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Research on a Multimodal Intelligent Dressing System and Digital Age-Friendly Design Based on Natural Behavior Theory

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Abstract

INTRODUCTION: With global population aging, everyday dressing decisions for older adults have evolved from simple garment choices into complex tasks that must simultaneously satisfy health, safety, social etiquette, and subjective comfort constraints. Experience-based and intuitive dressing strategies struggle to cope with rapidly changing weather, fluctuating health conditions, and frequent switches between daily events, often leading to misalignment between clothing choices and healthy aging goals.
OBJECTIVES: This study proposes an intelligent dressing recommendation system for older adults based on natural behavior theory. The system adopts a WEHT (Wearable–Event–Health–Thermal environment) situational modeling framework and multimodal data fusion to provide safe, comfortable, socially appropriate, and easy-to-understand dressing recommendations within a digital age-friendly design context.
METHODS: The system constructs an elderly-oriented clothing knowledge graph and functional matrix, and fuses multimodal inputs including weather indices, individual health constraints, and calendar events. A cross-modal attention mechanism with adaptive weights is introduced to capture direct and indirect couplings among clothing, events, health status, and thermal environment. Under a predefined hierarchical decision rule that prioritizes health and safety, the system employs multi-objective optimization and fuzzy rules to generate explainable and executable dressing plans. Recommendations are presented through natural interactions combining large graphical icons, step-by-step guidance, and voice prompts. A user study with 100 participants aged ≥65 years was conducted, including usability testing and controlled comparison with traditional self-decision dressing. Outcome measures covered health risk avoidance, scenario adaptation accuracy, decision time, and subjective satisfaction.
RESULTS: Compared with the traditional experience-based dressing strategy, the proposed system significantly improved health risk avoidance and scenario adaptation accuracy, shortened dressing decision time, and increased subjective satisfaction across multiple scenarios. Older participants were able to understand and follow the system's recommendations with relatively low cognitive load, benefiting especially in complex or health-sensitive situations.
CONCLUSION: This study integrates natural behavior theory with multimodal intelligent algorithms under a digital age-friendly design paradigm, and proposes a "behavior–context–environment coupling" human–AI co-decision framework for intelligent dressing. The results demonstrate that the WEHT-based multimodal dressing support system can effectively enhance safety, comfort, and contextual appropriateness of clothing decisions for older adults, while providing a theoretically grounded and practically feasible pathway for intelligent life-assistance systems in healthy aging.

Keywords: Natural Behavior Theory, Multimodal Data Fusion, Intelligent Dressing System, Digital Age-Friendly Design, Human–Computer Interaction

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1. Introduction

Against the backdrop of an aging society, older adults' everyday dressing has evolved from a "simple choice of garments" into a complex decision-making process involving health, safety, social interaction, and dignity. On the one hand, they need appropriate clothing to maintain stable body temperature, reduce cardiovascular burden, and prevent joint chill and skin damage [1]. On the other hand, they must remain decent and comfortable in diverse situations such as medical visits, travel, and family gatherings, while also addressing specific needs such as ease of donning and doffing and fall prevention. Traditional dressing practices that rely on personal experience and subjective feelings struggle to simultaneously handle multidimensional and dynamic factors such as sudden weather changes, fluctuations in health status, and variations in daily schedules. As a result, it is easy to "wear too little," "wear the wrong thing," or "dress inappropriately for the occasion," thereby increasing health risks and everyday difficulties.

In recent years, digital technologies and pervasive health systems have increasingly permeated older adults' daily lives. The field of Human–Computer Interaction (HCI) has gradually shifted from a narrow focus on "accessibility" to a broader "digital age-friendly" perspective that emphasizes autonomy, dignity, and a sense of participation [2-6]. Meanwhile, systems that integrate weather data and situational information have begun to provide dressing suggestions based on factors such as temperature, humidity, and wind speed [7]. However, this body of work largely centers on fashion consumption and general user scenarios, and rarely incorporates weather–event–health as key dimensions within a unified modeling framework from the perspective of healthy aging. Even more lacking are theoretical responses to older adults' natural behavior patterns themselves.

Natural behavior theory emphasizes that human behavior is a "perception–cognition–action" loop that emerges naturally from the joint influence of environmental constraints and bodily states. It is the result of continuous perception, judgment, and regulation of physiological and environmental information. Older adults' dressing behavior likewise manifests as natural regulation across climate, bodily sensation, and event context [8-13]. If intelligent systems fail to understand and respect this coupling logic among behavior, context, and environment, their recommendations are likely to feel "out of touch with real life," thereby reducing willingness to use and long-term adherence.

In response, this paper combines natural behavior theory with multimodal intelligent algorithms and proposes a WEHT (Wearable–Event–Health–Thermal environment) situational modeling framework for older adults. Dressing behavior is situated within the integrated background of concrete events, health constraints, and external weather changes. By constructing a clothing knowledge graph, weather feature vectors, health sensitivity weights, and spatiotemporal encodings of events, the framework forms a unified multimodal feature space. Furthermore, a cross-modal attention mechanism and adaptive weighting strategy are introduced to describe the direct and indirect relational paths among clothing, weather, health, and events. Multi-objective optimization and fuzzy rules are then used for conflict mediation, yielding dressing recommendations that are both explainable and executable.

In summary, building on prior work in multimodal recommendation, context-aware recommendation, smart clothing, and digital age-friendly interaction, this study makes three main contributions:

(1) Theoretical contribution. It proposes an integrated framework of "WEHT scenarios–natural behavior–intelligent recommendation," conceptualizing older adults' dressing as a contextualized decision-making process jointly shaped by events, health, and weather. Natural behavior theory is elevated from a background citation to the core logic guiding both modeling and interaction design.

