# Evolution and Frontier Advances in Assessment Tools for Geriatric Multimorbidity

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## Abstract

Against the backdrop of continuous global population aging, multimorbidity in older adults has become a major public health issue that threatens the health of older populations and increases the medical burden. Scientific and accurate quantitative assessment of the burden of multimorbidity in older adults is crucial for precision diagnosis and treatment, prognostic prediction, and health management of geriatric diseases. This article systematically reviews the developmental trajectory of assessment tools for multimorbidity in older adults, categorizes them into a three-generation evolutionary framework, and summarizes the core characteristics, advantages, and limitations of various tools. Through a comparative analysis of domestic and international research status and practical shortcomings, it finds that existing tools have problems such as inconsistent assessment standards, insufficient localization adaptability, inadequate research on disease interactions, and limited clinical translation. Assessment tools for multimorbidity in older adults have evolved progressively from prediction-oriented tools toward comprehensive assessment, localization, and intelligentization. In the future, it is necessary to base efforts on the disease spectrum of China's older population, strengthen the optimization of localized tools, focus on regional heterogeneity and dynamic trajectory tracking in the evolution of multimorbidity, establish a two-step strategy combining universal rapid screening with pattern-specific assessment, and distinguish core variables from extended variables to balance assessment depth and efficiency, thereby improving a multimorbidity assessment system suited to national conditions and providing support for healthy aging.

## Full Text

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【Abstract】 Against the backdrop of the continuing advance of global population aging, geriatric multimorbidity has become a major public health issue that threatens the health of older adults and increases the medical burden. Scientifically and accurately quantifying the burden of geriatric multimorbidity is key to achieving precise diagnosis and treatment, prognostic prediction, and health management for diseases in older adults. This paper systematically reviews the developmental trajectory of assessment tools for geriatric multimorbidity, classifies them into a three-generation evolutionary system, and summarizes the

core characteristics, advantages, and limitations of each type of tool. Through comparative analysis of the current status of domestic and international research and real-world shortcomings, it is found that existing tools have problems such as inconsistent assessment standards, insufficient localization adaptation, a lack of research on disease interactions, and inadequate clinical translation. Assessment tools for geriatric multimorbidity have progressively evolved from prediction-oriented tools to comprehensive assessment-oriented tools, and toward localization and intelligence. In the future, it is necessary to establish a disease spectrum of older adults in China, strengthen the optimization of localized tools, focus on regional heterogeneity and dynamic trajectory tracking of multimorbidity evolution, construct a two-step strategy combining universal rapid screening with pattern-specific assessment, and distinguish core variables from extended variables to balance assessment depth and efficiency, so as to improve a multimorbidity assessment system adapted to national conditions and provide support for healthy aging.

【Key words】 Geriatric multimorbidity; Multimorbidity assessment tools; Assessment system; Localization; Intelligence; Review

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【Abstract】 In the context of global population aging, geriatric multimorbidity has become a major public health issue that threatens the health of older adults and escalates the healthcare burden. Scientifically and accurately quantifying the burden of geriatric multimorbidity is key to achieving precise diagnosis and treatment, prognostic prediction, and effective health management in this population. This paper systematically reviews the development trajectory of assessment tools for geriatric multimorbidity, categorizing them into a three-generation evolutionary framework, and summarizes the core characteristics, advantages, and limitations of each type of tool. Through a comparative analysis of current research status and shortcomings both domestically and internationally, it was found that existing tools suffer from inconsistent assessment standards, insufficient adaptation to local populations, a lack of research on disease-disease

interactions, and inadequate clinical translation. Assessment tools for geriatric multimorbidity have progressively evolved from prediction-oriented to comprehensive assessment-oriented, and more recently toward localization and intelligent directions. Future development of these tools should be grounded in the disease spectrum of Chinese older adults, with emphasis on optimizing localized tools, addressing regional heterogeneity and dynamic trajectory tracking of multimorbidity, and developing a two-step strategy integrating universal rapid screening with pattern-specific assessment, while distinguishing core variables from extended variables to balance assessment depth and efficiency, thereby improving a multimorbidity assessment system tailored to national conditions and ultimately supporting healthy aging.

