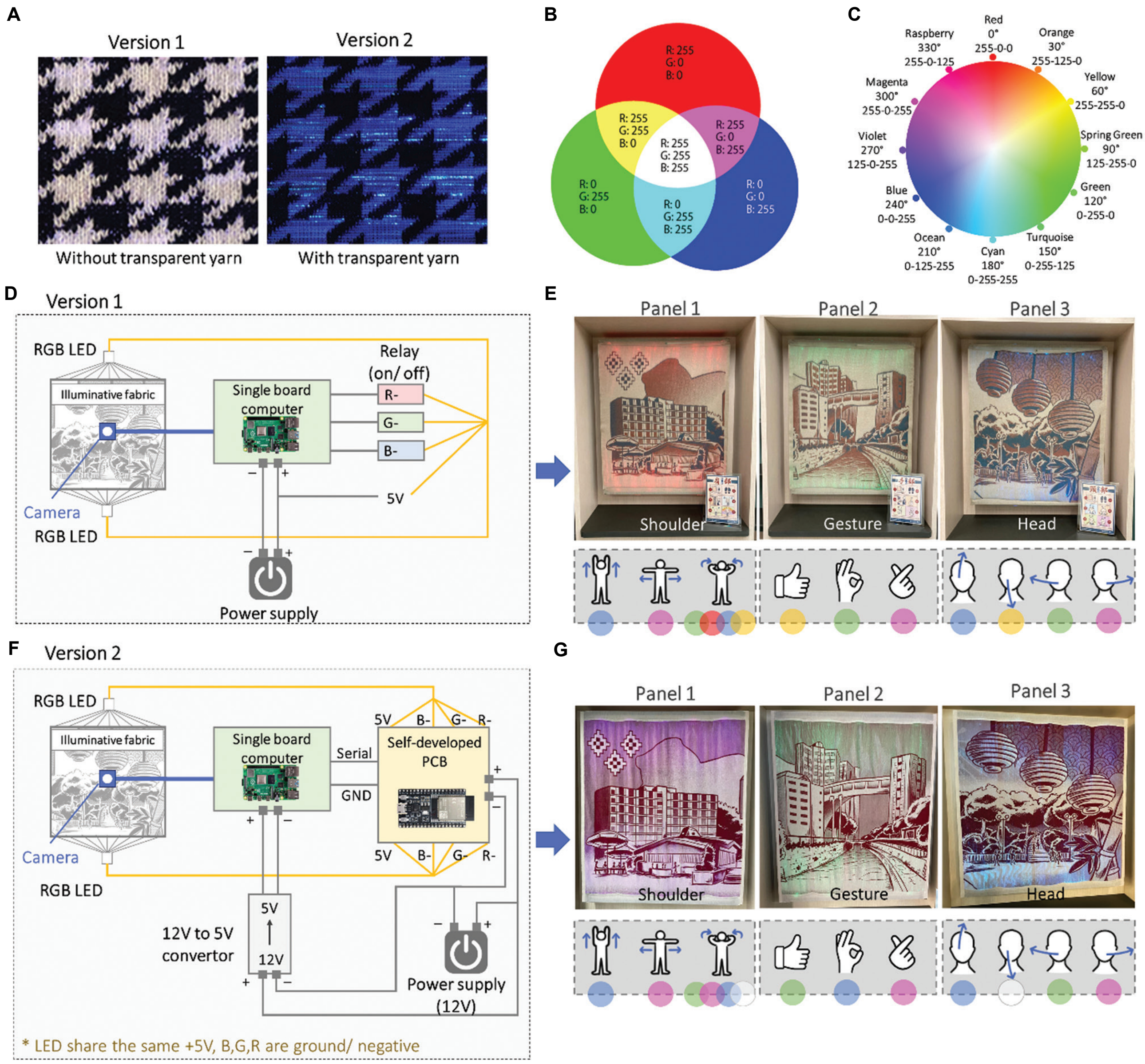

Figure 4. Light-emitting diode (LED) color configuration and system architecture of the textile-based gesture recognition panels. (A) Photos showing the illumination effects in wall panels for the first prototype (Version 1) and the advanced version (Version 2). LED color mapping in wall panels for (B) Version 1 and (C) Version 2. (D) Conceptual diagram illustrating the connection structure of the gesture recognition system in Version 1 and (E) Version 2. (F and G) Photos demonstrating different illumination colors in response to various gestures in Version 1 and Version 2, respectively.

