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# Constructing Multidimensional User Personas for Community-Based Chronic Disease Patients Based on Digital Literacy, Health Status, and Social Support: A Cross-Disciplinary Study for Digital Health Product Design

**Siqi Liu [1]*and HaoYu Wang [2]**

[1] University of Arizona; nonekaliyana15@outlook.com
[2] Auckland University of Technology; mvictorios1996@outlook.com
* Correspondence: nonekaliyana15@outlook.com

**Abstract**

Research Background and Gaps: With the global population aging and the prevalence of chronic diseases continuously rising, digital health products—such as wearable devices and chronic disease management applications—play an increasingly important role in the self-management of community-dwelling patients with chronic conditions. However, existing digital health product designs often adopt a "one-size-fits-all" approach, overlooking significant differences among patients in digital literacy, health status, and social support. Such technology-centered rather than capability-centered designs result in low adoption rates, poor user retention, and insufficient alignment with the real needs of patients across varying ability levels.
Research Methods: This study proposes a methodology for constructing user personas of patients with chronic diseases, suitable for large samples and multivariate analysis. By integrating three dimensions—digital literacy, health status, and social support—and employing a hybrid clustering strategy that alternates between manual screening and two-step clustering, the approach systematically segments large-sample data.
Practical Implementation: The study is based on health management tracking survey data of community-dwelling patients with chronic diseases in a certain city. A total of 3,856 residents aged 50—85 with one or more chronic conditions were selected as valid samples. Twenty-eight subdomain variables were extracted, encompassing demographic characteristics, comorbidity profiles, device operation skills,

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information acquisition capabilities, and family caregiving status. Using computer-assisted tools (SPSS and Python) to optimize the data analysis workflow, a multidimensional user persona framework was constructed.
Core Findings: The study ultimately identified 26 distinct user persona clusters among community patients with chronic diseases. Each cluster was defined comprehensively by digital literacy level, degree of health impairment, psychological traits, and social network background. The findings indicate a nonlinear negative correlation between age and digital literacy, while social support systems play a key moderating role in compensating for low digital literacy among elderly patients.
Significance and Contribution: The multidimensional user persona framework developed in this study provides a clear and practical pathway for inclusive design of digital health products. It not only offers a generalizable methodological reference for user research in interdisciplinary design and innovation but also provides scientific guidance for functional planning, interaction adaptation, and sample selection in digital medical devices and chronic disease management platforms. Ultimately, it facilitates the design of age-friendly and barrier-free solutions that precisely match the capabilities of target users.

**Keywords:** User Persona; Digital Health Products; Chronic Disease Management; Two-step Clustering; Inclusive Design

## 1. Introduction

Globally, population aging and the high prevalence of chronic non-communicable diseases (such as hypertension, diabetes, and cardiovascular diseases) have become major public health challenges. According to the World Health [1], chronic diseases account for over 70% of global mortality, and community-based home care and self-management are central strategies to address this challenge. In this context, digital health products (DHPs), including smart wearable devices, remote monitoring systems, and mobile health applications, are widely recognized for their potential to empower patients and enhance both health management efficiency and quality of life. Design plays a pivotal role in shaping these digital health support environments.

However, community-dwelling patients with chronic diseases exhibit substantial heterogeneity in physiological functioning, cognitive abilities, digital technology proficiency, and socio-economic backgrounds. Existing DHPs are often developed based on the usage patterns of younger or healthier populations, leaving many chronic patients facing a pronounced "digital divide"[2]. This mismatch between supply and demand not only limits the practical utility of these products but may also induce patient frustration and technology-related anxiety. Therefore, the concept of user-centered design (UCD) emphasizes the necessity of deeply understanding and accurately characterizing the multidimensional traits of target users to ensure that products and services align with users' capabilities and core needs[3].

User personas are among the most effective tools within the UCD process[4]. As an interaction design instrument, personas provide realistic depictions of target user groups, enabling designers, engineers, and other product developers to build empathy and clarify user goals, thereby guiding design decisions[5]. Constructing precise user personas for patients with chronic diseases facilitates insights into patients' willingness to adopt technology, interaction pain points, and functional preferences, which in turn supports more targeted inclusive design[6].

Theoretically, research on user personas has evolved along two main directions: one is demographic-oriented, segmenting groups based on attributes such as age and gender; the other is capability-centered, focusing on differences in users' abilities within specific contexts[7]. In the healthcare domain, researchers increasingly recognize that simple age-based segmentation cannot accurately reflect patients' interaction capabilities[8]. Segmentation based on digital literacy, health impairment, and other ability dimensions should be prioritized in product design[9]. In recent years, quantitative methods such as cluster analysis have been introduced into persona construction, improving the objectivity of large-sample studies[10]. Nonetheless, existing research is often limited to small-sample qualitative interviews or single-dimension clustering (e.g., by disease type only), lacking large-sample empirical studies that systematically integrate digital literacy and health status from an interdisciplinary design perspective[11]. Moreover, few studies provide concrete pathways for translating personas into design applications[12].

Against this backdrop, the present study aims to precisely define and address the challenge of "missing user capability models" in digital health product design[13]. Focusing on community-dwelling patients with chronic diseases in China, this study employs large-sample longitudinal survey data and innovatively incorporates three core dimensions: digital literacy, health status, and social support. Using a two-step clustering method, multidimensional user personas are constructed[14]. This research not only fills a methodological gap in large-sample, multidimensional persona construction in digital health but also clearly delineates the design requirement boundaries for different capability-based clusters[15].

## 2. Related Work

The construction and application of user personas have been a central topic of research in the fields of digital health products and inclusive design. A thorough analysis of prior studies' contributions and limitations is essential for establishing the necessity and novelty of the present research.

### 2.1. Application and Limitations of User Personas in Health Product Design

User personas serve as a bridge between user needs and product design and have been widely applied in the healthcare domain. LeRouge et al. (2013) examined the methodological value of personas in consumer health technology development, highlighting their effectiveness in reducing system complexity and enhancing user acceptance [16]. Ten Klooster et al. (2022) argued that focusing solely on health-related factors captures only part of the user story in eHealth technologies, emphasizing the need to incorporate psychological and social factors to construct more comprehensive personas that improve chronic disease self-management [17] . However, these early studies predominantly relied on small-scale qualitative interviews or focus groups, which, although providing deep insights into user motivations, suffer from limited representativeness and lack robust statistical validation for larger populations[18].

### 2.2. Introduction of Quantitative Clustering Methods in User Segmentation

To address the limitations of qualitative approaches, researchers have increasingly adopted quantitative clustering techniques for patient segmentation. Nittas et al. (2023) proposed a low-resource approach to understanding patients and targeting health technologies by capturing and clustering exposure levels [19]. Smith et al. (2025) used cluster analysis to identify patterns among individuals with multiple long-term conditions (MLTC), facilitating tailored healthcare provision [20]. In studies on digital literacy among elderly and chronically ill populations, Shin et al. (2025) applied latent profile analysis (LPA) to classify digital literacy profiles in community-dwelling older adults, identifying distinct literacy patterns [21]. Similarly, Lin et al. (2025) employed cluster analysis to explore user segmentation and related factors in the adoption of home-care technologies among older adults [22].