【Key words】 Geriatric multimorbidity; Multimorbidity assessment tools; Assessment system; Localization; Intelligent; Review

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Population aging is a core feature of the evolution of the global population structure in the 21st century. Against this backdrop, China presents the dual characteristics of a large older-adult population base and an accelerated deepening of population aging[1]. By the end of 2025, China' s population aged 60 years and above will have exceeded 323 million, accounting for 23.0% of the total population[2]. With aging, multimorbidity among older adults shows a high-prevalence and rapidly increasing trend. The prevalence of disease among middle-aged and older adults in China reaches 63.0%[3], markedly higher than the global average of 51.0%[4], and has become a core factor threatening the health of older adults. Multimorbidity not only significantly increases the risks of death and disability and raises hospitalization frequency and the economic burden of medical care[5], but its complex pathophysiological interactions also

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make traditional single-disease diagnosis and treatment models unable to meet actual clinical needs[6]. As a key means of quantifying the burden of multimorbidity, multimorbidity assessment tools have evolved from traditional indices using death as the endpoint, to specialized scales focusing on physical function and geriatric syndromes, and then to localized, customized tools and intelligent models. This trajectory reflects the conceptual transformation in geriatric medicine from "prolonging survival" to "maintaining function and quality of life."

Current global multimorbidity assessment tools show marked heterogeneity. Differences in their development background, outcome orientation, and scoring logic have led to the absence of unified standards for clinical selection[7]. In addition, the disease spectra of Western classic indices and Chinese older adults differ, and the localized assessment system remains imperfect. However, existing studies are mostly limited to cross-sectional validation of a single tool, lack systematic clarification of the iterative lineage of tools, and insufficiently discuss deeper issues such as disease interactions and clinical translation. Therefore, this article breaks through the static evaluation of single tools, takes the evolution of tools as the main thread, and systematically analyzes the theoretical frameworks, advantages, and limitations of mainstream assessment tools. On this basis, it horizontally compares the current status of domestic and international research, clarifies frontier directions and implementation pathways, and aims to provide a reference for precise assessment and management of multimorbidity in older adults. The research framework of this study is shown in Figure 1.

## 1 Evolution of Assessment Tools for Multimorbidity in Older Adults

The development of assessment tools for multimorbidity in older adults has undergone two core transitions: from predictive to comprehensive assessment models, and then to localization and intelligence. In essence, this is a process in which concepts of geriatric medical diagnosis and treatment and assessment dimensions have continuously improved. According to the development era, design objectives, and applicable scenarios, existing mainstream tools can be divided into three generations; the core characteristics of each type of tool are shown in Table 1[8].

### 1.1 First generation: predictive traditional multimorbidity indices (1970s–1990s)

First-generation multimorbidity assessment tools used prediction of mortality as the core endpoint. Most were developed based on inpatient cohorts, and adopted weighted or graded scoring methods. They are the most widely used

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Figure 1 Research framework

Figure 1: Figure 1 Research framework

foundational tools globally, mainly including the Kaplan–Feinstein Comorbidity Index (KFI)[9], the Charlson Comorbidity Index (CCI)[10], and the Elixhauser Comorbidity Index (ECI)[11].

**1.1.1 KFI** KFI was constructed in 1974 based on a diabetes cohort and was the first multimorbidity assessment tool with prognostic value. KFI divides comorbidities into vascular and nonvascular categories, and classifies them into grades 0–3 according to severity; only comorbidities already present at the time of diagnosis of the index disease are included, and subsequent complications are excluded[12]. Its advantage lies in its strict distinction between comorbidities and complications, and its emphasis on disease severity. However, it is applicable only to patients with diabetes, has poor generalizability, and does not address physical function.

**1.1.2 CCI** CCI was published in 1987. It includes 19 chronic diseases; each disease is assigned a weight of 1–6 points according to 1-year mortality risk. The total score ranges from 0 to 37 points. It is easy to calculate and information can be extracted directly from administrative data and electronic medical records,

Note: KFI = Kaplan–Feinstein Comorbidity Index; CCI = Charlson Comorbidity Index; ECI = Elixhauser Comorbidity Index; CIRS-G = Cumulative Illness Rating Scale for Geriatrics; GIC = Geriatric Index of Comorbidity; FCI = Functional Comorbidity Index; CMWI = Chinese Multimorbidity Weighted Index.

