

# A Dynamic Health Status-Based Framework for Personalized Older Adult Welfare Services and Policy: A Nursing-Informed Illustrative Application

Young Mi Cho<sup>1</sup> , Young-Ae Jung<sup>2</sup> , Hoon Ko<sup>3</sup> 

<sup>1</sup> Department of Nursing Science, Sunmoon University College of Health Science, Asan, Republic of Korea; <sup>2</sup> Department of AI Software Technology, Sunmoon University College of Engineering, Asan, Republic of Korea; <sup>3</sup> Department of Computer Science & Engineering, Sunmoon University College of Engineering, Asan, Republic of Korea.

## Abstract

**Objective:** This study proposed a conceptual and computationally structured health status-based framework as a preliminary foundation for future artificial intelligence (AI)-supported older adult welfare decision-making based on multidimensional health status rather than chronological age alone.

**Materials and Methods:** Diabetes mellitus, hypertension, and dementia were represented as component-level state vectors. Disease burden, interaction risk, functional impairment, and recent health changes were integrated into an Elderly Health Status Score, which was subsequently converted into a Health-Equivalent Age. The framework was illustrated using two hypothetical cases.

**Results:** The illustrative cases demonstrated that chronological age alone may not adequately reflect individual care needs. Using the predefined parameters for illustration, the framework estimated the Health-Equivalent Age of a healthy 70-year-old to be approximately 65 years, whereas a vulnerable 65-year-old was identified as potentially requiring more intensive health and welfare services. These results illustrate the operation of the proposed framework rather than clinically validated estimates. No statistical testing was performed because the cases were hypothetical.

**Conclusion:** The proposed framework may complement age-based eligibility criteria by reflecting individual health vulnerability and care needs in nursing, community care, and welfare-service prioritization. Validation of the model weights, state-transition parameters, and predictive performance using longitudinal clinical data is required before practical implementation.

**Keywords:** Multimorbidity, geriatric nursing, clinical decision support systems, health policy

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**Correspondence** Hoon Ko

**E-mail** [hoonko21@sunmoon.ac.kr](mailto:hoonko21@sunmoon.ac.kr)



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## INTRODUCTION

As the older population continues to grow, the allocation of welfare services based primarily on chronological age or single-disease criteria may not adequately reflect individual differences in health status and actual care needs, potentially resulting in the overprovision or underprovision of services. To address this issue, the present study selected hypertension, diabetes mellitus, and dementia as the initial target conditions because of their high prevalence among older adults and their potential interrelationships through vascular damage, metabolic abnormalities, and cognitive decline. These three conditions constitute an initial illustrative disease set rather than an exhaustive representation of older adults' health and welfare needs. The framework is designed to accommodate additional diseases, functional conditions, and social and environmental determinants in subsequent applications. Multimorbidity is particularly common among older adults and substantially increases the complexity of healthcare and caregiving needs (1,2). Therefore, even among individuals of the same chronological age, the required level of care may differ according to disease severity, physical function, cognitive ability, frailty, and recent changes in health status (2,3). Based on these considerations, this study proposes a Dynamic Health Status-Based Framework (DHSBF) for personalized older adult welfare services and policy decision-making. The framework represents each disease as a set of interacting components and evaluates not only current disease burden but also cross-disease interaction risk, functional impairment, and recent health changes (4–6). These factors are integrated into a quantitative health-status profile that can support the prioritization of nursing interventions, community care, and welfare services (7). The DHSBF does not constitute a developed artificial intelligence (AI) algorithm or a novel graph neural network (GNN)/recurrent neural network (RNN) architecture. Rather, it represents a pre-implementation conceptual framework that formalizes health components, component-level relationships, temporal transition logic, and policy-oriented outputs in a computationally representable form. Graph neural networks, recurrent neural networks, or alternative nonlinear models may subsequently be evaluated as possible implementation approaches after appropriate individual-level longitudinal data become available. Longitudinal health data will be required to estimate the interaction weights, state-transition parameters, and evaluation coefficients and to validate the predictive performance of the framework. Artificial intelligence-based functions may subsequently be incorporated to support health-status prediction, risk classification, and service recommendations. In this process, AI is intended to assist rather than replace

professionals, with nursing, medical, and policy experts retaining responsibility for final decisions (8,9).

## MATERIALS AND METHODS

This conceptual study used only hypothetical illustrative cases and did not involve human participants or identifiable clinical data; therefore, ethics committee approval and informed consent were not required.