wall panels that were knitted with POFs and embedded with RGB LEDs to enable illumination. These fibers guide emitted light across the textile surface, emitting the LED output and transforming it into soft, color-based visual feedback. In the first prototype (Version 1) shown in Figure 4D, the response system was relatively simple: Classified gesture data were sent from the Raspberry Pi to a basic relay switch connected to the RGB LEDs. This setup allowed the system to turn different colored light channels on or off based on the detected gesture or body posture, directly illuminating the textile surface in specific colors corresponding to each gesture and posture type. In the advanced version (Version 2) shown in Figure 4F, a more modular and intelligent infrastructure was implemented. The system included a self-developed PCB built around an ESP32 microcontroller, which decodes serial input from the single-board computer and distributes PWM signals to the RGB LEDs. The advanced system also supports potential Internet of Things applications, while simplifying hardware integration and improving system stability and responsiveness. The RGB LEDs, embedded along the edges of the textile panel and optically coupled through POFs, share a common +5V power source. Control signals (R, G, B) were adjusted through the PCB using serial data inputs processed by a state machine methodology, ensuring synchronized responses with gesture inputs. A unified 12V power supply supported all electronic components within the system, delivering power directly to the custom PCB and to a voltage converter that steps down the current to 5V for the single-board computer. This centralized power configuration ensures a compact, efficient, and easily maintainable setup, well-suited for integration in healthcare environments. Figure 4E and G show the color differences corresponding to various gestures and body movements in the fabric wall panels for Version 1 and Version 2, respectively. In Version 1, the left wall panel was designed to respond to shoulder movements. The illumination changed to blue, pink, and a dynamic “jumping” color effect when the system recognized the gestures “hands up,” “open arms,” and the WTSDHC slogan gesture “My Health, My Say!” performed by pointing to oneself, respectively. The middle panel was dedicated to hand gesture recognition, with color changes of yellow, blue, and pink corresponding to the gestures “good,” “OK,” and “love.” The right panel was designed for head and neck movements; when the user turned their head “up,” “down,” “left,” or “right,” the textile illumination changed accordingly to blue, yellow, green, and pink. Figure S3 illustrates the infographic interaction with the illuminative fabric wall panels through (a) shoulder, (b) hand, and (c) head movements, respectively.

The integration of illuminative fabric into an AI-driven gesture recognition system creates a novel multi-sensory and contactless interaction platform, specifically aimed at promoting engagement, exercise, and therapy in healthcare settings. From a design and engineering perspective, the knitted POF fabric served both esthetic and functional goals by emitting programmable RGB light in response to validated gestures. This visual feedback mechanism – subtle, localized, and dynamic – provided a soft and non-intrusive way for users, particularly elderly individuals, to interact with therapy-driven content. The iterative transition from the first prototype, which relied on basic relay control, to an advanced custom-made PCB solution demonstrates the scalability of the design. The upgraded use of an ESP32 controller introduced advanced data handling, reduced latency, and allowed greater precision over RGB transitions, thereby enabling alignment with the AI model and optimizing the best color combinations across different panel designs and illumination patterns. This technical refinement enhanced the responsivity and fluidity of the textile interface, making the system feel more intuitive and responsive to natural body movement. Furthermore, the edge-mounted RGB LEDs, optically coupled to the textile through POFs, enabled a contactless yet emotionally resonant interaction method, particularly valuable in post-pandemic healthcare environments focused on hygiene and psychological comfort. The textile’s ability to visually signify correct gestures with soft illuminations empowers elderly users through instant feedback, supporting self-guided physical and cognitive rehabilitation. Overall, this integration not only reinforces the practicality of smart textiles for ambient healthcare but also demonstrates how co-designed, AI-enhanced systems can drive inclusive and meaningful experiences in spatial interaction, particularly for vulnerable populations.

4.4. System validity and privacy considerations

To support real-world deployment in healthcare contexts, the design and implementation of the gesture recognition system deliberately accounted for environmental factors such as lighting conditions and gesture visibility. While no quantitative accuracy metrics were recorded at this stage, system latency was monitored through built-in software timers, which counted frame-processing loops based on timestamp differences. The average processing rate was approximately 5 – 7 times per second, confirming operational responsiveness suitable for real-time interaction. During participatory co-design workshops, the viewing angle and lighting conditions were thoroughly discussed with stakeholders. Based on this input, the optimal interaction distance was standardized at approximately 1 meter, with lighting conditions kept consistent to ensure gesture reliability, thus reducing variation due to angle or environmental brightness. Although false positives were not formally measured, gesture set definitions were refined collaboratively with users to minimize misrecognition. Only movements that were clearly distinguishable in both posture and motion were selected as trigger gestures. This co-design-driven filtering process effectively reduced the risk of unintended activations.