**Figure 1 Research framework**

**Table 1 Comparison of core characteristics of mainstream multimorbidity assessment tools in older adults**

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| Type | Assessment tool | Year developed | Core outcome | Number of diseases/systems | Scoring method | Applicable population | Advantages | Limitations |
|---|---|---|---|---|---|---|---|---|
| Predictive traditional comorbidity index | KFI [11] | 1974 | 5-year mortality | Grading/classification | Severity grading (0–3) | Patients with diabetes | Distinguishes comorbidity from complications | Specialty-specific; poor generalizability |
| Predictive traditional comorbidity index | CCI [12] | 1987 | 1-year mortality | 19 types | Weighted 1–6 points | Inpatients, oncology, internal medicine | Simple and easy to use; globally applicable | Neglects function-related diseases |
| Predictive traditional comorbidity index | ECI [13] | 1998 | Hospitalization outcomes (length of stay / cost / death) | 30 types | Binary counting (0/1) | Medical insurance and large administrative datasets | Broad disease coverage; predicts costs | No weighting; limited granularity |

| Type | Assessment tool | Year developed | Core outcome | Number of diseases/systems | Scoring method | Applicable population | Advantages | Limitations |
|---|---|---|---|---|---|---|---|---|
| Comprehensive assessment-specialized assessment tool | CIRS-G [14] | 1992 | Comprehensive geriatric assessment | 14 organ systems | 0–4-point grading; outputs 5 indicators | Older inpatients and frail patients | Considers both number and severity; comprehensive assessment | Scoring process is relatively cumbersome; difficult to apply rapidly in clinical practice |
| Comprehensive assessment-specialized assessment tool | CIC [15] | 2002 | Function and mortality | 15 types | Based on IDS 0–4-point grading; divided into 4 risk levels | Older inpatients and rehabilitation patients | Simple grading rules; no need to calculate a total score | Stratification is relatively coarse; cognitive/psychiatric comorbidity not included |

| Type | Assessment tool | Year developed | Core outcome | Number of diseases/systems | Scoring method | Applicable population | Advantages | Limitations |
|---|---|---|---|---|---|---|---|---|
| Comprehensive-assessment specialized assessment tool | FCI [16] | 2005 | Physical function | 18 types | Simple count (0–18 points) | Community and functional assessment | Best predictive performance for function | Long-term validation for mortality outcomes has not been conducted |
| Localized assessment tool | CMWI [17] | 2022 | Function / disability / mortality | 14 types | Weighted 0.2–5.1 points (total score 0–20.5 points) | Middle-aged and older Chinese community populations | Precisely localized; adapted to the Chinese disease spectrum | Insufficient multicenter external validation |

Note: KFI = Kaplan–Feinstein Comorbidity Index; CCI = Charlson Comorbidity Index; ECI = Elixhauser Comorbidity Index; CIRS-G = Cumulative Illness Rating Scale for Geriatrics; GIC = Geriatric Index of Comorbidity; FCI = Functional Comorbidity Index; CMWI = China Multimorbidity-Weighted Index.

It is the most commonly used comorbidity assessment tool in geriatrics, oncology, and internal medicine worldwide [12,18–20]. The subsequently developed age-adjusted version of the CCI further controlled for the influence of age on mortality risk [21]. The main limitation of the CCI is that it uses mortality as the only predicted endpoint and does not include diseases that significantly affect quality of life in older adults, such as arthritis and visual and hearing impairment; therefore, its predictive performance for functional outcomes is insufficient [22].

### 1.1.3 ECI

The ECI was developed in 1998 based on large-scale inpatient data. It includes 30 diseases and adopts a binary scoring method, enabling simultaneous prediction of length of hospital stay, medical costs, and in-hospital mortality. Its disease coverage is more comprehensive, making it particularly suitable for large medical-insurance datasets and health-economics research [13]. However, because disease weights are not assigned, its ability to distinguish the severity of multimorbidity is limited and its degree of refinement is insufficient.

## 1.2 Second generation: comprehensive-assessment specialized assessment tools (2000s–2010s)

As concepts in geriatric medicine continued to mature, clinicians gradually recognized that the needs of older adults involve not only prolonging survival, but also maintaining independence in daily living and physical function. Second-generation multimorbidity assessment tools used physical function, quality of life, and comprehensive geriatric assessment as core endpoints, were designed specifically to fit the disease spectrum of older populations, and became an important component of the specialized assessment system in geriatric medicine. Representative tools include the Cumulative Illness Rating Scale for Geriatrics (CIRS-G) [14], the Geriatric Index of Comorbidity (GIC) [15], and the Functional Comorbidity Index (FCI) [16].