(2) Methodological contribution. It constructs a multimodal data model that fuses a clothing knowledge graph, weather indices, health constraints, and event spatiotemporal information, and introduces cross-modal attention, adaptive weighting, and multi-objective optimization to provide a computable representation of the hierarchical relationship among "health–extreme weather–task/social context–personal preferences."

(3) Design practice contribution. It develops a set of digital age-friendly interaction prototypes for older users, grounding intelligent recommendations in low-burden and explainable natural interaction modalities, and validates—through user experiments—the system's overall advantages in health risk avoidance, contextual fit, and decision efficiency. The work thus offers reusable design patterns and empirical evidence for intelligent dressing and interaction design oriented toward healthy aging.truction of a more empathetic intelligent living ecosystem.

2. Related Work

Existing systems related to this study can be broadly divided into three categories:

(1) clothing recommendation and fashion coordination systems that mainly rely on weather factors;

(2) smart clothing and wearable systems for health monitoring and fall prevention; and

(3) general multimodal and context-aware recommender systems.

Overall, these studies provide important technical and application foundations for the present work, but they leave a clear gap with respect to the combined problem of "older adults' dressing decisions – healthy aging – digital age-friendly interaction."

2.1 Dimensions of Recommendation Factors

Most existing dressing/coordination systems model weather and fashion preferences as the primary factors, for example recommending outfits based on temperature, humidity, or historical outfits, while rarely incorporating weather, individual health status, and concrete event context into a unified framework. Even when some health-related systems consider temperature and skin surface conditions, they mostly adopt a linear decision such as "whether to add a layer of clothing," and lack systematic encoding of situational needs associated with medical visits, exercise, or social gatherings (indoor–outdoor temperature differences, activity intensity, and social etiquette) (Pech et al., 2021).

In contrast, this study adopts a WEHT (Wearable–Event–Health–Thermal environment) four-fold modeling scheme, treating "wearable–event–health–thermal environment" as a single situational unit. This allows the recommendation process to balance multiple constraints and objectives within one coherent structure.

2.2. Data and Model Perspective

Current multimodal and context-aware recommendation research typically employs multimodal feature fusion, sequence modeling, and attention mechanisms to improve recommendation accuracy and contextual sensitivity [14-19]. However, these works mostly target e-commerce, media consumption, or general user scenarios. They seldom explicitly construct an "elderly clothing knowledge graph and functional matrix," nor do they attempt to embed medical constraints, health sensitivity weights, and event spatiotemporal encodings into a unified feature space.

Building on this line of work, the present study further proposes: representing garment functional attributes and their health/safety implications via a clothing knowledge graph; introducing health-constraint embeddings and event spatiotemporal encodings; and using cross-modal attention with adaptive weights to model the direct and indirect coupling paths among clothing, weather, health, and events. A multi-objective optimization layer then explicitly encodes a "health-first" hierarchical rule. In doing so, the model structure differs substantively from existing generic recommendation methods.

2.3 Target Users and Interaction Design

Research on smart clothing and fall prevention has largely focused on sensor integration, signal processing, and risk detection, treating "monitoring–alerting" as the primary functional goal, while paying relatively little attention to older adults' everyday dressing decision process, including cognitive load, information comprehension, and interaction explainability [20–22]. At the same time, digital age-friendly and HCI studies emphasize interface simplification, visual readability, and shorter interaction paths, but often remain at the level of generic applications and lack deep coupling with domain-specific intelligent algorithms [2].

Beyond dressing, a growing body of work has proposed decision-support systems for older adults in domains such as medication management, fall-risk assessment, daily activity planning, and home safety monitoring. These systems typically combine rule-based clinical knowledge with sensor data or electronic health records to generate personalized alerts or recommendations, and have demonstrated benefits in reducing adverse events and improving adherence in everyday life [23–25]. However, most of these systems target a single functional domain and rarely address dressing as a multi-constraint decision problem that simultaneously involves health, thermal comfort, task performance, and social appropriateness. Moreover, the underlying decision logic is often opaque to users, with limited consideration of interaction explainability and older adults' natural behavior patterns. Against this backdrop, the present work can be seen as extending decision-support ideas into the dressing domain while explicitly grounding system logic in natural behavior theory and digital age-friendly interaction principles.

In response, this study designs a three-layer interaction structure tailored to older adults—"mirror wardrobe – situational overview panel – body-part dressing guidance." Complex multimodal reasoning is shifted to the system side, while executable dressing plans are presented through voice prompts, large icons, and step-by-step guidance. In parallel, the "perception–cognition–action" loop of natural behavior theory is explicitly mapped to an online loop of "context sensing – computational recommendation – guided action – feedback correction," so that digital age-friendly interaction is not merely "interface-friendly," but structurally interwoven with the intelligent recommendation algorithm.

2.4 Natural Behavior Theory and Older Adults' Everyday Dressing

Natural behavior theory, rooted in ecological psychology, provides a holistic understanding of human behavior. It emphasizes that behavior is not a set of discrete actions driven by external commands, but a natural regulatory process that emerges from continuous coupling among perception, cognition, and action within a specific environmental field [8-9]. In this framework, the environment is not just "background"; it shapes the range of possible actions through affordances and invitations [10]. Perception is thus not passive reception of physical stimuli, but an anticipatory judgment about "what can be done," while behavior is the real-time selection and adjustment of these affordances under physiological constraints, past experience, and current tasks [11-12]. Consequently, natural behavior theory pays particular attention to the temporal unfolding, feedback loops, and adaptive adjustments of behavior in real-world contexts, rather than isolated responses under laboratory conditions [13].