Regarding privacy and ethical considerations, the image-capturing software does not include any recording or data storage functions. Images captured by the camera are processed in real time for landmark detection and are continuously overwritten with the next frame. No visual data are stored locally or remotely, and all content is deleted immediately upon device shutdown. As the textile panels are designed for use in public or semi-public spaces (such as DHC), where CCTV systems are already in operation, and the use of non-recording cameras falls within acceptable practices. Nonetheless, privacy concerns were considered during the design phase, and the current system meets ethical expectations for deployment in environments frequented by elderly users and vulnerable groups.

4.5. Stakeholders' feedback

Co-designers' feedback (co-design session C) highlighted multiple significant advantages of integrating textile wall panels with the gesture recognition system. Table 2 summarizes the stakeholders' feedback during the pre- and post-design stages of the co-design process. Co-designers A and B contributed essential community insights that directly informed the integration of familiar local landmarks into the design. This incorporation notably enhanced emotional engagement, strengthened community identity, and improved user connectivity. Their recommendations underscored the importance of visual familiarity, with participants expressing a strong emotional resonance rooted in their personal histories and lifelong proximity to landmarks, such as Lion Rock. Users A and B consistently reported high levels of comfort, positively evaluating the system's ease of access and intuitive interactions. They particularly praised the soft and approachable materials, noting their pleasant tactile qualities, which significantly contributed to overall user satisfaction and engagement. In addition, users emphasized the system's inclusive nature, highlighting how effectively the design accommodated diverse physical abilities and age groups. The OT lead (co-design session B) reported improvements in therapeutic outcomes, specifically noting the system's effectiveness in enhancing rehabilitation processes. They acknowledged that the integration of diverse technologies and intelligent solutions substantially increased rehabilitation efficiency and operational performance. Furthermore, OTs emphasized the system's high level of accessibility and intuitive usability across a broad demographic, supporting user within the age range of 6 to over 80 years old. A detailed summary of stakeholder feedback is presented in Table S2 for the research lead, Table S3 for the OT lead, Table S4 for co-designers, and Table S5 for the end-users. Complete transcripts of stakeholder interviews are included in the supplementary materials to ensure comprehensive documentation and research transparency.

The participatory design approach effectively engaged stakeholders through structured activities and semi-structured discussions, capturing precise community insights and user preferences that informed the systematic refinement of technical parameters. These structured interactions enabled stakeholders to articulate specific needs clearly, contributing significantly to the development process. Content analysis of interview data further identified clear, recurrent themes that were translated into actionable design criteria, emphasizing user-driven

Table 2. Stakeholders' feedback in pre- and post-stages of the co-design process

Design aspect	Co-design workshop input (2021)	Post-implementation feedback (2023 – 2024)
Community integration	• Emphasis on incorporating district landmarks and natural elements • Recognition of local cultural significance • Strong advocacy for familiar environmental elements	• Strong emotional connection to implemented landmarks • Enhanced sense of community identity • Effective integration of neighborhood characteristics
Material and interface	• Preference for soft, non-threatening materials • Emphasis on multi-sensory engagement • Identification of relaxation as a key design priority	• Positive user response to textile-based interfaces • Effective implementation of a gesture recognition system • Enhanced operational effectiveness in center activities
Visual design	• Prioritization of pictorial over textual elements • Recommendation for vibrant, age-appropriate color schemes • Focus on intuitive visual recognition	• High user comprehension rates • Effective visual communication strategy • Effective age-appropriate design implementation
User engagement	• Emphasis on gamification elements • Focus on enjoyment-driven interaction • Recommendation for a non-didactic approach	• High accessibility across age groups • Widespread user adoption • Effective integration into the center's daily operation

product development and iterative improvement. Stakeholders consistently expressed appreciation for the opportunity to contribute directly to the design process, reinforcing the perceived value of their participation.

The interactive textile wall panels significantly promoted physical engagement among elderly visitors by integrating intuitive, playful gesture recognition interactions rather than explicit instructional methods. By emphasizing an enjoyment-driven, non-didactic approach, the installation effectively facilitated greater acceptance and consistent use among elderly users, who frequently exhibit resistance to more traditional, overtly instructional exercise interventions. This approach effectively aligned with healthcare objectives by encouraging physical activity in a non-intrusive, enjoyable manner, thus fostering a more sustainable integration of exercise into daily routines.