Although single clustering algorithms such as K-means have been applied in these studies, they are often sensitive to outliers and limited when handling mixed datasets containing both continuous and categorical variables[23]. Furthermore, clustering results in existing literature typically remain at the public health or sociological level, lacking translation into concrete product interaction design perspectives, such as interface layout or operational feedback mechanisms[24].

### 2.3. Cross-Disciplinary Approaches and Research Innovation

To overcome these challenges, the present study introduces the two-step clustering method from data science and integrates it with the capability-centered theory from design research[25]. The two-step clustering method efficiently handles large-scale mixed-type data and automatically determines the optimal number of clusters, demonstrating significant advantages when analyzing complex patient health and behavioral datasets[26]. Following Engström and Norin's (2022) action research guidelines for segment-based healthcare service design [27], this study adopts "digital literacy," "health status," and "social support" as three core dimensions for cross-disciplinary integration.

This cross-disciplinary approach is highly innovative and feasible. It breaks the conventional medical research habit of classifying patients solely by disease type and goes beyond traditional design practices that construct personas based only on experiential knowledge[28]. Driven by large-sample empirical data, the approach not only highlights the unique characteristics of marginalized groups—such as older adults with low digital literacy but high health management needs—but also establishes a complete technical chain from data mining to design decision-making[29].

## 3. Methodology

This study adopts a mixed research strategy that combines quantitative data-driven modeling with qualitative feature characterization, aiming to construct a reproducible and high-precision multidimensional user persona system for patients with chronic diseases[30]. The overall technical workflow follows a "model first, validate later; induce patterns from data" logic[31].

### *3.1. Research Strategy and System Architecture*

The study is structured into four core phases:

- Data Collection and Variable Reconstruction;
- Exploratory Manual Screening and Pre-Clustering;
- Multidimensional Two-Step Clustering Modeling;
- Persona Feature Extraction and Design Mapping[32].

This hybrid approach, which combines manual expert screening (for extreme outlier cases) with unsupervised machine learning (for the main sample), effectively mitigates distortion issues that can arise when a single algorithm processes highly imbalanced healthcare data[33]. The research framework is illustrated in Figure 1.

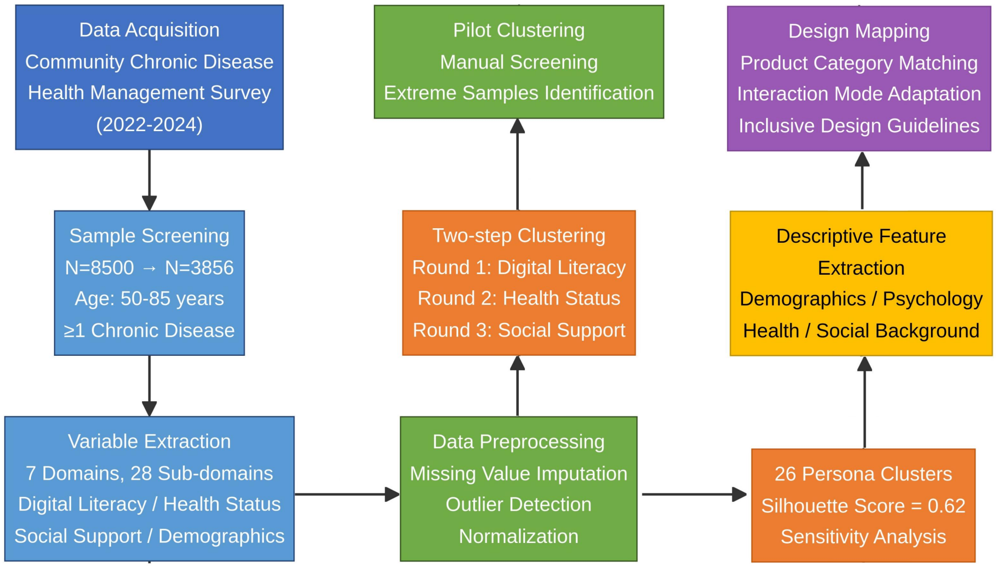


**Figure 1.** Research Framework for Constructing Multidimensional User Personas.

### *3.2. Data Collection and Variable Definition*

The data required for this study go beyond a simple enumeration of physiological indicators, encompassing a comprehensive set of capability variables that influence user interaction with digital health products[34]. Data collection was structured around three core dimensions:

- Digital Literacy: Reflecting users' ability to operate digital devices and access digital information. Variables include smartphone usage frequency, app installation and operational skills, online health information search capability, and self-efficacy in using digital technologies[35];
- Health Status: Reflecting the limitations imposed by chronic diseases on users' physiological and cognitive interaction capabilities. Variables include the number of comorbid chronic conditions (e.g., diabetes, hypertension combined with retinopathy), activities of daily living (ADL), fine motor skills of the upper limbs, and impairments in visual and auditory perception;
- Social Support: Acting as either a facilitating or moderating factor, this dimension reflects the external environment from which users can obtain assistance when encountering technological challenges. Variables include household living arrangements (living alone or with children), availability of daily caregivers, and sources of technical support.

### *3.3. Data Analysis and Clustering Method*

The detailed data analysis workflow is illustrated in Figure 2:

- Model Construction: The two-step clustering method was employed to build the user persona model. In the first step (pre-clustering), a Cluster Feature (CF) tree was constructed to compress the large sample into multiple sub–clusters. In the second step (final clustering), an agglomerative hierarchical clustering algorithm was applied to merge the pre–clusters, and the optimal number of clusters was automatically determined using the Bayesian Information Criterion (BIC);

- Alternating Manual Screening Mechanism: Due to the presence of extreme samples in healthcare data—such as individuals who are "severely disabled with no digital literacy" or "completely healthy with high digital literacy"—which are few in number but distinct in characteristics, an alternating manual screening mechanism was implemented. In a preliminary experiment, if the algorithm failed to isolate these extreme groups automatically, manual rules (e.g., ADL scores extremely low and never having used a smartphone) were applied to assign them to specific clusters, while the remaining samples proceeded through the two–step clustering model;
- Validation and Inference: Chi–square tests and analysis of variance (ANOVA) were conducted to statistically validate inter–cluster differences, ensuring that each persona cluster exhibited significant heterogeneity in core variables.