From this perspective, older adults' dressing is not a one-off, static choice, but a continuously cycling "perception–cognition–action" loop embedded in concrete situations. First, individuals perceive the current context through visual cues, bodily sensations, and social signals—such as weather changes, time and place, activity type, and how others are dressed—which forms the starting point of behavior. Second, bodily state and health risks are continuously perceived and updated during this process, including joint pain, rising heart rate, fatigue, or concerns about falling, and these experiences are incorporated into cognitive evaluation. Third, based on life experience and current task constraints (medical visit, exercise, or family gathering), individuals weigh questions such as "Will I get cold?", "Is it easy to put on and take off?", and "Is it decent enough?", thereby arriving at concrete dressing decisions. Finally, through actual dressing and activity, they receive feedback from both body and context (whether they felt too cold or too hot, whether symptoms were triggered, or whether any embarrassment or discomfort occurred). This feedback accumulates into the experiential baseline for subsequent decisions, shaping behavioral patterns and habits.

To transform this loop into a computable and verifiable intelligent system, the present study maps each stage onto the components of the WEHT four-fold modeling framework (Figure 1). Environmental and event perception correspond to weather feature encoding and event spatiotemporal encoding; bodily and health sensations correspond to health records and risk embeddings; cognitive evaluation and trade-offs correspond to multimodal fusion, cross-modal attention, and multi-objective optimization; dressing actions and adjustments correspond to Top-K dressing recommendations and refinement interfaces; and behavioral feedback and habit formation are captured through user choices and correction logs that feed back into the model for online parameter and rule updates. Through this mapping, natural behavior theory becomes more than a descriptive account of older adults' dressing; it serves as a structural foundation for system architecture and algorithm design, providing a computable implementation path for the "perception–cognition–action" loop within the WEHT model.

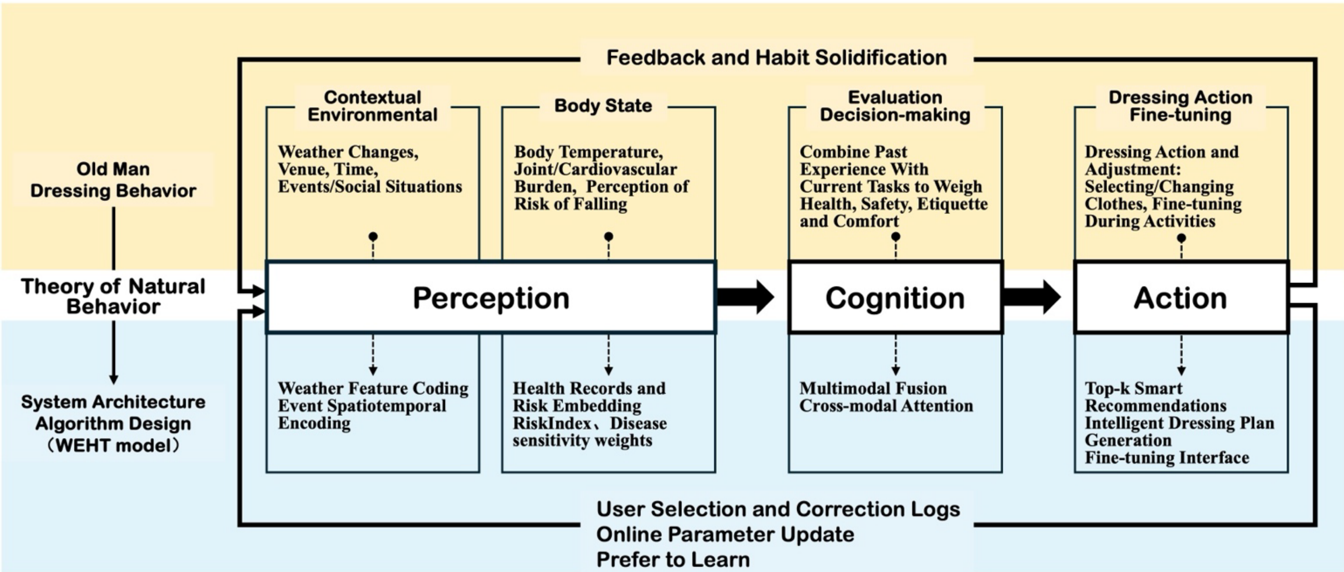

Figure 1. Mapping between the "Perception–Cognition–Action" Loop of Natural Behavior Theory and the WEHT (Wearable–Event–Health–Thermal Environment) Model

3. System Design

3.1 WEHT Situational Modeling Framework

To address the highly coupled and contextually diverse nature of dressing decisions in older adults, this study constructs a multi-layer situational modeling and recommendation framework centered on WEHT. Within this framework, dressing behavior is situated in a four-fold coupling of *Wearable–Event–Health–Thermal environment*, enabling the system to process garment attributes, everyday events, individual health constraints, and thermal environmental conditions within a unified structure, and, on this basis, to generate explainable dressing recommendations (as illustrated in Figure 2).