Technologically, the system implemented a user-friendly gesture recognition interface allowing elderly users to interact effortlessly with illuminative knitted textiles, customizing colors and illumination without specialized technical knowledge. This ease of use substantially lowered barriers to technology adoption among elderly populations, who might otherwise find digital interactions challenging. A noteworthy technical enhancement included the development of a customized wooden frame specifically designed to optimize the illumination effectiveness of POF under regular lighting conditions. This improvement demonstrates an iterative and responsive problem-solving process, reflecting a robust commitment to addressing real-world operational challenges encountered during the development and deployment phases.

Expert participation provided academic insights and specialized technical expertise throughout the project, effectively combining established technological capabilities with stakeholder-driven esthetics and functional requirements. Experts' contributions ensured that the system was both scientifically robust and contextually appropriate, bridging theoretical knowledge and practical application seamlessly. The semi-structured virtual interviews conducted with stakeholders yielded rich, detailed qualitative insights, further ensuring that the final design effectively responded to user requirements and preferences. The systematic approach to collecting and analyzing qualitative data allowed for targeted refinements, ultimately achieving strong operational integration within the healthcare facility's daily practices and demonstrating improvements in user engagement and therapeutic outcomes.

5. Limitations and future work

The illumination effect of POF tends to weaken in well-lit environments, posing challenges for healthcare settings where bright lighting is essential. To compensate, a customized wooden frame was used to extend shadows and enhance visibility. This solution proved effective in improving the illuminative performance of the textile in this study; however, it may introduce venue restrictions and limit the flexibility of POF textile installations in certain scenarios. Therefore, future development should focus on miniaturizing panel sizes to support more diverse applications. Smaller POF textiles could enable the creation of portable therapeutic tools beyond fixed installations. Refining gesture recognition algorithms to improve responsiveness, particularly for users with limited mobility, is another priority. In addition, integrating the system with educational programs, digital applications, and interactive public spaces could further expand the technology's potential beyond healthcare environments.

Regarding the improvement in engagement and rehabilitation outcomes, findings at this early stage are based on qualitative user feedback collected during co-design workshops and preliminary trials. Due to time constraints and limited participant availability, no structured quantitative assessment of engagement levels or rehabilitation outcomes was conducted. The feedback gathered was used primarily to guide iterative design decisions and to evaluate initial system usability. Future work will incorporate standardized evaluation metrics and longitudinal studies to assess engagement and therapeutic impact more rigorously in real-world healthcare environments. While the initial user feedback during workshops and trials was largely positive, it is acknowledged that early-phase co-design processes inherently involve practical trade-offs. The limited duration and resources available for subject recruitment restricted the possibility of broader testing and capturing a more diverse range of inputs. Future iterations will aim to incorporate longer-term engagement and structured usability metrics that reflect both positive and critical experiences to achieve a more comprehensive understanding of the system's impact and adoption potential.

In addition, future work could explore the integration of new multimodal deep learning models, such as large language models and video language models, to capture complex human gestures through face and body pose analysis, as well as voice or sound recognition.[66] This would enhance the system's ability to interpret multi-sensory input, opening new possibilities for richer human-computer interaction. It would also be valuable to personalize textile responses by incorporating real-time emotional analysis through facial recognition and physiological signals. For example, systems such as Irida Health offer pathways for combining gesture evaluation with affective computing, which may enrich the user experience and enable more human-centered therapeutic applications.[67,68]

6. Conclusion

This study presents a human-centered co-design approach to the design, development, and implementation of an AI-integrated gesture recognition system embedded in illuminative textile wall panels, aimed at enhancing spatial engagement in a healthcare setting. The findings demonstrate the effectiveness of the gesture-based illumination system, which provides immediate visual feedback through colored illuminations while accommodating ambidextrous gestures. Key contributions of the study include:

(i) Human-centered co-design and cultural integration: The study employed a co-design approach involving users, therapists, and stakeholders to develop an AI-integrated textile system. Workshops revealed preferences for soft materials, pictorial cues over text, and culturally significant graphic elements, aiming to create intuitive and emotionally resonant interactions, especially for elderly users.