### Disease Component Sets and State Representation

Figure 1 illustrates the overall structure and processing flow of the proposed DHSBF. The framework represents diabetes mellitus (X), hypertension (Y), and dementia (Z) as sets of detailed components. Rather than using only the presence or absence of each disease, it uses the deterioration levels of glucose and metabolic, blood pressure and vascular, and cognitive and functional components as input values (Table 1). The vectors  $X(t)$ ,  $Y(t)$ , and  $Z(t)$  represent the component states of diabetes mellitus, hypertension, and dementia, respectively, at time  $t$ . Each element  $x_{i(t)}$ ,  $y_{j(t)}$ , and  $z_{k(t)}$  indicates the degree of deterioration of the corresponding component. The overall state vector is defined by combining the component states of the three diseases as follows (10–12).

$$S(t) = [X_{(t)}^T, Y_{(t)}^T, Z_{(t)}^T]^T \in \mathbb{R}^n, n = p + q + r$$

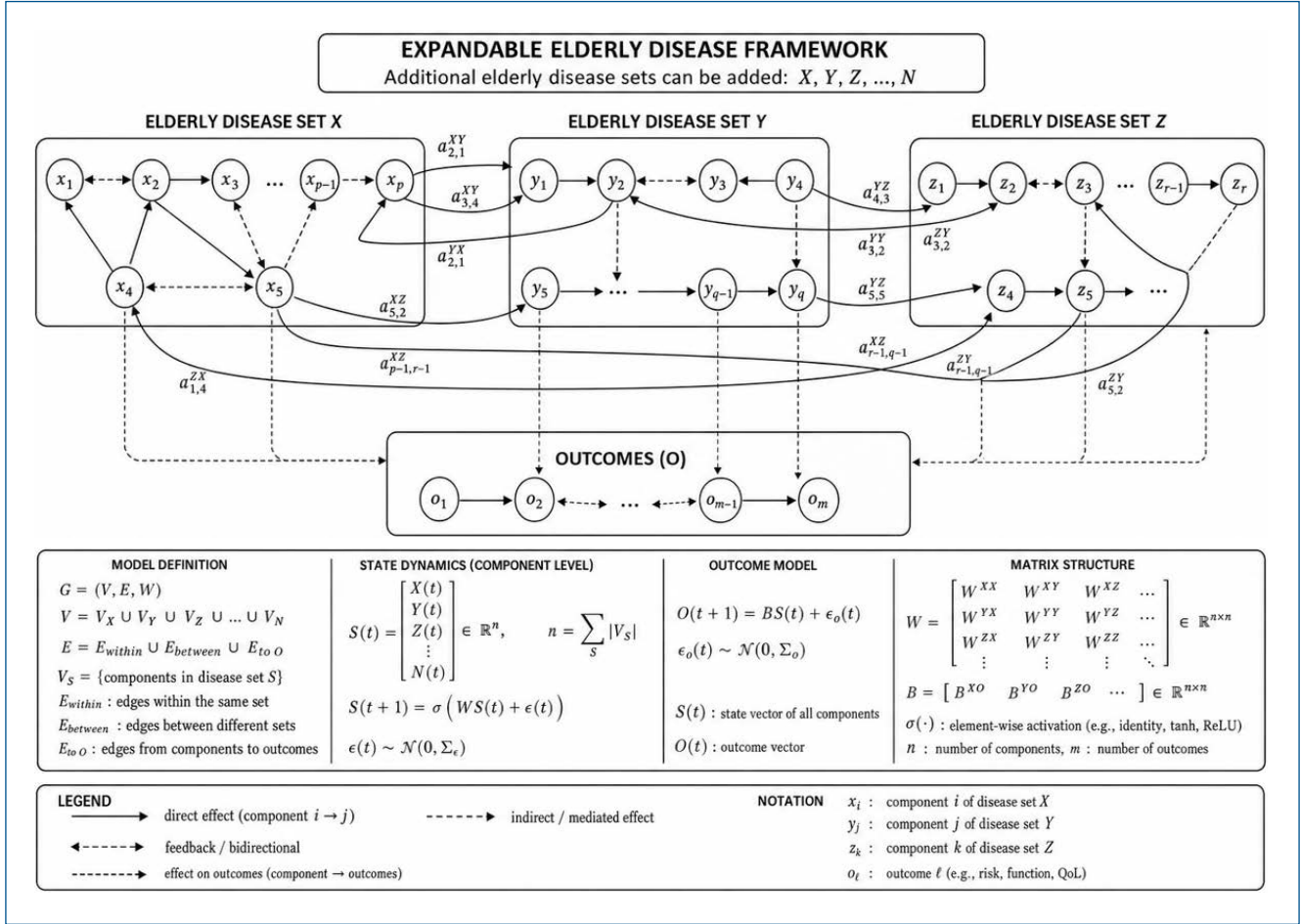
$S(t)$  represents the overall state of all disease components for an individual, and  $n$  denotes the total number of components associated with diabetes mellitus, hypertension, and dementia.