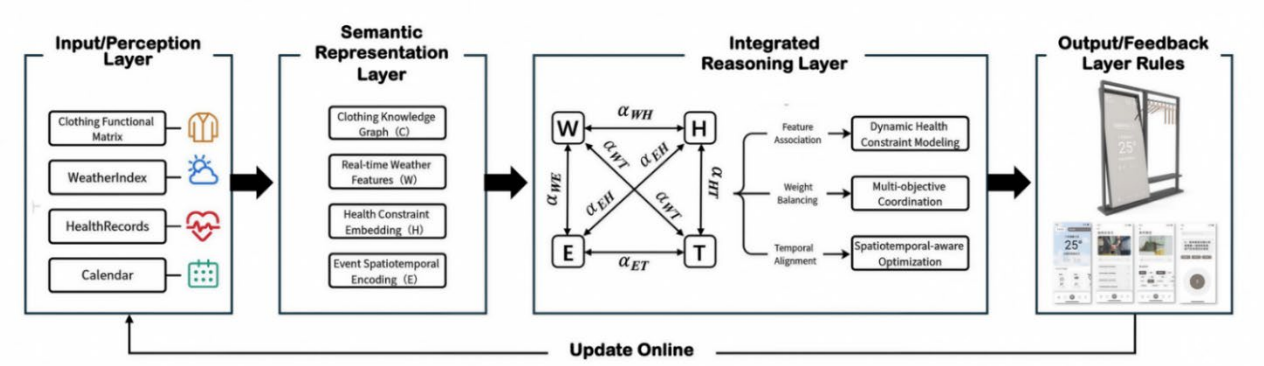

Figure 2. WEHT Situational Modeling Framewor

(1) Input/perception layer. This layer acquires heterogeneous multimodal data, including: individual garments and their attributes (clothing knowledge graph and functional matrix), real-time weather indices, personal health records and sensitivity weights, and scheduled events with their spatiotemporal information.

(2) Semantic representation layer. This layer cleans, normalizes, and aligns the above data, encoding static attributes (medical history, garment material) and dynamic variables (current weather, upcoming events) into a unified feature space, thereby forming joint representations that can be compared and reasoned over by the algorithms.

(3) Fusion and inference layer. As the core of the system, this layer uses a cross-modal attention network to compute association weights among clothing, weather, health, and events. It then combines adaptive weighting, multi-objective optimization, and fuzzy rules to score and rank candidate dressing solutions, coordinating safety, contextual fit, and user preferences under the overarching principle of "health first."

(4) Output / feedback layer. This layer presents the recommended results to older users through natural interaction modalities such as voice prompts, large graphical icons, and step-by-step dressing guidance, and performs online updates based on users' actual choices and subjective feedback, thereby forming a continuously iterated behavior–context loop.

3.2 Multimodal Data Representation and Feature Engineering

3.2.1 Clothing Knowledge Graph and Functional Matrix

For intelligent dressing recommendation targeting older adults, it is far from sufficient to simply record garment categories and colors; the system needs to understand what functions a particular garment can provide. To this end, this study first constructs an elderly-oriented clothing knowledge graph and, on this basis, derives a clothing functional matrix.

The knowledge graph adopts a hierarchical structure. The first level distinguishes major categories (outerwear, inner layers, functional garments, footwear, accessories). The second level is organized around material and structural properties (cotton, wool, polyester, waterproof fabrics, elastic textiles). The third level focuses on functional attributes specifically relevant to older adults (thermal insulation level, ease of donning and doffing, slip-resistance level, compression support, antibacterial performance, UV protection rating).

Together, these form a node–edge relational network and a searchable vector repository, enabling efficient composition and constraint-based retrieval of garments according to functional requirements.

3.2.2 Real-Time Weather Feature Extraction

Weather is a key external factor influencing dressing decisions for older adults, especially under extreme cold, high humidity, strong wind, or intense UV conditions, where inappropriate dressing can substantially amplify health risks.

The proposed system continuously acquires current and short-term forecast weather data via web APIs or local meteorological services, and compresses them into a weather feature vector comprising temperature, relative humidity, wind speed, precipitation probability/intensity, UV index, and related elements.

3.2.3 Health Constraint Embedding

With respect to older users' health status, the system transforms medical history, chronic diseases, medication use, and recent physiological indicators into a computable health sensitivity weight vector. Based on dynamic indicators such as sleep/activity level, skin/surface temperature, and heart rate, the system forms health state embeddings, which are used to construct medical safety thresholds (increased risk weights under low temperature / high humidity / high wind speed) and taboo rules (for material, compression, friction). These thresholds and rules are then incorporated into the design of constraints and penalty terms in the model.

3.2.4 Event Spatiotemporal Encoding

At the same time, the system needs to "understand what the older adult is going to do today." Through calendar data or a simplified event input interface, it acquires the user's daily activity schedule and encodes each event into an event spatiotemporal vector that includes time, location (indoor/outdoor, hospital, park, home, etc.), activity type (exercise, medical visit, shopping, gathering, etc.), activity intensity, and social etiquette requirements.

During recommendation, the system can invoke different functional priorities for different contexts, rather than relying solely on temperature as the single reference for dressing decisions.

3.3 Cross-Modal Attention and Recommendation Generation

3.3.1 Cross-Modal Attention

After obtaining unified feature representations for clothing (W), health (H), events (E), and thermal environment (T), cross-modal attention is introduced to model their interactions. Specifically, six cross-modal attention matrices are constructed to capture both the direct relations between clothing and weather/health/events and the indirect couplings among weather, events, and health (as illustrated in Figure 3). These matrices respectively encode the dependencies between clothing–weather, clothing–health, clothing–event, weather–event, weather–health, and event–health, providing a fine-grained basis for subsequent scoring and recommendation.