(ii) AI and textile system development: Illuminative textile wall panels were fabricated using POF-knitted fabrics integrated with a computer vision-based deep learning model for gesture recognition. Two workflow configurations were proposed; enabling color-changing feedback based on hand movements. The system supports ambidextrous gestures and provides real-time, interactive visual feedback.

(iii) Real-world implementation and impact: The prototypes were installed in a DHC to promote elderly physical activity and engagement. Stakeholder feedback confirmed high usability, accessibility, and emotional connection to the design. The research demonstrates the potential of AI-driven textile interfaces in healthcare, offering a scalable model for creating responsive, human-centered environments.

In conclusion, this research offers insights into the fabrication of a textile-based gesture recognition system through a co-design framework. The design features demonstrated a seamless integration of AI tools into daily life and healthcare interventions, particularly benefiting elderly users. This study lays the groundwork for further exploration into textile-based AI systems in interactive environments and provides practical guidance for healthcare administrators planning similar installations. The integration of intelligent textiles into healthcare spaces represents a vital step toward creating responsive, engaging, and human-centered environments that align technological innovation with human needs.

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Conflict of interest

Jeanne Tan is an Editorial Board Member of this journal, but was not in any way involved in the editorial and peer-review process conducted for this paper, directly or indirectly. Separately, other authors declared that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

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Writing – original draft: Jeanne Tan, Ching Lee
Writing – review & editing: Jeanne Tan, Ching Lee, Hiu Ting Tang, Wing Ki Yip, Ka Wing Tse

Ethics approval and consent to participate

The study received ethical approval from the Hong Kong Polytechnic University's Institutional Review Board (Approval no.: HSEARS20200123003). All participants provided informed consent before the commencement of the interviews.

Consent for publication

Written informed consent for publication of the data was obtained from all participants involved in the study.

Availability of data

Data used in this work are available from the corresponding author upon reasonable request.

References

1. Islam S, Shekhar R. *Smart Textiles and Wearable Technology: Opportunities and Challenges in the Production and Distribution*. Singapore: Springer Nature; 2025. p. 267-303.
2. Scataglini S, Moorhead A, Feletti F. A systematic review of

smart clothing in sports: Possible applications to extreme sports. *Muscles Ligaments Tendons J*. 2020;10(2):333-342.

doi: 10.32098/MLTJ.02.2020.19

3. Wang C, Fu L, Ametefe DS, Wang S, John D. E-textiles in healthcare: A systematic literature review of wearable technologies for monitoring and enhancing human health. *Neural Comput Appl*. 2025;37(4):2089-2111.

   doi: 10.1007/s00521-024-10947-z

4. Sajovic I, Kert M, Boh PB. Smart textiles: A review and bibliometric mapping. *Appl Sci*. 2023;13(18):10489.

   doi: 10.3390/app131810489

5. Shajari S, Kuruvinashetti K, Komeili A, Sundararaj U. The emergence of ai-based wearable sensors for digital health technology: A review. *Sensors (Basel)*. 2023;23(23):9498.

   doi: 10.3390/s23239498

6. Sarker MTH, Ahmed I, Rahaman MA. Ai-based smart textile wearables for remote health surveillance and critical emergency alerts: A systematic literature review. *Am J Scholarly Res Innov*. 2023;2(2):1-29.

   doi: 10.63125/ceqapd08

7. Yadav A, Yadav K. Transforming healthcare and fitness with AI powered next-generation smart clothing. *Discov Electrochem*. 2025;2(1):2.

   doi: 10.1007/s44373-025-00015-z

8. Avellar L, Stefano FC, Delgado G, Frizera A, Rocon E, Leal JA. AI-enabled photonic smart garment for movement analysis. *Sci Rep*. 2022;12(1):4067.

   doi: 10.1038/s41598-022-08048-9

9. Akter A, Apu MMH, Veeranki YR, Baroud TN, Posada-Quintero HF. Recent studies on smart textile-based wearable sweat sensors for medical monitoring: A systematic review. *J Sens Actuator Netw*. 2024;13(4):40.

   doi: 10.3390/jsan13040040

10. Tan J, Shao L, Lam NYK, Toomey A, Ge L. Intelligent textiles: Designing a gesture-controlled illuminated textile based on computer vision. *Text Res J*. 2022;92(17-18):3034-3048.

    doi: 10.1177/00405175211034245

11. World Health Organization. *Decade of Healthy Ageing: Baseline Report*. Geneva, Switzerland: World Health Organization; 2021.

12. Department of Economic and Social Affairs, United Nations. *World Population Prospects*. New York, NY: United Nations; 2019.