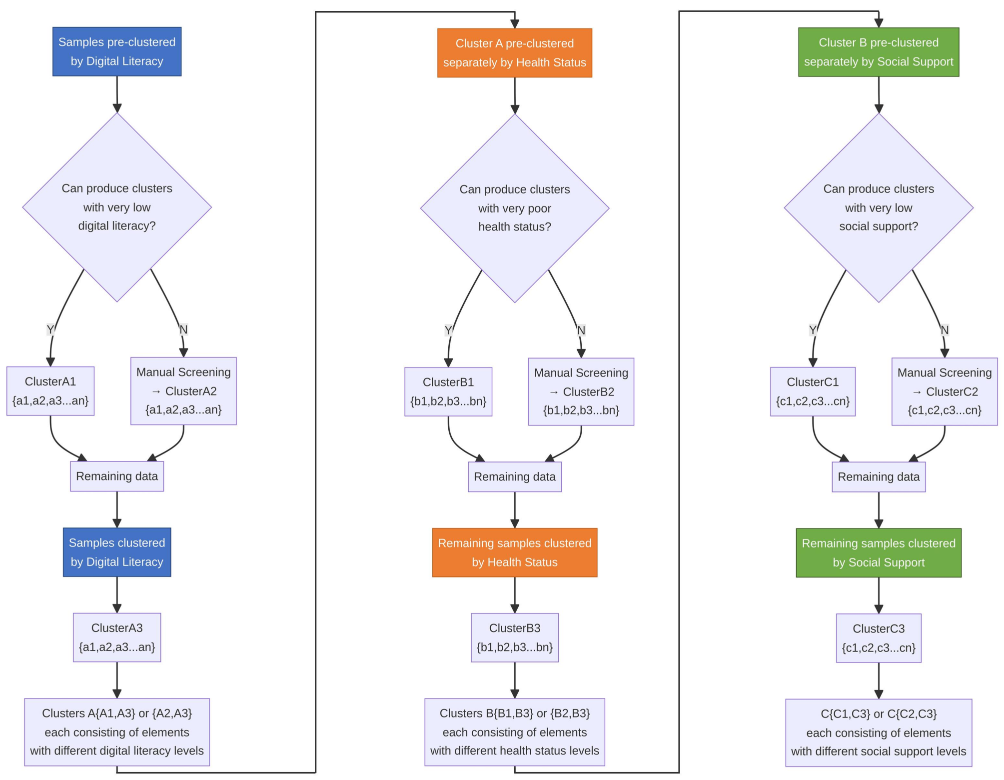


**Figure 2.** Hybrid Workflow of Alternating Manual Screening and Clustering.

## 4. Data

This section provides a detailed description of the dataset used in the study and the preprocessing procedures applied.

### *4.1. Dataset Overview*

The data for this study were obtained from the publicly available "National Community Health and Digital Life Tracking Survey for Middle-aged and Older Adults (2022—2024)." Data collection spanned two years and covered community health service centers in five representative cities across eastern, central, and western regions of China.

The initial dataset comprised 8,500 questionnaires and corresponding physical examination records. After applying inclusion and exclusion criteria (inclusion: aged 50—85 years and diagnosed with at least one chronic disease; exclusion: severe cognitive impairment preventing cooperation with the survey), a total of 3,856 valid samples were retained.

Descriptive statistics of key variables indicate that the mean age of the sample was 68.4 ± 8.2 years; 47.2% were male and 52.8% female. On average, participants had 2.1 ± 1.3 chronic conditions. The comorbidity profile of chronic diseases in the sample is illustrated in Figure 3, highlighting the complex interweaving of hypertension, diabetes, and cardiovascular diseases.

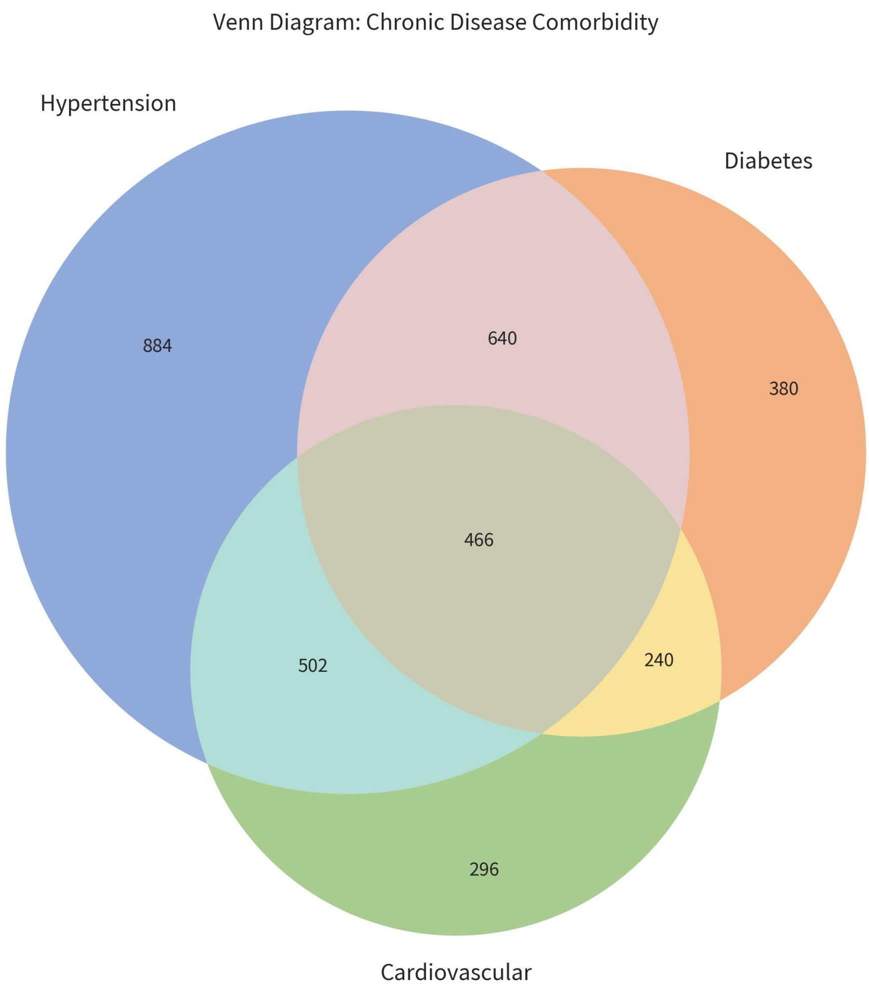


**Figure 3.** Distribution of Chronic Disease Comorbidities.

### *4.2. Dataset Overview*

The raw data underwent rigorous cleaning and transformation procedures:

- Missing Value Handling: A total of 112 samples (approximately 2.9%) contained partial missing data. For continuous variables with less than 5% missing values, multiple imputation was applied. Samples with missing values in core categorical variables were excluded from the analysis;
- Outlier Detection: Outliers in continuous variables were identified using boxplots and Z-score methods. Entries that were clearly inconsistent with physiological logic were either corrected or removed;
- Data Standardization: To account for differing measurement scales, all continuous variables were normalized to the [0,1] range using Min-Max scaling, thereby eliminating the influence of units on clustering distance calculations. Categorical variables were converted into dummy variable matrices. The correlations among key variables are shown in Figure 4.