Because each component may be measured using clinical indicators with different units, all values are normalized to a range between 0 and 1 before the model is applied, where 0 indicates no risk and 1 indicates a very high level of risk.  $v_{i(t)}$  denotes the original clinical value,  $L_i$  represents the normal lower bound or reference value, and  $U_i$  represents the high-risk threshold. The clip function restricts the calculated value to 0 when it is less than 0 and to 1 when it exceeds 1. This normalization process enables variables measured in different units, such as blood glucose, blood pressure, and cognitive scores, to be integrated into a single state vector  $S(t)$ .

$$s_{i(t)} = \text{clip}((v_{i(t)} - L_i) / (U_i - L_i), 0, 1)$$

### Component-Level Interaction Network

Rather than modeling only broad relationships among diseases, the DHSBF represents the influences and propagation pathways among the detailed components of each disease. The component-level interaction graph is defined as  $G = (V, E, W)$  (13), where  $V$  denotes the set of component nodes,  $E$  represents the set of connections between nodes, and  $W$  is a weighted matrix indicating the direction and strength of each connection. The complete



**FIGURE 1.** Structure and flow of the dynamic health status-based framework.

**Table 1.** Definitions of diabetes mellitus (X), hypertension (Y), and dementia (Z).

| Type             | Symbol                                                                               | Component                                                                                                                                                                                | Description                                                                                  |
|------------------|--------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------------|
| Diabetes Set     | $X_{(t)} = [x_{1(t)}, x_{2(t)}, \dots, x_{p(t)}]^T$<br>( $X = \{x_1, \dots, x_p\}$ ) | Hyperglycemia, impaired insulin secretion, insulin resistance, abnormal lipid metabolism, and inflammation/oxidative stress                                                              | A higher value indicates greater deterioration in diabetes-related components                |
| Hypertension Set | $Y_{(t)} = [y_{1(t)}, y_{2(t)}, \dots, y_{q(t)}]^T$<br>( $Y = \{y_1, \dots, y_q\}$ ) | Elevated blood pressure, sympathetic nervous system activation, renin-angiotensin-aldosterone system (RAAS) activation, sodium and fluid retention, and vascular endothelial dysfunction | A higher value indicates greater risk associated with blood pressure and vascular regulation |
| Dementia Set     | $Z_{(t)} = [z_{1(t)}, z_{2(t)}, \dots, z_{r(t)}]^T$<br>( $Z = \{z_1, \dots, z_r\}$ ) | Cognitive decline, memory impairment, cerebrovascular damage, neuroinflammation, and impaired activities of daily living                                                                 | A higher value indicates greater risk of cognitive and functional decline                    |

node set consists of components associated with diabetes mellitus, hypertension, and dementia (Table 2).

$$V = V_X \cup V_Y \cup V_Z$$

The edge set includes connections within the same disease, connections across different diseases, and

connections leading to functional and welfare outcomes, thereby representing how a specific health risk may propagate to other disease components and functional outcomes.

$$E = E_{\text{within}} \cup E_{\text{between}} \cup E_{\text{to } O}$$

**Table 2.** Component-level connection types in the dynamic health status-based framework.

| Connection                       | Type                                                                    | Dimension                                                                                                                                                                                                                       |
|----------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| Within-disease connections       | $x_i \rightarrow x_j$<br>$y_i \rightarrow y_j$<br>$z_i \rightarrow z_j$ | - Pathophysiological relationships among components within the same disease<br>- $x_3 \rightarrow x_1$ : Insulin resistance contributes to worsening hyperglycemia                                                              |
| Direct cross-disease connections | $x_i \rightarrow y_j$<br>$x_i \rightarrow z_k$<br>$y_j \rightarrow z_k$ | - A component of one disease directly affects a specific component of another disease<br>- $x_3 \rightarrow y_3$ : Insulin resistance contributes to RAAS activation                                                            |
| Mediated connections             | $x_i \rightarrow y_j \rightarrow z_k$                                   | - Risk propagates to another disease through intermediate components<br>- $x_3 \rightarrow y_1 \rightarrow z_3$ : Insulin resistance leads to elevated blood pressure, which subsequently contributes to cerebrovascular damage |
| Feedback connections             | $z_k \rightarrow x_i$ OR<br>$z_k \rightarrow y_j$                       | - Cognitive and functional decline worsens the management of existing diseases by reducing self-management capacity<br>- $z_5 \rightarrow x_1$ : Impaired activities of daily living lead to poorer blood glucose management    |

RAAS: Renin-angiotensin-aldosterone system.

The element  $w_{ij}$  of the weight matrix  $W$  represents the direction and strength of the influence of component  $j$  on component  $i$ .