13. Committee on the Future Health Care Workforce for Older Americans. *Retooling for an Aging America: Building the Health Care Workforce*. Washington, DC: National Academies Press; 2008.

14. Shah MN, Bazarian JJ, Lerner EB, *et al*. The epidemiology of emergency medical services use by older adults: An analysis of the national hospital ambulatory medical care survey. *Acad Emerg Med*. 2007;14(5):441-447.

    doi: 10.1111/j.1553-2712.2007.tb01804.x

15. United Nations Economic and Social Commission for Asia and the Pacific (UN ESCAP). *Asia-Pacific Report on Population Ageing 2022: Trends, Policies and Good Practices Regarding Older Persons and Population Ageing*. Bangkok, Thailand: UN ESCAP; 2022.

16. United Nations Department of Economic and Social Affairs (UN DESA). *Countries Forecast to Have the Highest Share of 65-Year-Old People Worldwide in 2050*. New York, NY: UN DESA; 2023.

17. Wilmoth JR, Bas D, Mukherjee S, Hanif N. *World Social Report: Leaving no One Behind in an Ageing World*. New York, NY: United Nations; 2023.

18. McClellan CB. Health care utilization and expenditures in health professional shortage areas. *Med Care Res Rev*. 2024;81(4):335-345.

    doi: 10.1177/10775587241235705

19. Research Office, Legislative Council Secretariat. *The 2025-2026 Budget*. Hong Kong: Legislative Council; 2025.

20. Wu X, Law CK, Yip PSF. A projection of future hospitalisation needs in a rapidly ageing society: A Hong Kong experience. *Int J Environ Res Public Health*. 2019;16(3):473.

    doi: 10.3390/ijerph16030473

21. Choy R. Implementation of community care policy for older adults in Hong Kong. In: Law VTS, Fong BYF, editors. *Ageing with Dignity in Hong Kong and Asia: Holistic and Humanistic Care*. Ch. 3. Singapore: Springer Nature Singapore; 2022.

22. Government of the Hong Kong Special Administrative Region (HKSAR). LCQ11: District Health Centres and District Health Centre Expresses. Press Releases from the Government of the Hong Kong Special Administrative Region. Available from: https://www.info.gov.hk/gia/general/202403/27/P2024032700591.htm [Last accessed on 2024 Apr 25].

23. *Wong Tai Sin District Health Centre, Key functions and features of DHC*. Available from: https://www.dhc.gov.hk/en/healthcare-service-providers.html#key-functions-and-features-of-dhc [Last accessed on 2024 Apr 25].

24. Ta AWA, Goh HL, Ang C, Koh LY, Poon K, Miller SM. Two Singapore public healthcare AI applications for national screening programs and other examples. *Health Care Sci*. 2022;1(2):41-57.

    doi: 10.1002/hcs2.10

25. Ang A. *Behind Singapore's Widespread AI Adoption in Public Health*. Healthc IT News. Available from: https://www.healthcareitnews.com/news/asia/behind-singapores-widespread-ai-adoption-public-health [Last accessed on

2024 Apr 25].

26. Raghavan A, Demircioglu MA, Taeihagh A. Public health innovation through cloud adoption: A comparative analysis of drivers and barriers in Japan, South Korea, and Singapore. *Int J Environ Res Public Health*. 2021;18(1):334.

    doi: 10.3390/ijerph18010334

27. Wright J. Inside Japan's long experiment in automating elder care. *MIT Technol Rev.* [Internet]. 2023. Available from: https://www.technologyreview.com/2023/01/09/1065135/japan-automating-eldercare-robots [Last accessed 2024 Apr 25].

28. Li LW, Ma CC. Application of AI in addressing challenges of primary healthcare in Hong Kong. In: *Ageing with Dignity in Hong Kong and Asia: Holistic and Humanistic Care*. Singapore: *Springer Nature Singapore*; 2025. p. 589-609.

29. Legislative Council. *Promotion of Smart Healthcare in Selected Places*. Hong Kong: Legislative Council; 2022.

30. Köttl H, Gallistl V, Rohner R, Ayalon L. But at the age of 85? Forget it!: Internalized ageism, a barrier to technology use. *J Aging Stud*. 2021;59:100971.

    doi: 10.1016/j.jaging.2021.100971

31. Zhang J, Wang H, Li Q, Luximon Y. What is the real-life experience of older adults on smart healthcare technologies? An exploratory interview study. *Gerontology*. 2024;70(9):978-990.

    doi: 10.1159/000539539

32. Millward P. The'grey digital divide': Perception, exclusion and barriers of access to the internet for older people. First Monday. Available from: https://firstmonday.org/ojs/index.php/fm/article/view/1066 [Last accessed on 2024 Apr 25].

