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Particle Swarm Optimization and Analytic Hierarchy Process for Functional Space Adaptation in Aging-in-Place Home Modifications: A Multi-Criteria Decision-Support Model for Accessibility and Independent Living in Elderly Housing

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Abstract

Older adults commonly face challenges such as insufficient spatial accessibility and a lack of safety facilities in their home environments. This paper proposes a multi-criteria decision-making (MCDM) model integrating the Analytic Hierarchy Process (AHP) and Particle Swarm Optimization (PSO) to enhance the scientific rigor and practicality of age-friendly renovation solutions. Based on 543 valid questionnaires and interview data, an evaluation system was constructed, covering four key dimensions: safety assurance, spatial accessibility, independent living capability, and environmental comfort. The weight allocation incorporates dual-source fusion of expert judgment and sample-aggregated resident preferences to improve model rationality and stability. Results demonstrate that the AHP-PSO model outperforms comparative models in prediction accuracy (MAE = 0.121), functional reasonableness (FDR = 0.136), dimensional balance (DBR = 0.912), and robustness (FSR = 94.8%). Comprehensive adaptation analysis reveals that while most residences satisfactorily meet the needs of the elderly, emergency response facilities, kitchen convenience, and furniture adaptability remain critical shortcomings constraining overall performance. The findings validate the effectiveness of the AHP-PSO model for age-friendly home modifications, providing methodological support for resource allocation optimization and aging-in-place policy formulation.

Keywords: age-friendly home modification; spatial function adaptation; multi-criteria decision-making model; Particle Swarm Optimization (PSO); Analytic Hierarchy Process (AHP)



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1. Introduction

Population aging has become a critical global challenge affecting housing, healthcare, and independent living. The population aged 60 years or older is projected to increase substantially worldwide, while China has also entered a rapidly aging stage with a large older population [1–3]. This demographic transition has increased the risks of mobility limitations and falls, making residential accessibility and safety essential for supporting aging in place [4,5]. Although large-scale accessibility-oriented home modification programs have been implemented, existing residential environments continue to exhibit functional barriers

in entrances, bathrooms, kitchens, circulation routes, and lighting facilities [6–10]. There is considerable demand among older adults for housing facility improvements, given that deficient residential environments have been consistently linked to a higher incidence of falls [11,12]. On this basis, developing comprehensive evaluation frameworks integrating safety, accessibility, independent living capability, and environmental comfort is necessary for prioritizing age-friendly home modification interventions.

Intelligent optimization methods have increasingly been applied to building design and spatial renovation, providing effective tools for multi-variable integration, objective balancing, and constrained solution searching [13–15]. Existing studies have demonstrated the potential of evolutionary, heuristic, machine-learning, reinforcement-learning, and metaheuristic algorithms, including PSO, ACO, and DE, in spatial optimization and multi-criteria decision-making [16–31]. Nonetheless, current age-friendly housing assessment methods remain limited in integrating resident preferences and adaptive optimization. Existing frameworks are largely expert-centered, while user information is mainly used for experience evaluation or intervention planning rather than directly guiding weighting processes [27,32–37]. In addition, static AHP weighting and insufficient validation across diverse housing contexts restrict model adaptability and group-level preference integration [38–43]. Therefore, a decision-support framework that integrates expert knowledge, resident preferences, and adaptive optimization mechanisms is still required.

AHP–PSO integration has been applied across diverse decision-making contexts, including product evaluation, pairwise-comparison-matrix optimization, risk assessment, power-distribution reliability, and environmental-resource evaluation [44–48]. Existing AHP–PSO-based decision-making studies have mainly focused on improving optimization efficiency and obtaining stable indicator weights through algorithmic search. However, in complex human-centered decision scenarios such as age-friendly home modification, a remaining challenge is ensuring that optimized weights reflect not only expert knowledge but also functional priorities reported by the study sample. Conventional AHP–PSO applications generally treat weighting results as objective optimization outcomes, while the relationship between optimized indicator priorities and the study sample’s aggregated adaptation priorities remains insufficiently explored.