- $w_{ij} > 0$ : component  $j$  aggravates component  $i$
- $w_{ij} = 0$ : no meaningful influence
- $w_{ij} < 0$ : component  $j$  alleviates component  $i$

For example,  $w_{\{x_3, y_3\}} > 0$  indicates that component  $x_3$  of diabetes mellitus, representing insulin resistance, has a deteriorating effect on component  $y_3$  of hypertension, representing renin-angiotensin-aldosterone system (RAAS) activation. Conversely, when intervention factors such as exercise, medication management, and nutritional management are included, their mitigating effects can be represented by negative weights  $w_{ij} < 0$  (Table 3).

$$W = \begin{bmatrix} W_{X \rightarrow X} & W_{Y \rightarrow X} & W_{Z \rightarrow X} \\ W_{X \rightarrow Y} & W_{Y \rightarrow Y} & W_{Z \rightarrow Y} \\ W_{X \rightarrow Z} & W_{Y \rightarrow Z} & W_{Z \rightarrow Z} \end{bmatrix}$$

The within-disease matrices  $W_{X \rightarrow X}$ ,  $W_{Y \rightarrow Y}$ , and  $W_{Z \rightarrow Z}$  represent interactions among components within each disease.  $W_{X \rightarrow Y}$  represents the effects of the components of  $X$  on those of  $Y$ ,  $W_{X \rightarrow Z}$  represents the effects of the components of  $X$  on those of  $Z$ , and  $W_{Y \rightarrow Z}$  represents the effects of the components of  $Y$  on those of  $Z$ . The rows of each matrix correspond to the components receiving the influence, whereas the columns correspond to the components exerting the influence.

### Dynamic State Transition and Propagation Mechanism

The state-transition model  $S(t+1)$  represents how the current states and interactions of the components affect health status at the next time point, thereby reflecting cascading changes over time (14,15).

$$S(t+1) = \sigma(WS(t) + \varepsilon(t))$$

In the basic state-transition equation,  $WS(t)$  represents the total effect of the current state on each component at the next time point,  $\varepsilon(t)$  represents uncertainty arising from factors such as measurement error and individual variability, and  $\sigma(\cdot)$  is a function that constrains the resulting values to the range of 0 to 1. To reflect the persistence of chronic conditions in older adults, this study employs an extended state-transition equation that includes a self-persistence term (Table 4).

$$S(t+1) = \sigma(\rho S(t) + W S(t) + \Gamma L(t) + \varepsilon(t))$$

$\rho S(t)$  represents the persistence of the current state, where  $\rho$ , ranging from 0 to 1, controls the degree to which chronic disease conditions persist over time.  $\Gamma L(t)$  reflects the effects of external contextual factors on health-state transitions. In the expanded framework,  $L(t)$  may include behavioral, social, environmental, and healthcare-access factors, such as lifestyle, medication adherence, physical activity, nutrition, sleep, socioeconomic status, education and health literacy, living environment, social isolation, caregiver support, healthcare access, place of residence, sex or gender, cultural background, and disability. These factors are informed by the Place of residence, Race/ethnicity/culture/language, Occupation, Gender/sex, Religion, Education, Socioeconomic status, and Social capital—Plus (PROGRESS-Plus) equity framework. This framework guides the consideration of social and contextual factors relevant to equitable health assessment and welfare service prioritization for older adults, ensuring that health and welfare needs are not interpreted solely through biomedical indicators. This equation provides a conceptual representation of the proposed transition mechanism rather than

**Table 3.** Structure and interpretation of submatrices in the interaction matrix  $W$ .

| Submatrix                                                       | Dimension                    | Implication                                                   |
|-----------------------------------------------------------------|------------------------------|---------------------------------------------------------------|
| $W_{x-x}$                                                       | $p \times p$                 | Internal influences among diabetes components                 |
| $W_{y-y}$                                                       | $q \times q$                 | Internal influences among hypertension components             |
| $W_{z-z}$                                                       | $r \times r$                 | Internal influences among dementia components                 |
| $W_{x \rightarrow y}$                                           | $q \times p$                 | Effects of diabetes components on hypertension components     |
| $W_{x \rightarrow z}$                                           | $r \times p$                 | Effects of dementia components on diabetes components         |
| $W_{y \rightarrow z}$                                           | $r \times q$                 | Effects of hypertension components on dementia components     |
| $W_{y \rightarrow x}, W_{x \rightarrow z}, W_{z \rightarrow y}$ | Each corresponding dimension | Used when reverse influences or feedback pathways are present |