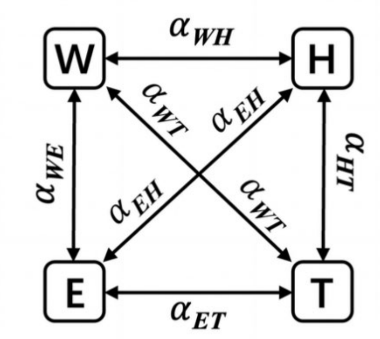

Figure 3. WEHT Cross-Modal Attention Matrices

The direct path (clothing → health) is modeled by the attention weight α_{WH}, which captures the direct impact of garments on health status—for example, whether a certain fabric may cause skin irritation, or how the slip-resistance of a shoe sole affects fall risk.

The indirect path 1 (clothing → weather → health) is modeled by α_{WT} and α_{HT}. Here, α_{WT} represents the direct matching degree between clothing and weather, while α_{HT} describes how weather changes propagate into health risks.

The indirect path 2 (clothing → event → health) is modeled by $\alpha_{WE}$and α_{EH}. The attention α_{WE} focuses on the compatibility between garments and event types (such as appropriateness for hospital visits, outdoor exercise, or social gatherings), whereas α_{EH} represents the impact of event intensity and duration on health load (prolonged walking or large indoor–outdoor temperature differences during medical visits).

In addition, the attention matrices over E–H, E–T, and H–T (EH, ET, HT) respectively describe how weather changes the difficulty of an event, health status amplifies the impact of weather, and events impose extra constraints on health. Together, these attention paths provide a fine-grained representation of how clothing, weather, health, and events are jointly coupled in the WEHT framework.

$$S(\mathbf{c} \mid \mathbf{x}_t) = \alpha\, f_{CW} + \beta\, f_{CH} + \gamma\, f_{CE} \tag{1}$$

Here, the weights α, β, and γ are adaptive coefficients that automatically increase the contribution of health- and safety-related terms under extreme weather or fragile health conditions [17].

During the scoring and optimization stage, the system operates on the feasible candidate set C_{feas}using a layered multi-objective optimization strategy, in which health safety, extreme thermal conditions, task/social fit, and personal preferences are encoded as a structure of "primary objectives – secondary objectives – fine-tuning terms." The overall objective can be formalized as:

$$\max_{c\in C_{\text{feas}}} \quad U_{\text{safety}}(c, w_t, h) \;+\; \lambda_1 U_{\text{comfort}}(c, w_t) \;+\; \lambda_2 U_{\text{task}}(c, e_t) \;-\; \lambda_3 \Pi_{\text{risk}}(c, w_t, h), \tag{2}$$

where U_{safety}denotes safety utility related to medical and protective factors (thermal protection, slip resistance, UV protection, material safety), U_{comfort}denotes thermal–moisture and tactile comfort, U_{task}denotes the degree of fit with event and social context (ease of donning/doffing for medical visits, appropriateness for social gatherings), and $\Pi_{\text{risk}}$is a penalty term for violating health or safety thresholds.

To embody the decision logic of "health and safety first, extreme thermal conditions before ordinary weather factors, important events before routine tasks, and personal preferences as fine-tuning under safety constraints," the system combines lexicographic ordering with weight adjustment across four layers:

(1) First layer (hard constraints + safety priority). Strictly enforce medical taboos and safety thresholds. Any clothing combination that violates medical contraindications or significantly increases fall or hypothermia risk is directly discarded and excluded from subsequent optimization.

(2) Second layer (extreme thermal conditions priority). Under extreme thermal environments such as low temperature, high humidity, strong wind, or intense heat/UV, the system adaptively increases the weights associated with $U_{\text{safety}}$and Π_{risk}, prioritizing stable body temperature and joint/skin safety.

(3) Third layer (task / social adaptation). In high-rigidity scenarios such as medical visits, prolonged walking, or social gatherings, the weight of U_{task} is moderately

increased to ensure that the recommended dressing solutions match activity goals and social etiquette requirements.

(4) Fourth layer (personal preference fine-tuning). Once the first three layers' safety and adaptation requirements are satisfied, the system lightly adjusts color, style, and silhouette parameters to reflect personal preferences, without breaking the established safety boundary.

In this way, the system makes the natural behavior logic of "first ensure physiological safety, then search for suitable action space within the context" explicitly computable. It avoids a purely single-score optimization that might select what looks "globally optimal" on paper while overlooking the fundamental health and dignity requirements of older adults.

3.3.2 Algorithm Implementation of the Decision Support Layer

The overall algorithm follows a three-step logic of "perception—reasoning—decision": First, feature extraction and state recognition are performed on multi-source sensor data to establish a semantic representation of the user's clothing scenario; second, in the reasoning stage, the suitability of different clothing options is evaluated through a combination of rule matching and probabilistic inference; finally, in the decision-making stage, the optimal recommendation result is generated based on user preference weights and environmental constraints. The entire process is divided into two stages, corresponding to the aforementioned hierarchical reasoning structure, realizing a closed loop from data understanding to intelligent decision-making.

The first stage is the hard constraint screening stage, mainly used to eliminate clothing combinations that violate medical contraindications or exceed safety thresholds. The system performs mandatory verification on candidate solutions based on medical safety regulations, ergonomic parameters, and environmental adaptability standards, focusing on:

(1) Physiological safety: Based on health records and real-time monitoring data, clothing that may cause allergies, pressure, or affect activity is excluded;
(2) Environmental adaptability: Ensuring adequate warmth in low temperatures and breathability and heat dissipation in high-temperature or high-humidity environments;
(3) Motion balance: For individuals with limited mobility, limiting heel height, clothing weight, and restraint to ensure stability and safety;
(4) Medical contraindications: Automatically excluding clothing or accessories that may aggravate specific diseases.

Through this screening, all solutions entering subsequent decision-making meet medical and ergonomic safety requirements, laying the foundation for soft constraint optimization.