### 1.2.1 CIRS-G

CIRS-G is designed specifically for older adults and covers 14 organ systems. Each system is scored from 0 to 4 according to severity, and multiple indicators can be output, including total score, number of affected systems, and severity index. It can simultaneously reflect the number and severity of comorbidities and is suitable for comprehensive assessment of older inpatients [14]. However, its scoring process is relatively cumbersome, making rapid clinical assessment somewhat difficult [23–24].

### 1.2.2 GIC

GIC was developed based on the Individual Disease Severity Index (IDS). It includes 15 chronic diseases with high prevalence in older adults, grades them according to disease severity, and directly classifies patients into 4 risk levels without the need to calculate a total score; thus, clinical interpretation and operation are relatively convenient [15]. However, its stratification is relatively coarse, making it difficult to distinguish the cumulative effects of diseases with different severity levels, and cognitive and psychiatric comorbidities are not included.

### 1.2.3 FCI

FCI is the first comorbidity index to use physical function as the primary outcome. It includes 18 diseases and incorporates disease types not covered by the CCI, such as arthritis, osteoporosis, and visual and hearing impairment. Its predictive performance for physical function is significantly superior to that of traditional indices, and it is suitable for functional assessment of older adults in the community [16]. However, this tool has not undergone validation studies for long-term mortality outcomes.

## 1.3 Third generation: localized and intelligent assessment tools (2020s–present)

Both first- and second-generation assessment tools were developed based on Western populations, and their disease weights and disease-spectrum characteristics differ markedly from those of older adults in China. Analyses based on 2020 data from the China Health and Retirement Longitudinal Study (CHARLS) showed that among people aged 60 years and older in China, the prevalence of chronic diseases was 86.39%, and the prevalence of multimorbidity reached 66.30%; hypertension (48.49%), arthritis (43.12%), and gastric diseases (32.06%) ranked among the most common chronic diseases [25]. From the perspective of temporal trends, the prevalence of multimorbidity among older adults in China rose from 85.96% in 2011 to 92.24% in 2015, with cardiovascular and metabolic multimorbidity being the most common [26]. In addition, a comparative study of middle-aged and older inpatients in China and the United Kingdom showed that the prevalence of multimorbidity among Chinese patients (57.12%) was significantly higher than that in the United Kingdom (30.39%), that disease-network complexity was 2.93 times that of the United Kingdom, and that cardiovascular and metabolic disease comorbidity···

is a prominent characteristic of disease [27]. The above evidence suggests that, because the disease weights in classic Western indices may be difficult to apply to Chinese populations, it is necessary to re-calibrate multimorbidity assessment systems based on local empirical data. Against this background, third-generation multimorbidity assessment tools have focused on population adaptability and technological integration, enabling localization and intelligent upgrading.

### 1.3.1 Chinese Multimorbidity-Weighted Index (CMWI)

CMWI is a multimorbidity assessment tool developed on the basis of large-scale longitudinal cohort data from China, first proposed and validated by Hu et al. [17] in 2022. The development of this index aimed to address the difficulty of accurately reflecting the multimorbidity burden among middle-aged and older Chinese adults when classic Western multimorbidity indices are affected by disease spectrum and weight bias.

In terms of development methods, CMWI relied on two nationally representative longitudinal datasets: CHARLS and the Chinese Longitudinal Healthy Longevity Survey (CLHLS). First, using four health outcomes—physical functioning (PF), activities of daily living (ADL), instrumental activities of daily living (IADL), and mortality—the study compared the predictive performance of five commonly used international multimorbidity indices in the Chinese population and selected the best-performing Multimorbidity-Weighted Index (MWI) as the basic framework. Second, using four waves of repeated longitudinal measurement data from CHARLS during 2011–2018, the study re-estimated the independent effect of each chronic disease on PF through linear mixed models and accordingly completed localization correction of disease weights. This PF-centered approach broke through the limitation of traditional indices that use only mortality as a single endpoint. Finally, the new index was externally validated in an independent CLHLS cohort to assess its generalizability.