Building on this methodological foundation, the present study develops and empirically evaluates a group preference-informed AHP–PSO decision-support model. The model uses the hierarchical structure of AHP to represent the logical relationships among functional dimensions and indicators, while introducing a sample-level preference-guided mechanism to constrain an improved PSO algorithm. During weight optimization, older users’ subjective preferences and daily living routines are transformed into preference-related guidance factors, thereby reducing the rigidity of conventional static weighting systems. The model integrates expert knowledge and resident-preference information to construct a sample-informed group-level weighting process and employs constrained optimization to improve the consistency between indicator priorities and functional adaptation requirements. Compared with conventional AHP–PSO applications that mainly emphasize weight optimization performance, the proposed model provides a systematic pathway for incorporating sample-aggregated resident-preference information into residential adaptation evaluation. The findings demonstrate the feasibility of integrating multi-source information and intelligent optimization mechanisms to improve the effectiveness of spatial-functional adaptability assessment [49–52]. AHP–PSO integration approach provides methodological support for scientifically grounded decision-making and community- and program-level interventions in age-friendly home modification. The contribution of this study therefore lies in extending the applicability of AHP–PSO-based decision-support methods in human-centered built environment assessment.

2. Literature Review

2.1. Spatial-Layout Optimization

Spatial-layout optimization addresses the allocation of functional zones, circulation, furniture, and facilities under spatial constraints. Evolutionary and heuristic algorithms have been widely applied to explore complex solution spaces and optimize multiple objectives. Existing studies have introduced genetic algorithms, deep learning, graph neural networks, and evolutionary search methods for residential layout generation, functional zoning, spatial-unit recognition, and facility configuration optimization [53–59]. In aging-related environments, Liu and Zhao [60] applied hybrid optimization algorithms to intelligent aging spaces, while Yu et al. [61] used path planning and spatial-interaction analysis to identify conflicts in aging-in-place housing. Although these studies demonstrate the potential of computational optimization for spatial decision-making, they mainly emphasize geometric efficiency or specific operational objectives. The integration of older residents' preferences with comprehensive dwelling-level requirements, including safety, accessibility, independence, and comfort, remains limited, indicating the need to combine spatial optimization with user-centered functional assessment.

2.2. Barrier-Free Design and Accessibility Research

Barrier-free design and accessibility research focuses on users' ability to access and utilize residential environments, extending evaluation from spatial configuration to functional adaptability. Existing studies have developed multidimensional accessibility frameworks incorporating mobility, safety, autonomy, and user capability. Luciano et al. [32] proposed an age-friendly housing framework with 71 indicators across eight domains, while AHP-based evaluations have highlighted autonomy, mobility, safety, and comfort as important assessment dimensions [27,32]. Other studies have applied interactive genetic algorithms and AHP to improve assistive product personalization and identify user–product interaction barriers [62,63]. Recent machine-learning and data-driven methods have further supported personalized accessibility assessment and barrier identification [64,65]. Current approaches mainly focus on individual facilities or standardized requirements and insufficiently consider the interactions among different residential functions and variations in older residents' preferences. In summary, age-friendly home modification requires an adaptive evaluation framework that integrates professional accessibility standards with resident-informed group-level decision-making.

2.3. Environmental Comfort and Safety Research

Environmental comfort and safety are essential dimensions of age-friendly residential assessment, determining whether accessible spaces can support sustained and independent living. Existing studies have applied reinforcement learning, genetic algorithms, and PSO-based methods to optimize visual, thermal, ventilation, structural, and material-related objectives in residential environments [66–69]. Research on older-adult housing further demonstrates that environmental conditions directly influence safety and usability. Li et al. [12] found that poor housing environments and squatting toilets were associated with higher fall risks, while Jang et al. [70] identified environmental hazards and emergency response issues in senior housing. In addition, Ainsworth et al. [35] showed that home modification outcomes involve not only physical accessibility but also autonomy, well-being, and long-term adaptability. However, existing studies mainly focus on individual environmental factors or isolated risks, with limited integration of comfort, safety, accessibility, and independence within a unified evaluation framework.