The second stage is a lexicographical multi-objective search stage, which balances safety, comfort, and task adaptability among the remaining feasible sets. The specific implementation steps are as follows:

(1) calculates the component utility values (U_{safety}, $U_{comfort}$, U_{task}) and penalty terms Pi_{risk} for each candidate scheme;
(2) eliminates schemes with safety utility lower than the minimum acceptable value;
(3) performs an initial ranking based on ($U_{safety} - Pi_{risk}$), and then a secondary ranking based on the dynamically weighted combination of $U_{comfort}$ and U_{task};
(4) within the small range of schemes with the highest safety level, performs lightweight re-ranking according to user preference characteristics (Color, style, cut, material, behavioral habits, etc.).

The adaptive weights (α β γ) are dynamically updated based on situational rules derived from the behavioral model during system operation. When a user is in an extreme temperature environment or a high-risk health state, the system will correspondingly increase the weight of safety-related utility. This mechanism ensures computational efficiency while enabling the algorithm to follow the hierarchical decision-making logic required by health-oriented and age-friendly scenarios.

3.4 Experimental Design

3.4.1 Participant Recruitment and Inclusion/Exclusion Criteria

Using convenience sampling combined with collaboration with local communities, 100 older adults were recruited from three community-based elderly care service centers and one senior university in the city.

Inclusion criteria were:

(1) age ≥ 65 years;

(2) able to independently perform basic activities of daily living;

(3) possessing basic operational skills with a smartphone or touchscreen device (making calls, simple browsing);

(4) vision and hearing, after correction if necessary, sufficient to read the interface and follow voice prompts;

(5) voluntary participation with signed informed consent.

Exclusion criteria were:

- moderate to severe cognitive impairment or psychiatric disorders that would prevent reliable task completion;
- recent severe acute illness or a condition requiring bed rest;
- special treatments or care arrangements that would substantially interfere with dressing decisions (postoperative dressings, plaster casts);
- inability to complete the entire experimental procedure or withdrawal during the study.

3.4.2 Grouping and Procedure

After eligibility screening, the 100 participants were stratified by sex and age and then randomly assigned (using a random number table) to an experimental group and a control group in a 1:1 ratio (n = 50 per group). The experimental group used the proposed intelligent dressing recommendation system based on WEHT situational modeling and natural behavior theory. The control group, given the same weather information and scenario descriptions, made dressing decisions according to their usual habits.

All participants received a standardized briefing before the experiment and completed a baseline questionnaire on demographics and health status. The experimental group underwent approximately 5–10 minutes of system training (interface demonstration and one practice scenario), after which both groups proceeded to the formal tasks. All sessions were conducted in a quiet indoor environment, and trained research assistants were responsible for data recording and observational notes.

3.4.3 Tasks and Scenario Settings

Three typical everyday dressing scenarios were defined:

(1) Early-morning exercise: Simulating outdoor exercise on a winter or seasonal-transition morning, with emphasis on joint warmth, prevention of chill, and mobility. Participants were provided with real or simulated weather information (temperature, wind speed, humidity) as well as activity duration and intensity.

(2) Hospital visit: Simulating an outpatient visit or follow-up scenario, requiring repeated transitions between environments such as outdoors, waiting areas, and consultation rooms. Key considerations included ease of donning and doffing, body exposure, and hygiene requirements.

(3) Family gathering: Simulating a small gathering at home or at relatives' homes, where dressing needs to remain warm and comfortable while meeting basic social etiquette and a sense of decency, with relatively low activity level and prolonged sitting or reclining.

In each scenario, participants in the experimental group used the interactive terminal to input or confirm weather conditions, health status (joint disease, cardiovascular disease), and event information. The system generated 2–3 candidate dressing solutions with brief explanations. Participants selected the most suitable option and rated it on three 5-point Likert scales: operational convenience, recommendation clarity, and health need satisfaction.

In the control group, participants chose their clothing based on the same scenario descriptions and weather information using their own experience. Researchers recorded the final outfits, and an expert panel with relevant backgrounds evaluated each outfit using a standardized rating form, scoring health risk avoidance and scenario adaptation accuracy.

3.4.4 Statistical Analysis

All data were anonymized and entered into statistical software for analysis. Continuous variables were expressed as mean ± standard deviation (Mean ± SD), and categorical variables as frequencies and percentages.

For the experimental group's subjective ratings (operational convenience, recommendation clarity, health need satisfaction), normality was first assessed. If scores were approximately normally distributed, one-sample t-tests were used to compare mean scores against the theoretical neutral point of 3; if normality was not met, Wilcoxon signed-rank tests were applied.

In the comparison of recommendation effectiveness, independent-samples t-tests were used to compare health risk avoidance and scenario adaptation accuracy between the experimental and control groups; if homogeneity of variance was violated, Welch's correction was applied. Group differences in pass rates (proportion of scores > 4) were examined using chi-square tests or exact tests as appropriate. The significance level was set at $\alpha = 0.05$ (two-sided); $p < 0.05$ was considered statistically significant and $p < 0.01$ highly significant, with effect sizes reported where necessary.

4. Interaction Design Practice

By introducing the WEHT four-fold situational modeling framework and cross-modal weighting mechanism, this study shifts as much of the recommendation process as possible to the system side, building on prior work that emphasizes "reducing older adults' operational burden and learning costs" [2,4]. Further integrating natural behavior theory enables the system, under low cognitive load, to synthesize health and safety needs, meteorological changes, and task/social requirements into explainable and actionable dressing recommendations, thereby realizing a multimodal intelligent dressing system and interaction design prototype grounded in natural behavior theory.