**Table 4.** Components and interpretations of the baseline state-transition model.

| Assessment Component | Description                            | Implication                                                                                                                                      |
|----------------------|----------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------------|
| $\rho S_{(t)}$       | State persistence                      | The extent to which the current deteriorated state persists at the next time point due to the chronic nature of the disease                      |
| $W S_{(t)}$          | Propagation effects among components   | The effect by which deterioration in a specific component is transmitted to other connected components                                           |
| $\Gamma L(t)$        | Effects of external contextual factors | The effects of behavioral, social, environmental, and healthcare-access factors on health-state transitions and welfare needs                    |
| $\varepsilon(t)$     | Uncertainty and unexplained variation  | Represents measurement error, individual heterogeneity, unobserved determinants, and unpredictable events that limit individual-level prediction |
| $\sigma(\cdot)$      | Range adjustment                       | Maintains interpretability by constraining state values to the range of 0 to 1                                                                   |

an empirically trained prediction model. At the present stage,  $W$ ,  $\rho$ , and  $\Gamma$  are not learned parameters. Their data-driven estimation requires individual-level longitudinal observations containing repeated measurements of disease components, functional status, and relevant contextual factors. Although the transformation function  $\sigma(\cdot)$  introduces nonlinearity into the state-transition process, the interaction term  $WS(t)$  remains an additive weighted representation. Accordingly, the present equation should be interpreted as an interpretable baseline formulation and not as a validated representation of abrupt or highly nonlinear health transitions. In particular, the current formulation has not been demonstrated to identify tipping points associated with events such as falls or delirium or to detect delayed recovery as an indicator of declining resilience. To conceptually accommodate such nonlinear dynamics in future empirical implementations, the baseline model may be generalized as follows:

$$S(t+1) = \sigma(\rho S(t) + W S(t) + H_{\phi}(S(t), L(t)) + \Gamma L(t) + \varepsilon(t))$$

Here,  $H_{\phi}(S(t), L(t))$  denotes a generalized nonlinear function representing threshold effects and higher-order

interactions among disease components and contextual factors. Its functional form and parameters are not specified in the present conceptual study and must be learned and validated using sufficiently dense individual-level longitudinal data. The uncertainty term  $\varepsilon(t)$  reflects measurement error, individual heterogeneity, unobserved biological and contextual determinants, and unpredictable acute events. Its inclusion acknowledges that individual health trajectories cannot be completely explained by the observed components or interaction structure. Accordingly, the state-transition equation should be interpreted as a probabilistic and uncertainty-aware conceptual representation rather than as a deterministic prediction of an individual's future health state.

$$S_{i(t+1)} = \sigma(\rho_i S_{i(t)} + \sum_j w_{ij} S_{j(t)} + v_{iT} L(t) + \varepsilon_{i(t)})$$

This means that the next state of the  $i^{\text{th}}$  component is determined by its previous state, the influences of other components, external factors, and uncertainty. For example,  $y_s$  may be influenced by  $x_s$  (insulin resistance),  $y_1$  (elevated blood pressure), and lifestyle-related factors.

### Integrated Evaluation Function

The health status and care needs of older adults cannot be adequately explained solely by the presence or absence of a single disease. Therefore, this study evaluates individual health status and service needs by integrating current disease burden, the risk of propagation among components, functional status, and recent changes in health status. The definition of each assessment component, the meaning of a high value, and its potential applications are summarized in Table 5 (1–3,10).

Here,  $\alpha$  and  $\beta$  are weight vectors that reflect the clinical importance of the disease components and the functional and welfare outcomes, respectively.  $W^+ = \max(W, 0)$  denotes a matrix obtained by extracting only the positive influences associated with deterioration from the interaction matrix  $W$ . The functional and welfare outcome vector  $O(t+1)$  is calculated as  $O(t+1) = BS(t) + \varepsilon_o(t)$ , where  $B$  represents the effects of the disease components on physical function, cognitive function, activities of daily living, fall risk, and long-term care needs.  $\theta_1$ – $\theta_4$  represent the relative importance of disease burden, propagation risk, functional decline, and the rate of health deterioration. In the present conceptual application, these parameters are predefined solely to

demonstrate the computational procedure and should not be interpreted as clinically estimated or validated weights. In subsequent empirical studies, they must be learned or calibrated using individual-level longitudinal data and validated in independent cohorts. The Elderly Health Status Score [EHS(t)] is an integrated indicator that summarizes an individual's overall health vulnerability and need for services, whereas the component propagation potential [CPP<sub>*i*</sub>(t)] serves as a supplementary indicator for identifying the components that should be prioritized to reduce cascading deterioration. Health-Equivalent Age (HEA) is intended as a supplementary communication and policy-support indicator rather than as a stand-alone clinical or welfare eligibility criterion. Because conversion of multidimensional health information into a single age-equivalent value may conceal important differences among individuals, HEA should be interpreted together with the underlying EHS dimensions—disease burden  $D(t)$ , interaction risk  $I(t)$ , functional impairment  $F(t)$ , and recent health change  $C(t)$ —as well as the component-level state profile and major CPP contributors. This layered presentation preserves traceability from the summary indicator to the health components and interactions responsible for the estimated value.