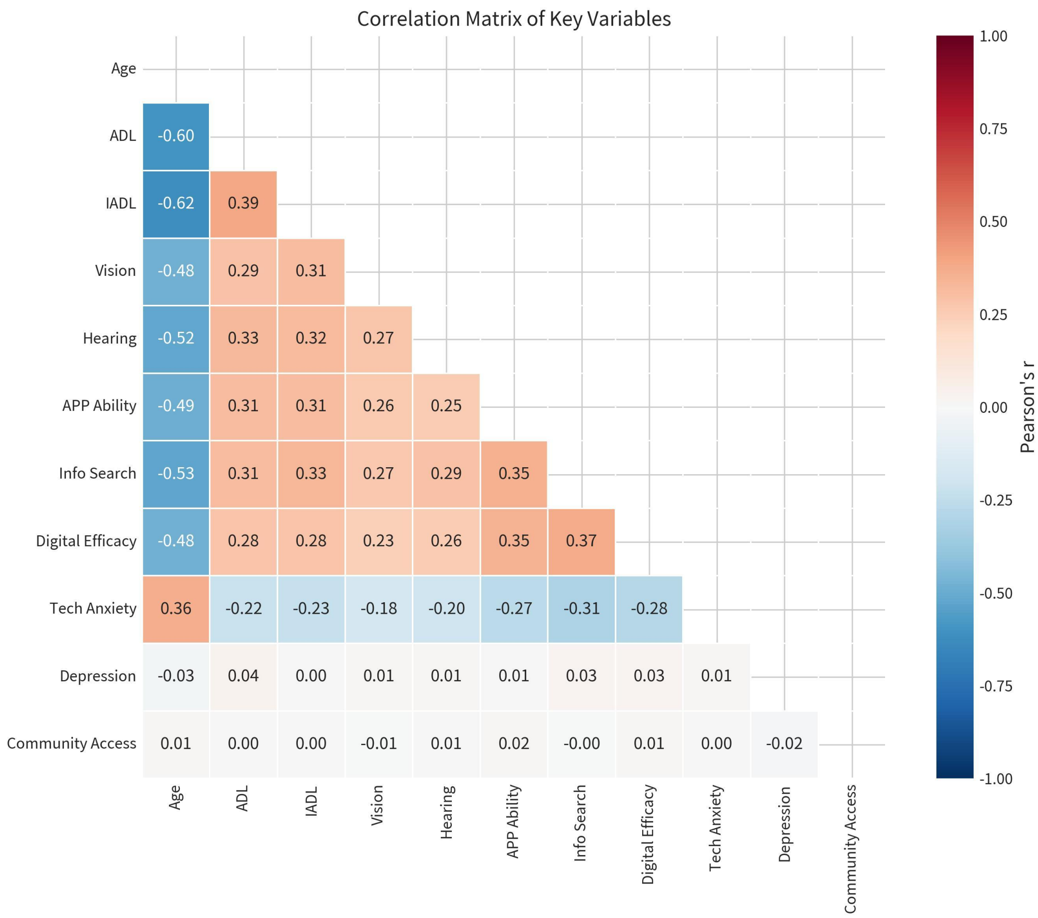


**Figure 4.** Heatmap of Correlations Among Core Variables.

## 5. Results

Through systematic data analysis and the hybrid clustering workflow, this study identified significant patterns in the capability distribution of community-dwelling patients with chronic diseases and successfully constructed multidimensional user persona clusters.

### *5.1. Distribution of Core Capabilities Across Age Groups*

The analysis objectively demonstrates the significant impact of age on various patient capabilities. As shown in Figure 5, with increasing age, patients exhibit declining trends in activities of daily living (ADL), app operational skills, visual and auditory perception, and digital self-efficacy.

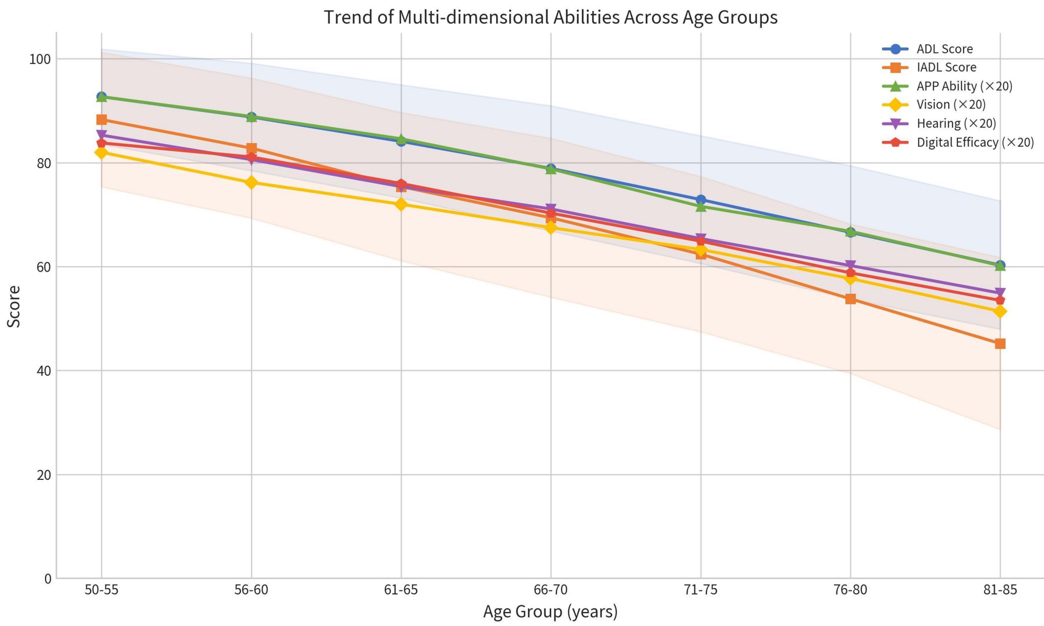


**Figure 5.** Multidimensional Capability Decline Across Different Age Groups.

Specifically, within the digital literacy dimension, Figure 6 illustrates the distribution of smartphone usage frequency, app operational skills, online information search capability, and digital self-efficacy across different age groups. Chi-square tests indicated a highly significant negative correlation between age and digital literacy level ($p < 0.001$). Notably, among participants aged 75 and above, the vast majority exhibited very low digital capabilities. The violin plot in Figure 7 further corroborates the differences in the distribution density of app operational skills across age groups.