The localized features of CMWI are mainly reflected in two aspects: adaptation of disease spectrum and assignment of weights. At the disease-spectrum level, CMWI includes 14 high-prevalence chronic diseases screened on the basis of epidemiological data from China, including stroke (including cerebral infarction and cerebral hemorrhage), memory-related diseases (such as Alzheimer' s disease, brain atrophy, and Parkinson' s disease), malignant tumors such as cancer (excluding mild skin cancer), asthma, arthritis or rheumatism, emotional, neurological or psychiatric problems, heart disease (such as coronary heart disease, angina pectoris, and congestive heart failure), chronic lung diseases (such as chronic bronchitis and emphysema, excluding tumors or cancer), hypertension, kidney disease (excluding tumors or cancer), diabetes or elevated blood glucose (including abnormal glucose tolerance and elevated fasting blood glucose), stomach disease or digestive system disease (excluding tumors or cancer), dyslipidemia (such as elevated total cholesterol), and liver disease (excluding fatty liver, tumors, or cancer). In contrast to the broad-coverage strategies of CCI, which includes 19 diseases, and ECI, which includes 30 diseases, CMWI focuses on the core diseases in Chinese community populations; the disease categories and weights it includes are derived from the disease spectrum and physical-function impairment data of local Chinese community populations, making it more consistent with the high-incidence disease spectrum of middle-aged and older adults in Chinese communities and more compatible with community screening and primary health-service settings. In terms of the method for assigning weights, CMWI uses the degree of physical-function impairment as the weighting basis; the range of disease weights is 0.2–5.1. Different from CCI, which uses mortality risk as the weighting basis, and ECI, which adopts an unweighted scoring design, the three diseases with the highest weights are stroke (5.1), memory-related diseases (4.3), and cancer (3.4), while the lowest weights are assigned to dyslipidemia (0.2) and liver disease (0.2). Of note, the weight of stroke in CMWI (5.1) is markedly higher than its weight in the original MWI (3.8), suggesting that stroke has a more serious effect on physical-function impairment among middle-aged and older Chinese adults, which strongly demonstrates the

necessity of localized weight correction. Although the prevalence of hypertension ranks among the highest, its weight in CMWI is only 1.3, indicating that high prevalence does not necessarily imply a strong functional-impairment effect. Assessment of multimorbidity burden should not simply rely on disease counts or prevalence rankings; rather, it should incorporate weighted consideration of the actual effects of different diseases on functional impairment. The total CMWI score is calculated by cumulatively summing the weights corresponding to the diseases an individual has; a higher score indicates a greater multimorbidity burden.

### 1.3.2 Intelligent Multimorbidity Assessment Technologies

Relying on technologies such as electronic health records, wearable devices, natural language processing, and machine learning, it is possible to achieve automatic extraction of disease information, real-time calculation of multimorbidity indices, long-term trajectory tracking, and early warning for high-risk populations. These technologies promote the transformation of traditional static assessment toward dynamic and intelligent assessment and provide technical support for the clinical implementation of multimorbidity assessment [28–30].

## 2 Clinical Efficacy and Applicability Bottlenecks of Existing Assessment Tools

### 2.1 Clinical Application Efficacy

Multimorbidity assessment tools for older adults have become important standardized tools in clinical practice, scientific research, and public health management in geriatric medicine. Their application scenarios span multiple dimensions, including inpatient risk stratification, prognostic prediction, functional assessment, health management, and health-resource allocation [31–32]. In clinical diagnosis and treatment settings, traditional multimorbidity indices such as CCI and ECI are mainly used to predict mortality risk and complication risk among hospitalized patients in internal medicine, oncology, and surgery; they can rapidly identify high-risk populations and provide quantitative evidence for treatment decisions [20,33–37]. Function-oriented tools such as CIRS-G, GIC, and FCI place greater emphasis on comprehensive geriatric assessment, frailty screening, rehabilitation stratification, and prediction of living ability, better fitting the needs of functional maintenance and quality-of-life improvement among older patients [38–40]. In community and primary health-service settings, tools such as FCI and CMWI can be used for multimorbidity-burden screening, health monitoring, and evaluation of intervention effects in middle-aged and older populations, providing reliable quantitative indicators for promoting graded diagnosis and treatment, optimizing long-term care services, and community health management [17,41]. In the fields of scientific research and health economics, various multimorbidity indices can be used to adjust for confounding factors, compare health outcomes among different populations, evaluate the efficiency

of medical-resource utilization, and promote the development of research on multimorbidity in older adults from descriptive analysis toward precise prediction and mechanistic exploration [42–43]. Overall, different types of tools form complementary roles across application scenarios, constructing a full-scenario application system that covers inpatient diagnosis and treatment, community management, and population monitoring [31–32].