**Table 5.** Components, interpretations, and applications of the integrated health evaluation.

| Assessment Component                                        | Formula                                                                  | Description                                                                                                                     | Meaning of a high value                                                                | Application                                                                                    |
|-------------------------------------------------------------|--------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------|----------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------|
| Disease Burden $D(t)$                                       | $D(t) = \alpha^T S(t)$                                                   | Evaluates the current deterioration levels of disease components by weighting them according to their clinical importance       | The current disease severity and multimorbidity burden are high                        | Intensive chronic disease management, referral to specialized care, and medication management  |
| Propagation Risk $I(t)$                                     | $I(t) = S(t)^T W S(t)$                                                   | Evaluates the potential for cascading deterioration among interconnected components                                             | The risk of deterioration spreading to other diseases or functional domains is high    | Early identification of high-risk components and preventive interventions                      |
| Functional Decline $F(t)$                                   | $F(t) = \beta^T O(t)$                                                    | Evaluates physical and cognitive function, activities of daily living, and care needs                                           | Functional decline and actual care needs are substantial                               | Home-visit nursing, rehabilitation, long-term care, and support for activities of daily living |
| Rate of Deterioration $C(t)$                                | $C(t) = \ S(t) - S(t-1)\ $                                               | Evaluates recent changes in health status compared with the previous time point                                                 | The individual's health status has recently been deteriorating rapidly                 | Early monitoring, health counseling, and timely intervention                                   |
| Elderly Health Status Score, EHS(t)                         | $EHS(t) = \theta_1 D(t) + \theta_2 I(t) + \theta_3 F(t) + \theta_4 C(t)$ | Provides an integrated assessment of disease burden, propagation risk, functional decline, and the rate of health deterioration | Overall health vulnerability and the need for healthcare and welfare services are high | Classification of individuals at risk and prioritization of healthcare and welfare services    |
| Component Propagation Potential CPP <sub><i>i</i></sub> (t) | $CPP_i(t) = s_i(t) \sum_j \max(w_{ji}, 0)$                               | Evaluates the potential of a specific component to promote deterioration in other components                                    | The component has a strong potential to cause cascading deterioration                  | Prioritization of nursing interventions and disease management                                 |

**EHS:** Elderly Health Status Score, **CPP:** Component propagation potential.

**Table 6.** Interpretation of health-equivalent age based on the Elderly Health Status Score.

| Condition              | Description                                                           | Implication                                                                           |
|------------------------|-----------------------------------------------------------------------|---------------------------------------------------------------------------------------|
| $EHS(t) < E_{ref(CA)}$ | Better health status than the average for the same age group          | May be assessed as having a health status-based age lower than the chronological age  |
| $EHS(t) = E_{ref(CA)}$ | Health status comparable to the average for the same age group        | May support policy decisions comparable to those based on the chronological age       |
| $EHS(t) > E_{ref(CA)}$ | More vulnerable health status than the average for the same age group | May be assessed as having a health status-based age higher than the chronological age |

**HEA:** Health-equivalent age, **EHS:** Elderly Health Status Score, **CA:** Chronological age.

### Health-Equivalent Age (HEA)

To address the limitations of age-centered policies, the DHSBF converts EHS(t) into HEA, a health status-based age indicator intended to support policy decision-making. In this formulation, HA(t) represents Health-Equivalent Age, CA represents chronological age,  $E_{ref(CA)}$  denotes the mean health status score of the corresponding age group, and  $\kappa$  is a scaling coefficient that converts the difference in health status scores into an age difference. The score EHS(t) represents an older adult's overall health status and care needs as a single value. When EHS(t) is lower than the mean score of the corresponding age group, HA(t) is lower than the individual's chronological age. Conversely, when EHS(t) is higher than the age-group mean, HA(t) is higher than the individual's chronological age, as shown in Table 6. The main output indicators of the framework are summarized in Table S1.

$$HA(t) = CA + \kappa[EHS(t) - E_{ref(CA)}]$$

$$P(t) = [CA, HA(t), EHS(t), D(t), I(t), F(t), C(t)_{1-n}]$$

P(t) represents an individual health status profile used to support policy decision-making. D(t) denotes disease burden, I(t) represents the risk of cascading deterioration, F(t) reflects functional decline and care needs, and C(t) indicates the rate of recent health deterioration.

## RESULTS

Using the predefined illustrative parameters, the 70-year-old adult with stably managed chronic conditions and preserved physical and cognitive functions had an estimated HEA of approximately 65 years, which was lower than the chronological age. In contrast, the 65-year-old adult with multiple chronic conditions, poor nutritional status, insufficient physical activity, and persistent functional decline had an estimated HEA higher than the chronological age. The input characteristics and HEA results of the two illustrative cases are

presented in Table S2. These values were generated solely for framework illustration and were not derived from clinical data.