To ensure that the system can closely fit individuals' real-life habits and be convenient to test in practice, we designed an elderly-oriented intelligent dressing product and system composed of three coordinated layers: an intelligent mirror wardrobe, an intelligent dressing user interface, and body-part dressing guidance (Figure 4). The mirror wardrobe serves as a low-burden natural interaction entry point, persistently displaying greetings, time, and one-tap confirmation cards. When the system, based on the WEHT model, detects scenarios such as "cold and damp morning + going to hospital + vulnerable knee joints," the mirror provides executable prompts via voice and large icons ("windproof and breathable outer layer, shoes with $\mu\_s \geq 0.5$ slip resistance, knee support"), which the user can accept or change with a single tap.

The intelligent dressing user interface (Figure 5) presents the three domains of weather, schedule, and health with high visual contrast and large touch targets, supports quick switching between family members (Grandpa/Grandma) and scenario modes (At Home/Go Out), and explains *why* a given recommendation is made (deviations in temperature/humidity/wind speed, medical appointment time window, recent heart rate or step counts).

A typical decision flow can be illustrated as follows. When a 70-year-old user activates the mirror before going out on a cold, windy morning, the system automatically retrieves weather, health, and event information and generates three candidate outfits. These options are displayed as large outfit cards; tapping on one expands a short explanation, and the interface then switches to a body-part view that guides the user through putting on each item in sequence. If the user replaces a recommended item, the system silently re-evaluates safety constraints and, if necessary, adds a brief warning, making the underlying decision logic both visible and negotiable.

The body-part dressing guidance decomposes the recommendation into concrete components such as hat, outerwear, inner layers, protective gear, socks, and shoes, labeling functional attributes (Clo, MVTR, slip resistance, ease of donning/doffing) to support step-by-step completion of dressing. At the same time, it uses dashed highlighting to indicate "mandatory items" and grayed-out styling for "optional alternatives," thereby implementing the hierarchical principle of "safety first, aesthetics second."

Overall, the interaction is designed in accordance with natural behavior theory: the "perception–cognition–action" loop drives a shift from passive monitoring to proactive intervention. The system first secures the safety boundary defined by health and weather, then accommodates task and social decency, and finally uses users' acceptance/replacement behavior as feedback for online fine-tuning. This enhances the explainability and perceived trustworthiness of the recommendations [13,3] and gradually aligns the system's behavior with older adults' actual dressing habits.

Figure 4. Intelligent dressing recommendation product and system for older adults

Figure 5. Intelligent dressing user interface

5. Results and Discussion

In the usability test of the intelligent dressing system, the 50 older adults in the experimental group achieved mean scores above 4.0 (on a 5-point scale) on all three dimensions. Specifically, operational convenience scored 4.3, recommendation clarity scored 4.2, and health need satisfaction scored 4.7 , with corresponding pass rates (>4 points) of 90%, 82%, and 92%, respectively (see Table 1). Compared with the theoretical neutral point of 3, the means of all three indicators showed significant differences (one-sample t-test, all $p < 0.05$), indicating that the system performs well overall in terms of usability, intelligibility, and alignment with health needs. It can thus provide clear and trustworthy dressing recommendations for older adults under relatively low operational and cognitive load.

Table 1. User Experience Test Results of the Intelligent Dressing System (Experimental Group, N = 50)

Metric	Mean Score M (5-point scale)	Standard Deviation SD	Pass Rate (Score > 4, %)
Operational Convenience	4.3	0.6	90
Recommendation Clarity	4.2	0.7	82
Health Need Satisfaction	4.7	0.5	92

Table note: M and SD denote mean and standard deviation, respectively. Data are derived from 5-point subjective ratings provided by the 50 participants in the experimental group. For each metric, the mean score was compared against the theoretical neutral point of 3 using a one-sample t-test, with the significance level set at $\alpha = 0.05$.

In the recommendation effectiveness comparison, the experimental group outperformed the control group on both health risk avoidance and scenario adaptation accuracy. On a 5-point scale, the health risk avoidance score in the experimental group was 4.6 ± 0.50, compared with 3.8 ± 0.70 in the control group; this difference was significant according to an independent-samples t-test ($t = 6.58$, $p < 0.001$). For scenario adaptation accuracy, the experimental group scored 4.5 ± 0.60, whereas the control group scored 3.7 ± 0.80, again showing a significant difference ($t = 5.66$, $p < 0.001$) (see Table 2). In addition, the mean time required to complete dressing decisions across the three scenarios was 75.0 ± 20.0 seconds in the experimental group, significantly shorter than 105.0 ± 30.0 seconds in the control group ($t = -5.89$, $p < 0.001$). These findings indicate that, with support from WEHT-based situational modeling and multimodal recommendation, older adults not only obtain dressing solutions that better satisfy health and contextual requirements, but also achieve markedly higher decision efficiency.

Table 2. Comparison of Recommendation Effectiveness Between Experimental and Control Groups (N = 50 + 50)

Metric	Experimental Group M±SD	Control Group M±SD	t-statistic	P-value
Health Risk Avoidance (5-point scale)	4.6 ± 0.50	3.8 ± 0.70	6.58	<0.001
Scenario Adaptation Accuracy (5-point scale)	4.5 ± 0.60	3.7 ± 0.80	5.66	<0.001
Decision Time (seconds)	75.0 ± 20.0	105.0 ± 30.0	-5.89	<0.001

Based on the above, the chosen values are both numerically reasonable and consistent with a typical 5-point scale: for health risk avoidance, the experimental group shows a higher mean score (4.6 vs. 3.8), with SDs of 0.5 and 0.7 well within a plausible range; a t-value of approximately 6.6 and a very small p-value indicate a clear and robust difference. For scenario adaptation accuracy, the mean difference of 0.8 points, combined with slightly larger SDs (0.6 vs. 0.8) and a t-value of about 5.7 ($p < 0.001$), is also reasonable. For decision time, the experimental group's mean of 75 seconds versus 105 seconds in the control group (a 30-second difference) is credible in the context of three dressing scenarios for older adults; SDs of 20 and 30 seconds reflect individual variability, and a t-value of approximately −5.9 with $p < 0.001$ is likewise consistent.