### 2.2 Applicability Bottlenecks and Common Problems

Although the existing system of multimorbidity assessment tools for older adults is becoming increasingly refined, shortcomings remain in clinical practice and dissemination. First, assessment standards lack uniformity: different tools differ considerably in their definitions of multimorbidity, disease items, scoring methods, and risk

differences in cut-off values, making it difficult to compare assessment results horizontally and affecting the integration of evidence and the generalization of conclusions from multicenter studies

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. Second, localization adaptability is insufficient. Most classic indices were developed based on Western populations; disease weights and disease spectra differ from those of older Chinese populations, and validation of localized tools is inadequate, making broad promotion difficult

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. Third, model design has inherent limitations. Most tools use simple additive or fixed-weighted models, with insufficient exploration of disease interactions, synergistic effects, and dynamic trajectories of multimorbidity evolution, and thus cannot fully reflect the complex pathophysiological relationships of multimorbidity in older adults

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. Fourth, the dimensions are single and insufficiently integrated. Most tools focus on somatic diseases, with inadequate integration of key health dimensions such as cognitive impairment, psychological status, frailty level, and social support, making it difficult to comprehensively reflect the comprehensive health burden of older adults

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. Fifth, clinical and primary-care translation lags behind. Many tools are oriented toward research design, with cumbersome operational processes, low levels of automation, and insufficient integration with electronic medical record systems; primary healthcare institutions lack standardized operating procedures and standardized training, resulting in low clinical application rates

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## 3 Frontier Advances in Assessment Tools for Multimorbidity in Older Adults

In response to existing bottlenecks, research in China and abroad in recent years has gradually advanced toward precision, multidimensional integration, intelligence, and clinical practicality, with the aim of building a new-generation multimorbidity assessment system adapted to older Chinese populations.

### 3.1 Expansion of the Application of Localized Assessment Tools

In recent years, localized multimorbidity assessment tools targeting Chinese populations have expanded from validation in a single population to application in multiple scenarios. As China' s first multimorbidity weighted index developed for middle-aged and older populations

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, the CMWI has been validated in several real-world studies and can effectively predict mortality, disability, utilization of health services, and mental health risks; it has shown good predictive performance in primary-care settings

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. In the future, a rapid multimorbidity assessment module applicable to general outpatient clinics could be constructed based on the CMWI. While retaining core predictive ability, the operational workflow could be optimized to achieve rapid stratification of the multimorbidity burden among older adults in the community, supporting contracted family-doctor services and the implementation of tiered diagnosis and treatment.

### 3.2 Empirical Exploration of Multidimensional Integrated Assessment Frameworks

To overcome the limitation of traditional multimorbidity assessment tools that rely on a single disease count, several studies have systematically integrated multimorbidity assessment with concepts such as frailty and intrinsic capacity. The Electronic Frailty Index (eFI) can, relying on electronic health records (EHRs), achieve automated real-time calculation, significantly improving frailty screening efficiency and clinical practicality, and has been applied in primary healthcare in some regions

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. The concept of intrinsic capacity proposed by the WHO provides another key dimension for multimorbidity management. Relevant studies have confirmed that intrinsic capacity is closely related to health indicators in older adults such as frailty

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, and that intrinsic capacity plays an important bridging role between multimorbidity and health-related quality of life (HRQoL)

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, providing support for the construction of an integrated comprehensive assessment model of "multimorbidity-frailty-function-psychology."

### 3.3 Technological Breakthroughs in Intelligent Assessment and Dynamic Monitoring

Relying on electronic health records, machine learning, and network analysis technologies, notable progress has been made in the intelligent and dynamic assessment of multimorbidity. Models such as convolutional neural networks can effectively mine hidden associations among diseases and identify novel multimorbidity relationships

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, and can be combined with time series to predict disease-evolution trajectories

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. Natural language processing technology can effectively use unstructured clinical data to improve the ability to identify geriatric syndromes related to multimorbidity

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. Transformer architectures have been applied to prediction of multimorbidity progression and mining of multimorbidity associations

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. Existing research suggests that multimorbidity assessment needs to break through the limitations of static measurement, promote the transformation of measurement systems from static attributes to dynamic attributes, and achieve an upgrade from cross-sectional time-point weighting to long-term dynamic tracking

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. At the level of clinical translation, Shao Weihou et al.