33. Rice RE, Katz JE. Comparing internet and mobile phone usage: Digital divides of usage, adoption, and dropouts. *Telecomm Policy*. 2003;27(8-9): 597-623.

    doi: 10.1016/S0308-5961(03)00068-5

34. Brown T. Design thinking. *Harv Bus Rev.* 2008;86(6):84-92.

35. Sanders EBN, Stappers PJ. Co-creation and the new landscapes of design. *CoDesign*. 2008;4(1):5-18.

    doi: 10.1080/15710880701875068

36. Steen M, Manschot M, De KN. Benefits of co-design in service design projects. *Int J Des*. 2011;5(2):53-60.

37. Bate P, Robert G. Experience-based design: from redesigning the system around the patient to co-designing services with the patient. *Qual Saf Health Care*. 2006;15(5):307-310.

    doi: 10.1136/qshc.2005.016527

38. Robert G, Cornwell J, Locock L, Purushotham A, Sturmey G, Gager M. Patients and staff as codesigners of healthcare services. *BMJ*. 2015;350:g7741.

    doi: 10.1136/bmj.g7714

39. Locock L, Robert G, Boaz A, *et al*. Testing accelerated experience-based co-design: A qualitative study of using a national archive of patient experience narrative interviews to promote rapid patient-centred service improvement. *Health Serv Deliv Res*. 2014;2(4):1-122.

    doi: 10.3310/hsdr02040

40. Norman DA, Verganti R. Incremental and radical innovation: Design research vs. Technology and meaning change. *Des Issues*. 2014;30(1):78-96.

    doi: 10.1162/desi-a-00250

41. Rafael S, Santiago E, Rebelo F, Noriega P, Vilar E. Bio-centred interaction design: A new paradigm for human-system interaction. In: *International Conference on Human-Computer Interaction*. Cham: Springer International Publishing; 2022. p. 69-79.

42. Woods B, O'Philbin L, Farrell EM, Spector AE, Orrell M. Reminiscence therapy for dementia. *Cochrane Database Syst Rev.* 2018;2018(3):CD001120.

    doi: 10.1002/14651858.cd001120.pub3

43. Lazar A, Demiris G, Thompson HJ. Evaluation of a multifunctional technology system in a memory care unit: Opportunities for innovation in dementia care. *Inform Health Soc Care*. 2016;41(4):373-386.

    doi: 10.3109/17538157.2015.1064428

44. Poupyrev I, Gong NW, Fukuhara S, Karagozler ME, Schwesig C, Robinson KE. Project jacquard: Interactive digital textiles at scale. In: *Proceedings of the 2016 Chi Conference on Human Factors in Computing Systems*. New York: Association for Computing Machinery; 2016. p. 4216-4227

45. Gorka R, Subramaniyan AK, Velu R. Integrating advanced technologies in post-operative rehabilitation: 3D-knitting, 3D-printed electronics, and sensor-embedded textiles. In: Zheng Y, Chow H, editors. *Digital Health Innovation*. Ch. 10. Singapore: Springer Nature; 2023.

46. Caldani L, Pacelli M, Farina D, Paradiso R. E-Textile platforms for rehabilitation. In: *2010 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Piscataway, NJ: IEEE; 2010. p. 5181-5184.

47. Meena JS, Choi SB, Jung SB, Kim JW. Electronic textiles: New age of wearable technology for healthcare and fitness solutions. *Mater Today Bio.* 2023;19:100565.

    doi: 10.1016/j.mtbio.2023.100565

48. Khatwani P, Desai K. Interactive smart textile fabrics. Interactive smart textile fabrics. In: *Functional and Technical Textiles.* United Kingdom: Woodhead Publishing; 2023. p. 293-311.

49. Bai ZQ, Tan J, Johnston CF, Tao XM. Connexion development of interactive soft furnishings with polymeric optical fibre (POF) textiles. *Int J Cloth Sci Technol.* 2015;27(6):870-894.

    doi: 10.1108/IJCST-05-2014-0058

50. Cochrane C, Mordon SR, Lesage JC, Koncar V. New design of textile light diffusers for photodynamic therapy. *Mater Sci Eng C Mater Biol Appl*. 2013;33(3):1170-1175.

doi: 10.1016/j.msec.2012.12.007

51. Schrank V, Beer M, Beckers M, Gries T. Polymer-optical fibre (POF) integration into textile fabric structures. In: *Polymer Optical Fibres*. United Kingdom: Woodhead Publishing; 2017. p. 337-348.