## DISCUSSION

### Principal Findings

This study proposed the DHSBF to support welfare-service allocation and policy decision-making based on changes in older adults' multidimensional health status and individual care needs rather than chronological age alone. The framework integrates disease burden, interactions among health-related components, functional impairment, and recent health changes into the EHS and HEA. These indicators may help distinguish health vulnerabilities that cannot be adequately identified using chronological age alone and support the prioritization of nursing interventions, chronic disease management, community-based care, and welfare services. The DHSBF is intended to complement, rather than replace, existing age-based eligibility criteria by providing additional information on individual health status, functional capacity, and care needs. However, the proposed framework remains a preliminary and conceptual decision-support model, and its clinical validity and predictive performance have not yet been established. Future studies should use longitudinal clinical data to estimate the interaction weights, state-transition parameters, and evaluation coefficients and should incorporate relevant social and environmental factors. They should also examine whether the EHS and HEA provide additional predictive value for long-term care utilization, hospitalization, functional decline, and mortality beyond chronological age. Future extensions of the framework may incorporate AI-based functions for health-status prediction, risk classification, and welfare-service recommendation. Within this human-AI collaborative approach, AI would support the analysis and prediction of multidimensional health data, while nurses, physicians, and policy experts would retain responsibility for final decisions based on

clinical circumstances, ethical considerations, and individual preferences. Further evaluation should therefore address not only model validity and predictive accuracy but also explainability, fairness, privacy protection, accountability, and feasibility in real-world practice. The illustrative cases suggest that chronological age alone may not adequately represent individual health vulnerability and care needs. The HEA may complement age-based criteria by distinguishing between an older adult with relatively preserved health status and a younger adult with greater disease burden and functional decline. However, because these cases were based on predefined illustrative parameters rather than clinical data, the findings should not be interpreted as evidence of clinical validity or predictive performance.

### Comparison with Previous Research

Previous studies have identified multimorbidity, frailty, and functional impairment as major health indicators associated with healthcare utilization, hospitalization, long-term care needs, and mortality among older adults. In gerontological nursing, increasing attention has been given to Comprehensive Geriatric Assessment (CGA), which integrates medical, functional, psychological, and social domains to support the development of individualized care plans. Frailty-based assessments may also provide clinically meaningful information beyond chronological age alone for identifying health vulnerability and the risk of adverse outcomes in older adults (16). The DHSBF proposed in this study conceptually builds on this multidimensional approach by incorporating dynamic interactions among health-related components and changes in health status over time. Rather than treating diabetes mellitus, hypertension, and dementia solely as independent conditions, the framework represents them as sets of interacting components and considers interactions both within and across diseases, as well as their potential effects on functional outcomes. This dynamic perspective is consistent with the integrative approach of gerontological nursing, which recognizes that chronic disease progression and functional status are continuously influenced by biological, behavioral, social, and environmental factors. A comparison of the proposed framework with existing older adult assessment approaches is presented in [Table S3](#). Although previous studies have introduced indicators such as biological age and the frailty index (17), comparatively less attention has been given to translating multidimensional health assessments into interpretable policy input indicators for welfare-service planning and prioritization. The HEA proposed in this study may therefore serve, following empirical validation, as a complementary indicator that links individual-level health assessment with welfare policy decision-making and informs eligibility assessment and service prioritization.

### Clinical, Nursing, Technological, and Policy Implications

The clinical, nursing, technological, and policy implications of the framework are summarized in [Table S4](#). Personalized assessment remains an important foundation for person-centered care (18). Nurses routinely assess older adults' physical function, cognitive function, nutritional status, medication adherence, and social support, all of which influence health status and care needs. By integrating this multidimensional information, the DHSBF may help identify individuals who require early intervention before functional decline becomes severe. In addition, the CPP may identify health-related components with a high potential to propagate risk to other components or contribute to subsequent functional deterioration. This information may support the prioritization of nursing interventions and chronic disease management. Such an approach is consistent with preventive gerontological nursing and integrated community care, which emphasize the early identification and management of risk factors rather than intervention only after substantial deterioration has occurred. From a policy perspective, classifying welfare-service recipients solely according to chronological age may not adequately reflect individual differences in health vulnerability and care needs. Many healthcare and welfare systems use a common eligibility threshold of 65 years or older despite substantial variation in health and functional status among individuals (19). Following empirical validation, HEA may serve as a complementary policy indicator for prioritizing healthcare and welfare resources according to individual health status and care needs rather than age eligibility alone. As illustrated by Cases A and B, an older adult with stable chronic disease management and preserved functional capacity may require relatively limited support, whereas a younger individual with multimorbidity, frailty, cognitive decline, and reduced self-management capacity may require earlier and more intensive community-based services. The proposed approach may therefore contribute to more efficient and equitable resource allocation while supporting preventive care and healthy aging. Individuals with similar HEA values may have substantially different combinations of disease burden, functional impairment, interaction risk, recent health changes, and contextual vulnerability. Therefore, HEA should not be used as a stand-alone threshold for automatically allocating, restricting, or denying welfare services. Any service recommendation should be accompanied by the underlying health profile and reviewed by nursing, medical, and policy professionals.