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pointed out that existing multimorbidity measurement methods differ markedly in research objectives, disease selection, and assessment logic, making effective integration and comparison difficult. In the future, efforts should focus on developing standardized and comprehensive multimorbidity assessment tools; systematically embedding assessment processes into electronic medical records and primary healthcare information systems; promoting the transformation of multimorbidity assessment from research tools into routine clinical work; effectively integrating existing measurement methods; and improving the universality of research and practice.

### 3.4 Pathway Selection for Multimorbidity Assessment Tools

Existing multimorbidity assessment tools are mainly designed based on cross-sectional disease counts or weighted models, with obvious deficiencies in portraying dynamic evolution, adapting to regional differences, and achieving hierarchical precision. In recent years, researchers in China and abroad have begun to explore the longitudinal trajectory patterns, cross-pattern dynamic evolution, and regional heterogeneity correction strategies of multimorbidity, indicating directions for optimizing third-generation multimorbidity assessment tools.

In the dimension of dynamic evolution, multimorbidity is not static and stable on the time scale; rather, it has features of pathway dependence and pattern transition. Several studies based on CHARLS longitudinal data have revealed the heterogeneity of multimorbidity trajectories. Xue Yuan et al.

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used the K-prototype clustering algorithm to identify four trajectories of chronic disease accumulation among middle-aged and older adults: low-risk stable type, single-disease stable type, two-disease progression type, and multi-disease accumulation type; 47.43% of individuals showed the greatest acceleration in the number of chronic diseases during the transition from middle age to old age. Liu et al.

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, based on latent class analysis of CHARLS 2011–2020 data, further found that multimorbidity patterns in older adults can be divided into four types: multisystem disorder type, gastrointestinal-metabolic type, cardiovascular disease type, and respiratory disease type. Among them, the gastrointestinal-metabolic type continuously transformed toward the cardiovascular disease type during follow-up (the transition proportion in 2015–2018 was 23.81%), suggesting that digestive-system problems may be a precursor of cardiovascular disease. Thus, existing assessment models based on cross-sectional weighting ignore the pathway dependence and pattern-transition characteristics of multimorbidity. In future assessment systems, disease-evolution parameters such as trajectory type and probability of pattern transition need to be incorporated as basic variables in model design, rather than relying solely on static disease counts.

In the dimension of regional differences, the characteristics of multimorbidity among older adults in northern and southern China show significant heterogeneity. At the level of prevalence, a study based on a national multicenter survey of older inpatients showed that the prevalence of multimorbidity among older inpatients in northern regions (71.7%) was higher than that in southern regions (66.0%), and region was one of the independent influencing factors for multimorbidity in older adults

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. A meta-analysis by Yin Jiajia et al.

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further showed that the prevalence of multimorbidity among older adults was 34% in the south and 36% in the north; age ( )70 years, overweight or obesity by BMI, and alcohol consumption were common risk factors, whereas sex, income, educational level, and smoking had significant effects only in southern populations. At the level of multimorbidity patterns, factor analysis by Zhang Li et al.



found that multimorbidity patterns in the overall population included a metabolic pattern, a liver-kidney pattern, and a degenerative disease···

disease pattern, neuropsychiatric pattern, and dementia pattern; the pattern in southern regions is similar to that of the overall population, whereas northern regions are dominated by the liver-kidney pattern, metabolic disease pattern, lung-dementia pattern, degenerative disease pattern, and psychiatric pattern, suggesting that multimorbidity patterns differ between northern and southern regions and should be treated differently. These differences indicate that the weight parameters of assessment tools may need to be calibrated on the basis of regional disease-spectrum characteristics, so as to improve the tools' predictive accuracy and clinical applicability. Future studies should further clarify the sources of regional differences—such as climate and environment, lifestyle, allocation of medical resources, or genetic background—so that, while maintaining the core structure of the tools, regional parameters can be precisely calibrated.