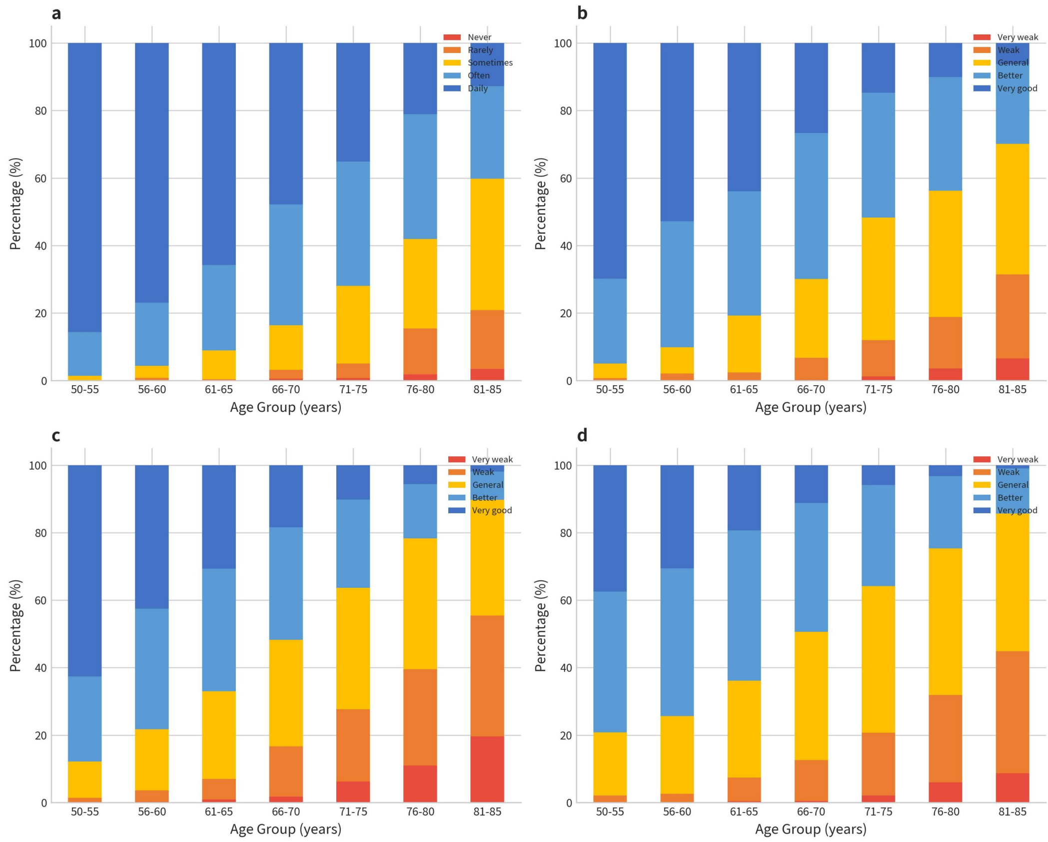


**Figure 6.** Distribution of Digital Literacy Dimensions Across Different Age Groups.

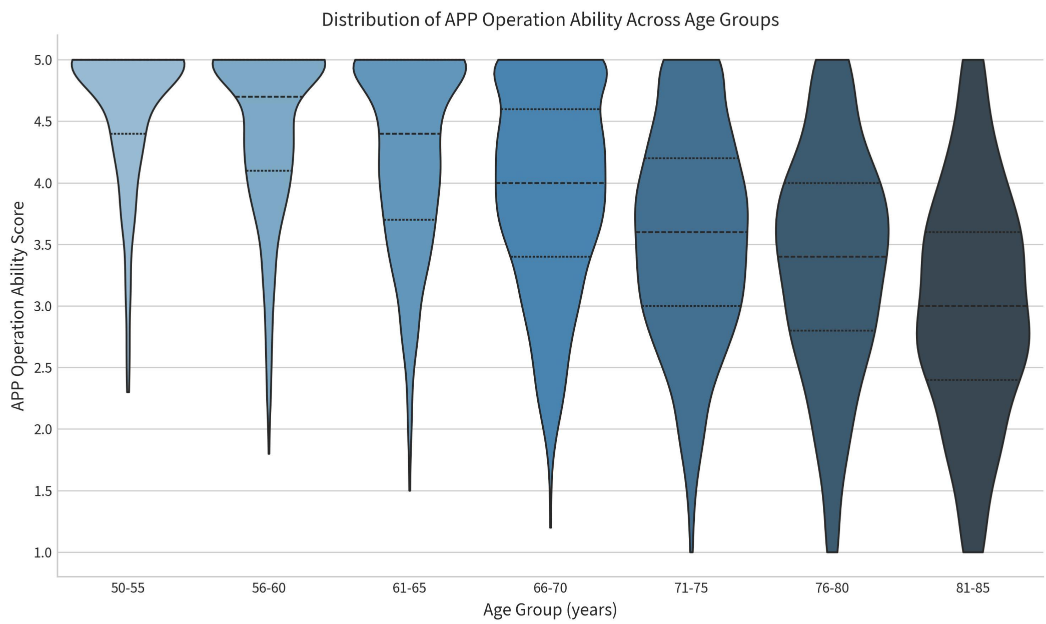


**Figure 7.** Violin Plot of App Operational Skills Across Different Age Groups.

Within the health status dimension, Figure 8 illustrates the age-related distribution of activities of daily living (ADL), instrumental activities of daily living (IADL), and motor coordination abilities. The decline in upper-limb fine motor skills and visual-auditory perception abilities is also closely associated with increasing age. However, data on perceptual abilities presented in Figure 9 reveal an interesting phenomenon: among the relatively younger chronic disease group aged 60—65, some patients exhibit pronounced deterioration in visual perception, primarily attributable to complications such as diabetic retinopathy.