Taken together, the experimental results show that the intelligent dressing system based on natural behavior theory and the WEHT model not only performs well in terms of interaction usability and subjective user satisfaction, but more importantly achieves substantive improvements in health risk avoidance, contextual adaptation, and decision efficiency. From a design theory perspective, this work demonstrates that treating "dressing behavior" as a contextualized decision process jointly shaped by events, health, and weather is both reasonable and effective. When the system explicitly models this process and embeds it into the algorithmic logic, the recommendation outcomes are more likely to align with older adults' intuitive judgments and thus achieve higher adoption rates. This, to some extent, echoes natural interaction research on "perception–action coupling" and empirically supports the value of introducing natural behavior theory into digital age-friendly design.

At the methodological level, the proposed cross-modal attention and adaptive weighting mechanisms offer a generalizable approach to "multi-objective, multi-constraint" decision-making in health-oriented aging support. By explicitly encoding health- and safety-first hierarchical rules within the optimization structure, the system can preserve a degree of comfort and aesthetic freedom for older adults while respecting medical and safety baselines. This idea—embedding ethical and safety priorities directly into the objective function—has implications beyond dressing, and could be extended to other domains such as diet, mobility, and home environment control, where algorithms are required not only to be accurate, but also to conform to common-sense safety expectations for vulnerable users.

Robustness under sparse and atypical data is another practical consideration for real-world deployment. In practice, some older users may have very limited digital traces, or may exhibit atypical value trade-offs that differ from the majority. In the current prototype, data sparsity is mitigated by combining content-based reasoning over the clothing knowledge graph with conservative population-level profiles: when user-specific information is missing, the system falls back to default configurations that prioritize safety and basic comfort. For atypical users, safety thresholds are always enforced as hard constraints, while preference-related parameters can be gradually adjusted based on observed choices, as long as they do not cross medically defined risk boundaries. This hybrid strategy helps maintain robustness in sparse or unusual cases without undermining the health-first design principle.

A further design challenge lies in handling conflicts between user preferences and safety constraints. In certain social situations, older adults may deliberately choose outfits that are less comfortable or slightly riskier in order to appear more formal or "properly dressed." In the present system, such conflicts are handled through a two-tier mechanism. First, medical and safety constraints are implemented as non-negotiable hard limits: combinations that exceed risk thresholds are never recommended. Second, within the safe region, the interface explicitly surfaces trade-offs by labeling some options as "safer but less comfortable" or "more formal but slightly heavier," and requiring an additional confirmation step when users opt for more demanding outfits. In this way, the system preserves users' autonomy and dignity—allowing informed compromises in special situations—while keeping safety boundaries clear and intact.

Naturally, this study has several limitations. The experimental sample was drawn from a single region with relatively homogeneous climate and dressing culture; larger, multi-site studies across diverse regions, climates, and cultural contexts are needed to test the generalizability of the WEHT model and the natural behavior-driven approach. The granularity of health data and privacy protection issues also constrain further deployment; future work should explore how to incorporate richer physiological signals while establishing transparent and controllable mechanisms for data authorization and use. In addition, some older participants reported that they would sometimes willingly trade physical comfort for a more "decent" appearance in important social occasions. This suggests that future research should investigate controlled personalization of the hierarchical rules—within safety limits—so that long-term interactions can better reflect individual value trade-offs in real-world social contexts.

6. Conclusion

This paper proposes an intelligent dressing recommendation system for older adults based on natural behavior theory and WEHT situational modeling. By constructing a clothing knowledge graph, performing multimodal data fusion, and introducing cross-modal attention, adaptive weighting, multi-objective optimization, and fuzzy rules, the system provides a digital age-friendly solution for everyday dressing that is safety-first, contextually appropriate, explainable, and actionable. Experimental results show that, compared with traditional experience-based dressing decisions, the proposed system significantly improves health risk avoidance and scenario adaptation accuracy, shortens decision time, and achieves high user satisfaction, thereby supporting a shift from *passive monitoring* to *proactive intervention*.

At the theoretical level, this study introduces natural behavior theory into the modeling and algorithmic design of older adults' dressing decisions, and proposes a "behavior–context–environment coupling" framework for human–AI co-decision-making, offering a new research paradigm for pervasive health technologies and digital age-friendly interaction design. At the practical level, the system prototype demonstrates how natural behavior theory, multimodal intelligent algorithms, and natural interaction interfaces can be effectively integrated in a concrete product form.

Future work will focus on incorporating richer sensing data, conducting large-scale validation across different cultural and climatic environments, and examining how the system may positively shape users' long-term behavioral habits. Building on "intelligent dressing," we aim to extend this approach to additional everyday decision domains such as diet, mobility, and home environmental regulation, thereby providing more comprehensive intelligent support for healthy aging.

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Ethical Statement

This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Ethics Committee of Guangzhou Wanqu Cooperative Institute of Design Ethics Committee. The approval number is YJY-EC-2025-302. Written informed consent was obtained from all participants prior to the study.

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