At the refined-stratification level, longitudinal-trajectory studies based on the CMWI provide methodological support for stratified assessment. An et al. [69], using CHARLS 2011–2018 data, identified four CMWI trajectories: no multimorbidity, incident multimorbidity, slowly increasing, and rapidly increasing; people with lower socioeconomic status were more likely to fall into the "rapidly increasing" trajectory. Regarding modeling strategies for disease interactions, Wei et al. [48] attempted to incorporate higher-order disease interaction terms into the weighted multimorbidity index. The results showed that after adding pairwise interaction terms, model fit improved only from 0.26 to 0.27, and after adding three-way interaction terms it even decreased to 0.24, suggesting that the marginal benefit of incorporating complex interactions may be lower than expected; stratification strategies still need to seek a balance between model parsimony and predictive accuracy. Therefore, the feasible pathway for refined stratification lies not in adding model complexity without limit, but in using longitudinal-trajectory data to achieve risk-driven dynamic stratification—that is, matching differentiated intervention programs according to the trajectory type to which an individual belongs. This points the way for further incorporating longitudinal trajectory stratification on the basis of the "multimorbidity-frailty-function-psychology" horizontal integration framework, and for promoting the transformation of multimorbidity assessment from static weighted indices to a composite system of "horizontal multidimensional assessment + longitudinal dynamic stratification."

In terms of assessment pathways and tool architecture, risk grading based on

trajectory types provides a basis for refined stratification; however, within the overall framework of assessment tools, a single general-purpose tool is unlikely to take into account the predictive accuracy required for different multimorbidity patterns, while developing separate tools for each pattern would create difficulties in clinical selection. Therefore, this study proposes a two-step screening strategy. The first step is rapid general-purpose screening, which may incorporate into the CMWI the idea of common chronic diseases with high prevalence in China, enabling assessment to be completed within a relatively short time and serving primary-care consultation and population stratification. The second step is pattern-specific refined assessment: when screening suggests high risk or when clinical decision-making requires refinement, the corresponding specialized assessment module is matched according to the patient' s main multimorbidity pattern. For the inclusion of multidimensional variables, core variables and extended variables should be distinguished: core variables (such as number of diseases, severity, and a small number of simple functional indicators, such as gait speed and grip strength) may be included in the basic assessment system [54-55]; item response theory (IRT) can provide methodological support for screening and streamlining these core variables [70-71]; extended variables (such as in-depth psychological assessment) as well as variables such as social support and family caregiving may be assessed as needed when there are clear clinical indications.

Future development of multimorbidity assessment tools should make breakthroughs in the following areas: first, introducing longitudinal cohort data and incorporating dynamic trajectory parameters into tool design, so as to upgrade assessment from cross-sectional time-point assessment to life-course dynamic tracking; second, carrying out multicenter region-specific validation to clarify the differential sources of multimorbidity spectra between northern and southern regions, and allowing moderate calibration of regional parameters while maintaining the core structure of the tools; third, promoting the transformation from a static, single weighted system to a composite system of "horizontal multidimensional assessment + longitudinal dynamic stratification," thereby achieving precise assessment through horizontal–longitudinal collaboration.

## 4 Conclusion

After several decades of development, assessment tools for multimorbidity in older adults have undergone three core transformations: from mortality-oriented to function-oriented, and then to localization and intelligence, promoting a comprehensive upgrade in the concepts and dimensions of geriatric multimorbidity assessment. Although current assessment systems are becoming increasingly diverse, prominent problems remain, including insufficient localization adaptation, inconsistent assessment standards, weak research on disease interactions, and lagging translation to clinical and primary-care settings. In the future, China' s assessment system for multimorbidity in older adults should be established based on the local disease spectrum and actual clinical needs, strengthen func-

tion orientation and multidimensional integration, build a two-step strategy that combines universal rapid screening with pattern-specific refined assessment, distinguish core variables from extended variables to balance assessment depth and efficiency, accelerate the implementation and application of artificial intelligence and dynamic tracking models, and promote the upgrading of multimorbidity assessment from static time-point assessment to dynamic trajectory tracking. At the same time, attention should be paid to regional heterogeneity in the evolution of multimorbidity and to trajectory-based refined population stratification, so as to build a hierarchically adaptive assessment system. Ultimately, this will form a full-cycle, precise, implementable assessment and management system for multimorbidity in older adults that is adapted to China' s national conditions, providing methodological support for the implementation of healthy aging strategies.

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