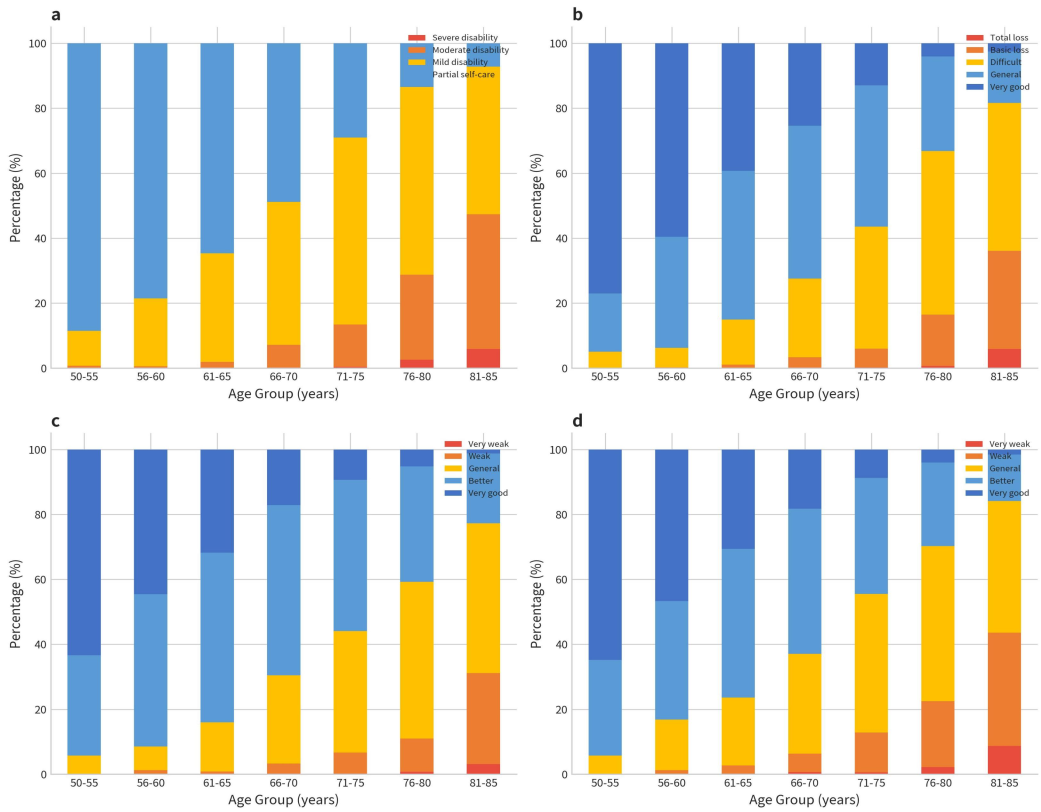


**Figure 8.** Distribution of Health Status and Motor Abilities Across Different Age Groups.

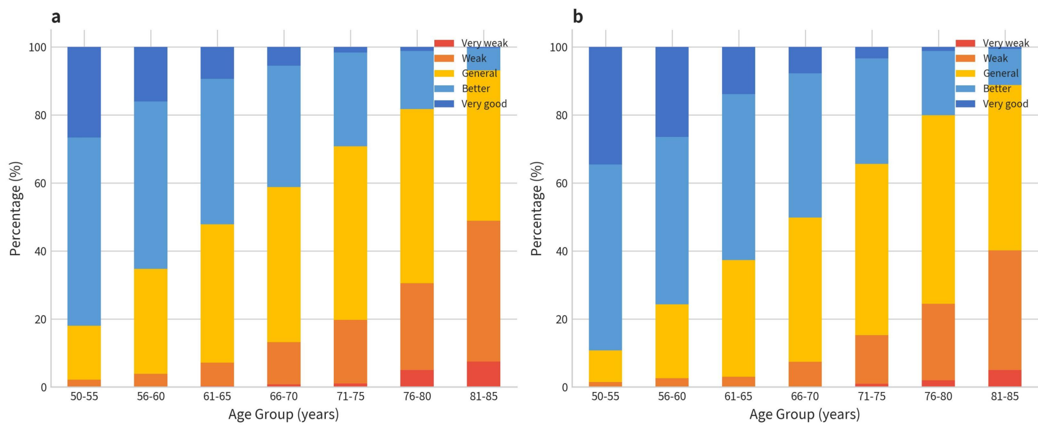


**Figure 9.** Distribution of Visual and Auditory Perceptual Abilities Across Different Age Groups.

## *5.2. Persona Clustering Results and Performance Metrics*

Through three alternating rounds of clustering and manual screening across the dimensions of digital literacy → health status → social support, the 3,856 samples were ultimately classified into 26 user persona clusters exhibiting significant characteristic differences. Figure 10 presents the sample size distribution of each cluster, highlighting the heterogeneity in group scales. Figure 11 shows boxplots of ADL scores for the ten largest clusters, confirming significant differences in physiological capabilities between clusters. The scatter plot in Figure 12 visually illustrates the joint distribution patterns of ADL scores and app operational skills across different clusters.