2.4. From Expert-Centered to User-Centered Evaluation of Home Environments

Expert-centered evaluation established the foundation for systematic residential accessibility assessment by translating functional limitations and environmental barriers into standardized criteria. Tools such as the Housing Enabler and AHP-based frameworks provide reproducible evaluation structures through professional judgment and structured weighting, with advantages in comparability and technical consistency [71]. However, these approaches generally define indicators and priorities from expert perspectives, while residents' daily routines, risk perceptions, and modification preferences have limited influence on the final weighting structure.

Subsequent studies incorporated user-informed evaluation to capture the lived experiences of older residents. Fänge and Iwarsson [72] demonstrated that professionally assessed accessibility and self-reported usability represent complementary dimensions of housing adaptation outcomes. Other studies further showed that users' perceptions of successful modification involve not only physical accessibility but also autonomy, well-being, and the meaning of home [34,35]. Consumer-directed and participatory approaches have strengthened the role of residents in adaptation decisions; however, these methods are often based on case-specific consultation, predefined evaluation items, or intervention outcomes, which limits scalability and their ability to dynamically adjust evaluation priorities [36]. Therefore, the key challenge is not whether user preferences should be considered, but how such information can be incorporated into a transparent and scalable weighting mechanism while maintaining professional accessibility knowledge.

Existing AHP–PSO hybrid studies provide a methodological basis for addressing this challenge. Previous applications have used AHP for criterion structuring and PSO for optimization, including decision priority adjustment, comparison-matrix improvement, and domain-specific evaluation problems [28,44,45,48]. Beyond these applications, AHP–PSO frameworks have been explored in information-security risk assessment, supply-chain risk evaluation, distribution-network reliability, and environmental assessment [46,47,73–78]. These studies confirm the effectiveness of AHP–PSO integration in multi-criteria decision-making. Nevertheless, its application in aging-in-place housing remains insufficiently explored, particularly regarding how aggregated resident preferences can guide weight refinement while balancing safety, accessibility, independence, and comfort.

2.5. Comparative Characteristics of Optimization Algorithms and Rationale for Selecting PSO

Population-based optimization algorithms differ in their search mechanisms and suitability for different decision problems. PSO updates candidate solutions through individual and social learning mechanisms, making it suitable for continuous optimization problems involving real-valued variables [79–81]. ACO is mainly designed for constructive and graph-based optimization, while DE and genetic algorithms employ evolutionary operators for continuous and multi-objective search problems [82–86]. These differences determine their applicability to specific optimization tasks. Table 1 summarizes the comparative characteristics of representative algorithms in relation to the continuous and constrained weight-allocation problem.

PSO is selected as the core optimizer because the optimization objective involves a continuous weight vector with normalization and feasibility constraints. The AHP-derived weights provide the initial decision structure, while PSO enables iterative refinement by incorporating optimization objectives and sample-aggregated preference information. Compared with algorithms requiring discrete solution construction or additional evolutionary operations, PSO provides a direct mechanism for continuous weight adjustment. Although PSO may encounter premature convergence, adaptive strategies and feasibility constraints can improve search stability [80,87]. For multi-objective extensions, MOPSO introduces

Pareto-based mechanisms for handling multiple objectives [29]. The present study adopts a scalarized fitness formulation for constrained weight optimization rather than Pareto-front generation. PSO is selected as an appropriate optimizer for the proposed group preference-informed AHP–PSO framework, while DE and GA are retained as benchmark algorithms for empirical comparison.

Table 1. Comparative characteristics of representative optimization algorithms.