### Strengths and Limitations

As summarized in [Table S5](#), this study has several strengths and limitations. A major strength is its interdisciplinary approach, which combines systems engineering, computationally structured conceptual modeling,

gerontological nursing, and health and welfare policy within a unified preliminary decision-support framework. The DHSBF should not be interpreted as a functional AI architecture, and the present study does not establish architectural novelty in GNNs, RNNs, or other machine-learning methods. Its contribution is limited to formalizing the domain-specific components and relationships that may support subsequent AI implementation. Its ability to manage measurement noise, missing observations, irregular follow-up intervals, and real-world clinical complexity remains to be evaluated. The proposed DHSBF also represents chronic diseases as sets of interacting components rather than as independent conditions, thereby reflecting dynamic relationships within and across diseases. In addition, HEA provides an intuitive and interpretable indicator that may facilitate communication between healthcare professionals and policymakers. However, this interpretability involves a trade-off because summarizing multidimensional health information as a single age-equivalent value may result in information loss and may obscure heterogeneous pathways leading to similar HEA values. The health-equivalent age should therefore always be accompanied by its underlying EHS dimensions, component-level states, major CPP contributors, and relevant contextual factors. Its incremental value, calibration, subgroup fairness, and potential effects on actual service-allocation decisions require external validation before practical use. In addition, this study is a preliminary conceptual case study. The interaction weights, state-transition parameters, and evaluation coefficients have not yet been estimated or validated using large-scale longitudinal clinical data. External validation across diverse populations and healthcare settings is therefore required before practical implementation. Although the framework includes an external-factor vector ( $L(t)$ ), its current illustrative application remains centered on three biomedical conditions and does not empirically quantify the independent contributions of social determinants. Future studies should systematically operationalize PROGRESS-Plus-informed factors, including socioeconomic status, education and health literacy, living environment, social and caregiver support, healthcare access, place of residence, sex or gender, cultural background, and disability. Their effects on health-state transitions, service prioritization, subgroup calibration, and fairness should be evaluated before policy implementation. The current weighted interaction structure provides interpretability but may not adequately represent threshold effects, abrupt state transitions, or nonlinear recovery trajectories. Although the model includes a nonlinear transformation function, its ability to identify clinical tipping points has not been established. Future longitudinal studies should evaluate

nonlinear interaction functions and resilience-related early-warning indicators, including delayed recovery, increasing autocorrelation, and increasing variability following health perturbations. Future empirical implementation of the DHSBF will depend on the availability, continuity, quality, and representativeness of individual-level longitudinal data. Health records from older populations may be incomplete or irregular because of device-use difficulties, cognitive impairment, hospitalization, care transitions, unstable health conditions, or differential access to healthcare. Because such missingness may itself be associated with frailty or health deterioration, future studies should document its extent and causes, incorporate observation timing and data-quality indicators, and conduct sensitivity analyses under alternative missing-data assumptions. Moreover, cohorts consisting predominantly of relatively healthy volunteers may produce parameters that are poorly calibrated for frail, cognitively impaired, institutionalized, or socially vulnerable older adults. Future validation should therefore include diverse populations from community, hospital, home-care, and long-term care settings and evaluate subgroup performance, calibration, and fairness.

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## CONCLUSION

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This study proposed the DHSBF to support welfare-service allocation and policy decisions based on older adults' multidimensional health status rather than chronological age alone. The framework integrates disease burden, health-component interactions, functional impairment, and recent health changes into the EHS and HEA. These indicators may reveal vulnerabilities not captured by age and help prioritize nursing interventions, chronic disease management, community care, and welfare services. However, the DHSBF remains a preliminary conceptual framework whose clinical validity and predictive performance have not been established. Future studies should use longitudinal data to estimate model parameters, incorporate social and environmental factors, and evaluate predictive value for care utilization, hospitalization, functional decline, and mortality. AI-based prediction, risk classification, and service recommendation should be compared with simpler models and evaluated for uncertainty, calibration, explainability, fairness, privacy, and feasibility. AI would support multidimensional data analysis, while professionals would retain final decision-making responsibility. Thus, the DHSBF represents a pre-implementation foundation for future model development, requiring parameter estimation, implementation, performance evaluation, and external validation.

**Ethical Approval:** This conceptual study used only hypothetical illustrative cases and did not involve human participants or identifiable clinical data; therefore, ethics committee approval was not required.

**Informed Consent:** This conceptual study used only hypothetical illustrative cases and did not involve human participants or identifiable clinical data; therefore, informed consent was not required.

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