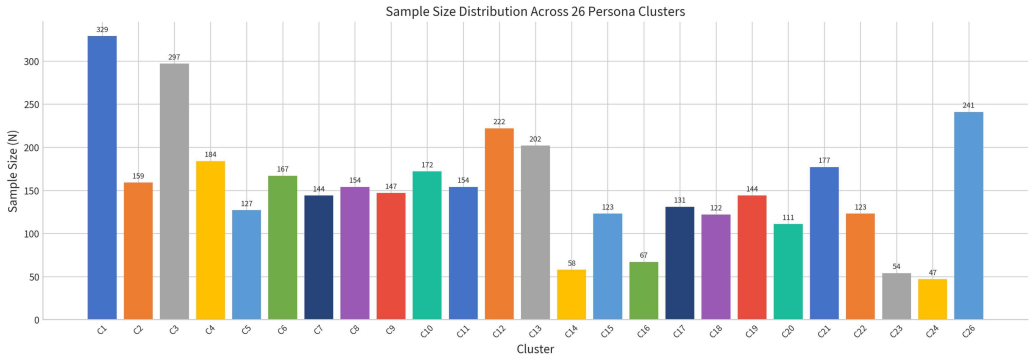


**Figure 10.** Sample Size Distribution of the 26 User Persona Clusters.

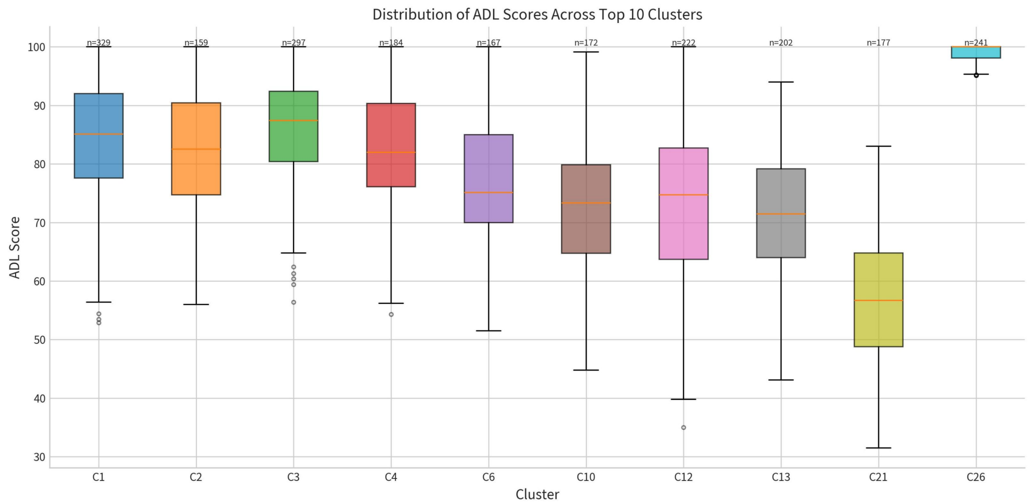


**Figure 11.** Boxplot Distribution of ADL Scores for the Top 10 Clusters.

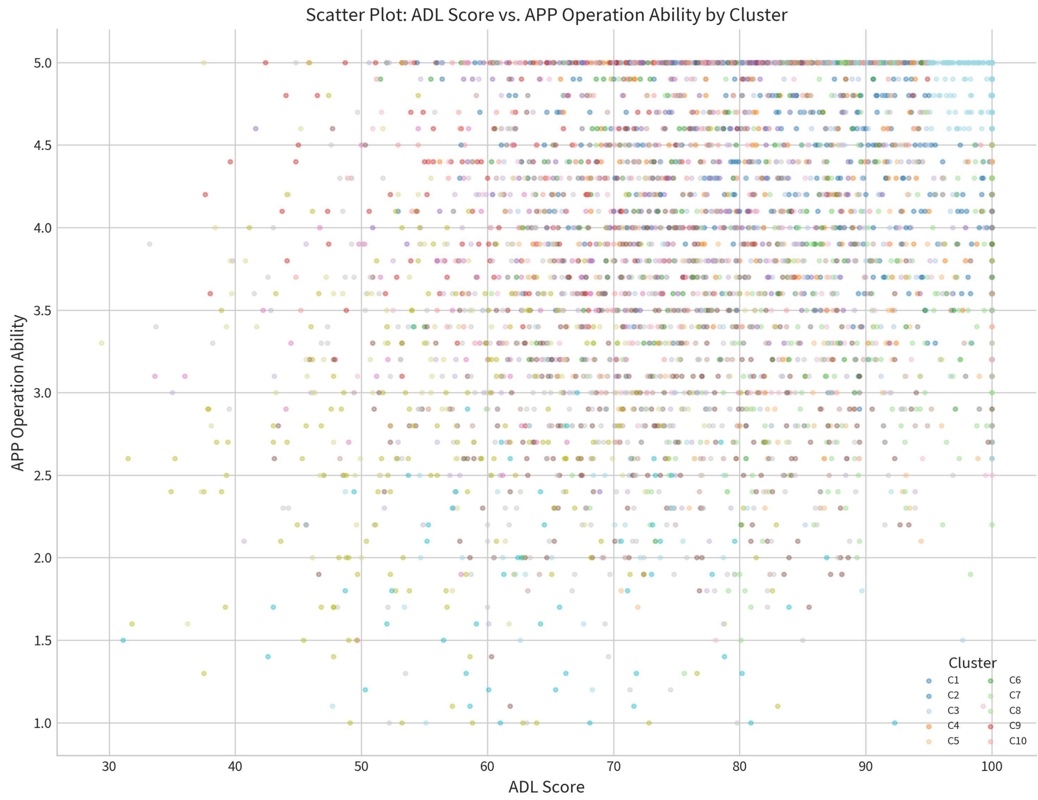


**Figure 12.** Scatter Plot of ADL Scores and App Operational Skills Across Different Clusters.

Model fit indices indicate that the final two-step clustering model achieved a Silhouette coefficient of 0.62, reflecting good clustering quality. The heatmap in Figure 13 presents the standardized mean values of the 26 clusters across all core capability indicators, clearly depicting the characteristic profiles of each cluster.

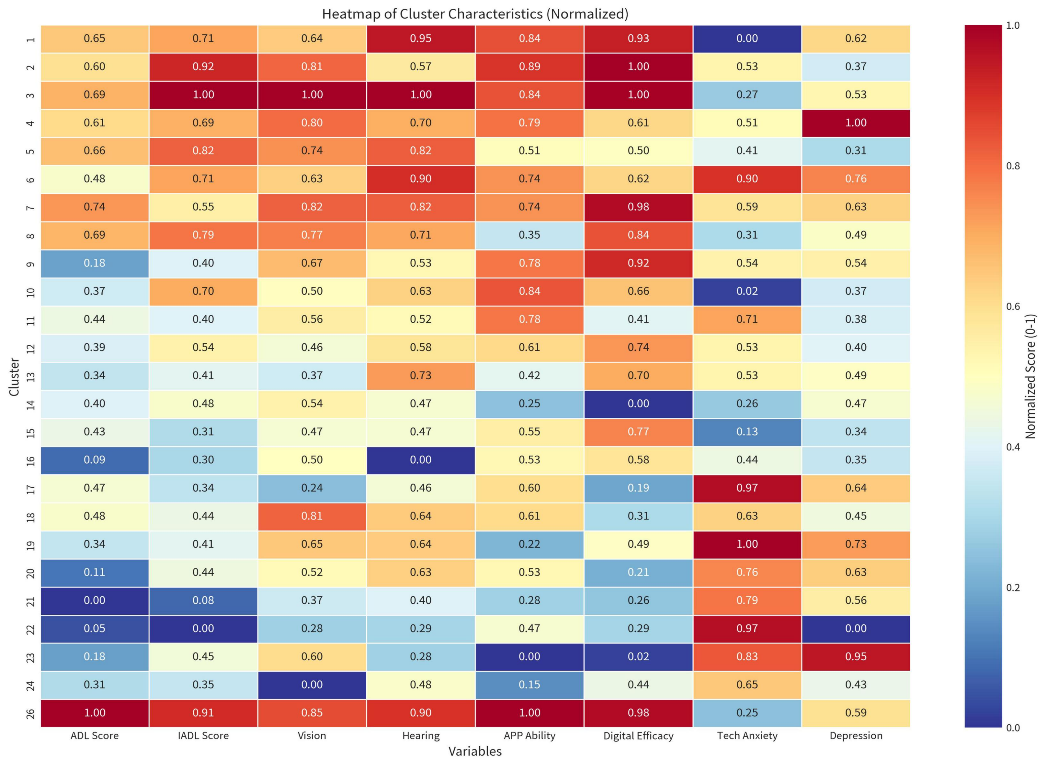

**Figure 13.** Standardized Heatmap of Characteristics Across the 26 User Persona Clusters.

### *5.3. Analysis of Typical User Persona Characteristics and Social Support Structures*

Social support plays a critical role in compensating for patients' capability limitations. Figure 14 illustrates the distribution of primary caregivers and sources of technical assistance across the overall sample, highlighting the important supportive role of family members—particularly children—when patients use digital health products.

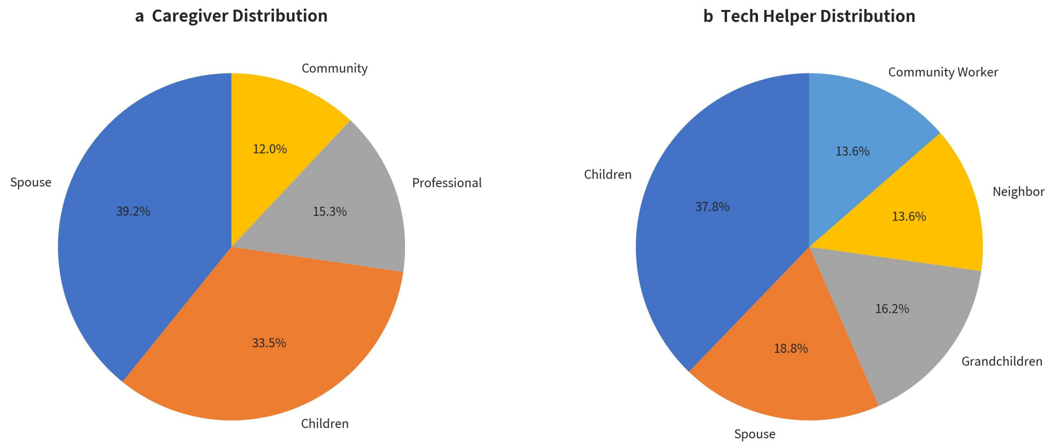


**Figure 14.** Distribution of Social Support Networks Among Community-Dwelling Patients with Chronic Diseases.

To provide design-oriented guidance, the 26 clusters were mapped into several representative user persona prototypes based on capability levels. Figure 15 presents a radar chart comparing two highly representative clusters—Cluster 8 and Cluster 19—across multidimensional capabilities:

- Cluster 8 (12.4%, n = 478): Characterized by "moderate digital literacy + mild physiological impairment + high social support." The mean age of this group was 64.5 ± 4.2 years, and they typically had a single chronic condition. Upper-limb function was preserved, although mild presbyopia was observed. These individuals demonstrated a strong willingness for health management and could operate basic app functions. When encountering technical difficulties, they primarily relied on cohabiting adult children for assistance;
- Cluster 19 (5.8%, n = 224): Characterized by "extremely low digital literacy + moderate-to-severe physiological impairment + living alone/low social support." The mean age was 78.2 ± 5.1 years, and members of this group had multiple chronic conditions with complications, along with pronounced fingertip tremors and hearing loss. They were unable to independently perform device pairing or complex interactions and lacked routine familial technical support.