52. Avellar L, Frizera A, Leal JA. POF smart pants: A fully portable optical fiber-integrated smart textile for remote monitoring of lower limb biomechanics. *Biomed Opt Express*. 2023;14(7):3689-3704.

doi: 10.1364/BOE.492796

53. Gong Z, Xiang Z, OuYang X, *et al*. Wearable fiber optic technology based on smart textile: A review. *Materials*. 2019;12(20):3311.

doi: 10.3390/ma12203311

54. Tan J, Shao L, Lam NYK, *et al*. Evaluating the usability of a prototype gesture-controlled illuminative textile. *J Text Inst*. 2024;115(3):350-356.

doi: 10.1080/00405000.2023.2193790

55. Lam NYK, Tan J, Toomey A, Cheuk KCJ. Illuminative knitted textiles: Machine knitting with polymeric optical fibres (POFs). *Res J Text Appare*. 2024;28(2):317-335.

doi: 10.1108/RJTA-12-2021-0144

56. Chen A, Tan J, Henry P, Tao X. The design and development of an illuminated polymeric optical fibre (POF) knitted garment. *J Text Inst*. 2020;111(5):745-755.

doi: 10.1080/00405000.2019.1661937

57. Tam EY, Chi CM. The hong kong geriatrics society annual scientific meeting 2024. *Asian J Gerontol Geriatr*. 2024;19(2):50-51.

58. Park M, Park T, Park S, Yoon SJ, Koo SH, Park YL. Stretchable glove for accurate and robust hand pose reconstruction based on comprehensive motion data. *Nat Commun*. 2024;15(1):5821.

doi: 10.1038/s41467-024-50101-w

59. Glauser O, Wu S, Panozzo D, Hilliges O, Sorkine-Hornung O. Interactive hand pose estimation using a stretch-sensing soft glove. *ACM Trans Graph*. 2019;38(4):162.

doi: 10.1145/3306346.3322957

60. Panagiotou C, Faliagka E, Antonopoulos CP, Voros N. Multidisciplinary ML techniques on gesture recognition for people with disabilities in a smart home environment. *AI*. 2025;6(1):17.

doi: 10.3390/ai6010017

61. Guo K, Orban M, Lu J, Al-Quraishi MS, Yang H, Elsamanty M. Empowering hand rehabilitation with AI-powered gesture recognition: A study of an sEMG-based system. *Bioengineering (Basel)*. 2023;10(5):557.

doi: 10.3390/bioengineering10050557

62. Oudah M, Al-Naji A, Chahl J. Elderly care based on hand gestures using kinect sensor. *Computers*. 2020;10(1):5.

doi: 10.3390/computers10010005

63. Munoz NM, Kristoffersen MB, Sunnerhagen KS, Naber A, Alt MM, Ortiz CM. Upper limb stroke rehabilitation using surface electromyography: A systematic review and meta-analysis. *Front Hum Neurosci*. 2022;16:897870.

doi: 10.3389/fnhum.2022.897870

64. Jaramillo YA, Benalcázar ME, Mena ME. Real-time hand gesture recognition using surface electromyography and machine learning: A systematic literature review. *Sensors (Basel)*. 2020;20(9):2467.

doi: 10.3390/s20092467

65. MediaPipe. *MediaPipe - Hand Landmarker and Pose Landmarker*. Google AI; 2023. Available from https://ai.google.dev/edge/mediapipe/solutions/vision/hand-landmarker [Last accessed on 2024 Apr 28].

66. Anthropic. *Claude: Helpful, Honest, and Harmless AI Assistant*. Anthropic Website; 2023. Available from: https://www.anthropic.com [Last accessed on 2024 Apr 27].

67. IRIDA. *IRIDA Project - AI-Driven Mental Health Support Platform*. IRIDA Website; 2023. Available from: https://irida.health [last accessed on 2024 Apr 27].

68. Koulieris GA, Kannengiesser N, Noristani A. Affect recognition through multimodal fusion of face, body pose, and physiological data using deep learning. *Neurocomputing*. 2023;540:127171.

doi: 10.1016/j.neucom.2023.127171