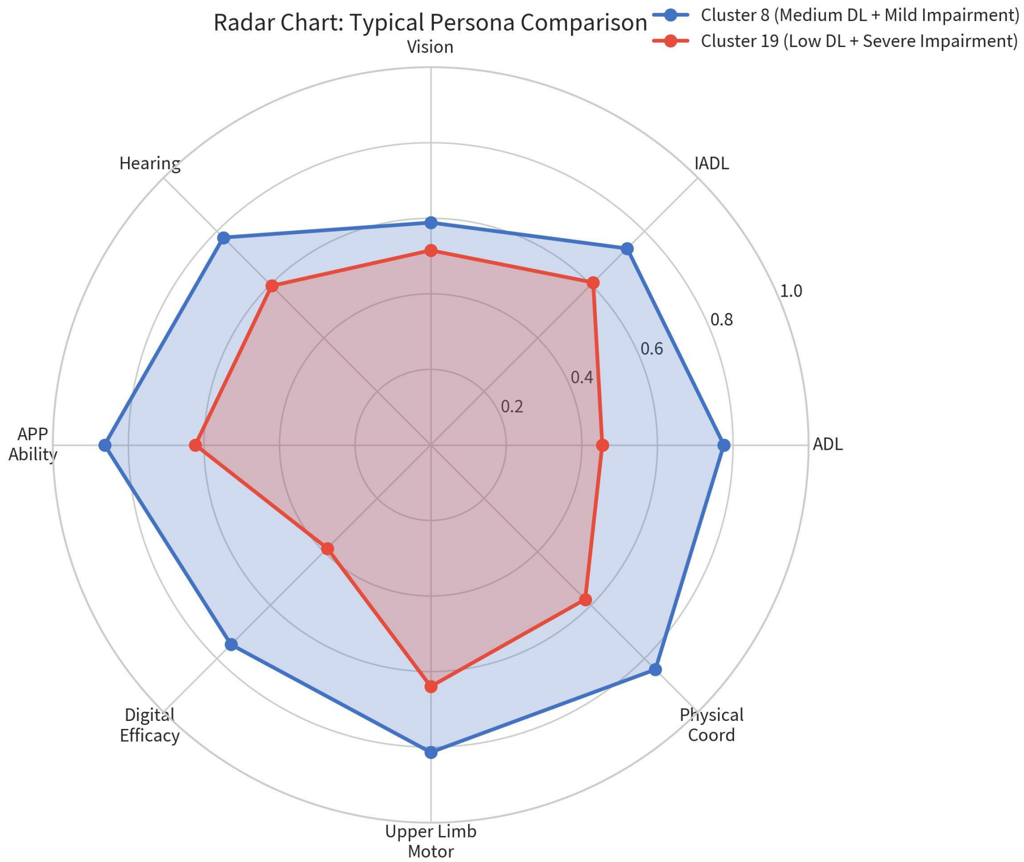


**Figure 15.** Radar Chart Comparison of Multidimensional Capabilities for Representative User Persona Prototypes.

## 6. Discussion

The multidimensional user persona framework developed in this study provides profound theoretical insights and practical guidance for the age-friendly and inclusive design of digital health products.

### *6.1. Horizontal Comparison: Beyond Unidimensional Persona Construction*

A horizontal comparison of our results with existing literature highlights the advantages of multidimensional capability mapping. Traditional studies often focus on a single variable, such as "technology usage frequency," for patient segmentation , or rely solely on "disease type" for medical classification. Our study reveals that even patients with the same chronic condition may exhibit dramatically different success rates in interacting with digital health products depending on the structure of their social support networks. The three-dimensional model developed here captures patient pain points in real-world usage scenarios more accurately than conventional models. For instance, clusters like Cluster 19, representing "dual disadvantages" (physiological impairment and low social support), are easily overlooked in usability testing conducted from a younger-user perspective.

### *6.2.Vertical Relationships: Capability Compensation and Design Intervention Mechanisms*

Analyzing the internal vertical logic of the study results reveals the critical role of the “capability compensation” mechanism in interaction design. The findings indicate that, although some elderly patients exhibit severe declines in cognitive and visual-perceptual abilities, those with high levels of social support maintain relatively high retention rates for digital health devices. This internal logic suggests that design strategies should go beyond superficial age-friendly adjustments, such as “larger fonts” or “higher contrast,” and incorporate system-level “social support compensation” mechanisms. For example, for low-digital-literacy groups, products could implement a “caregiver-managed mode,” delegating complex configuration and data analysis tasks to digitally literate caregivers while providing the patient with only the most essential and minimal operations.

### *6.3.Attribution of Differences and Translation into Design Strategies*

Certain findings in this study that deviate from previous research—for example, the observation that visual impairment may precede hearing loss in younger chronic disease patients—can be attributed to specific pathological mechanisms of chronic disease complications, such as diabetic retinopathy, which selectively impair perceptual abilities. These differential attributions have direct implications for design practice:

For hardware devices such as smart blood pressure monitors and glucometers, designers should avoid blindly applying a “visual-priority” interaction paradigm. For groups like Cluster 19, who experience visual impairment and fingertip tremors, multimodal interaction (e.g., voice output, physical buttons, haptic feedback) is essential to mitigate the precision demands of touchscreen interactions. Conversely, for clusters like Cluster 8, which possess moderate digital literacy, design should emphasize readability of data visualizations and motivational mechanisms for health interventions, rather than over-simplifying functionality and thereby reducing user engagement.

## 7. Conclusion

### *7.1. Key Findings*

From the perspective of design-driven interdisciplinary innovation, this study systematically proposed and validated a methodology for constructing user personas of community-dwelling patients with chronic diseases based on three core dimensions: digital literacy, health status, and social support. Through empirical analysis of a large sample and application of the two-step clustering method, highly heterogeneous patient populations were successfully segmented into 26 representative personas with clearly defined capability boundaries. The study demonstrates that moving away from traditional "age/disease type" classifications toward a segmentation strategy centered on comprehensive interaction capabilities allows a more objective and precise mapping of patients' real challenges and needs in using digital health products.

### *7.2. Research Implications*

At the theoretical level, this study extends the application of inclusive design within the healthcare domain and establishes an interdisciplinary framework for persona development that integrates data science, public health, and interaction design. Practically, the generated persona repository provides digital health companies and community health management platforms with a direct "virtual user" reference. Designers can align specific persona clusters with product positioning to set realistic usability thresholds, thereby substantially reducing the cost and uncertainty associated with preliminary user research.

### *7.3. Limitations and Future Research*

This study has certain limitations. Data collection was primarily concentrated in urban communities in first- and second-tier cities, limiting coverage of patients in remote rural areas. Additionally, the study lacked long-term objective tracking of actual device operation logs. Future research could focus on incorporating multimodal data sources, combining real-world operation logs from wearable devices with physiological measures such as eye-tracking and electromyography, to dynamically calibrate the static personas. Comparative design experiments could further quantify the effectiveness of multidimensional personas in enhancing product adherence and improving health intervention outcomes.

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