Algorithm	Search Mechanism and Typical Application	Principal Strengths	Limitations and Relevance to This Study
PSO	Real-valued particles updated through position, velocity, personal-best, and social-best information. Commonly used for continuous nonlinear parameter and weight optimization; Pareto-based MOPSO variants support multiple objectives.	Direct continuous encoding; simple vector update; retains individual and collective search memory; rapid early convergence; AHP-derived weights can initialize the swarm and preference terms can be added directly to the update equation.	May lose diversity and converge prematurely; performance depends on inertia and acceleration parameters; a genuine Pareto multi-objective formulation requires an external archive and leader-selection mechanism. High structural fit for the present normalized weight-vector problem.
ACO	Probabilistic construction of solutions using pheromone and heuristic information. Native applications include routing, scheduling, assignment, and other discrete graph problems; ACOR extends the method to continuous variables.	Strong constructive search for discrete feasible paths; positive feedback reinforces useful components; distributed search can discover high-quality combinatorial solutions.	Pheromone storage, evaporation, and solution construction add operator overhead and may cause stagnation. Continuous use requires an archive and kernel-sampling design that does not map as directly to a 12-dimensional normalized weight vector.
DE	Real-valued population search based on differential mutation, crossover, and one-to-one selection. Widely applied to continuous global and engineering optimization.	Simple formulation; strong global exploration; difference vectors scale search steps to population dispersion; effective for nonlinear continuous spaces.	Sensitive to population size and mutation/crossover controls; standard DE has no explicit personal-best or global-best memory through which AHP priors and sample-level preference guidance terms can be embedded. It remains a strong continuous-optimization benchmark rather than an unsuitable algorithm.
GA/NSGA-II	Population evolution through selection, crossover, and mutation; NSGA-II adds elitist nondominated sorting and crowding-distance preservation for Pareto multi-objective optimization.	Flexible encoding for discrete, continuous, and mixed variables; strong diversity maintenance; mature Pareto-front treatment for genuinely conflicting objectives.	Requires problem-specific encoding, crossover, mutation, selection, and often constraint-repair rules. The additional operator and sorting pipeline are less direct for fine adjustment of an AHP-initialized continuous weight vector, although GA remains an appropriate benchmark.

2.6. Critical Synthesis of Methodological and Practical Limitations

The reviewed studies provide important foundations for age-friendly housing assessment, but existing approaches remain fragmented across spatial optimization, accessibility evaluation, environmental assessment, and user participation. Table 2 summarizes the main methodological and practical limitations of these research streams and the corresponding responses adopted. Rather than replacing previous approaches, the proposed framework integrates their complementary strengths by combining multidimensional housing criteria, older residents' preference information, adaptive weight refinement, and empirical validation within a unified decision-support process.

Table 2. Critical synthesis of prior research and methodological response.

Research Stream	Critical Methodological and Practical Limitation	Response and Retained Scope
Spatial-layout optimization	Optimization objectives are commonly defined by geometric efficiency, path length, automated generation, or a single operational actor. Several studies are simulation-based, and direct aging-in-place applications may be tested in only one dwelling configuration; for example, Yu et al. [61] acknowledged the limited generalizability of a single single-story case.	A shorter route or computationally efficient layout may still conflict with residents' routines, retained furniture, building structure, or simultaneous safety and comfort requirements. The present study therefore evaluates 12 dwelling-level indicators across four functional domains and uses questionnaire and interview evidence from actual urban communities. It prioritizes adaptation needs rather than claiming to generate universally optimal floor plans.
Expert-centered and user-centered housing evaluation	Expert-centered instruments and AHP frameworks offer reproducibility and technical consistency but predefine criteria and priorities. User-informed instruments add perceived usability, while participatory and consumer-directed studies incorporate lived experience and choice. However, these approaches commonly use preferences for needs elicitation, co-design, or post hoc evaluation; evidence may be small-scale, context-specific, labor-intensive, or based on predefined outcomes [34–36,71,72].	The present study preserves expert-derived safety and accessibility structure but incorporates older residents' evidence at two computational stages: correction of the initial AHP matrix and guidance of iterative PSO weight refinement. The larger survey supports scalable group-level prioritization, while contextual interviews aid interpretation. The model does not replace individualized co-design or shared decision-making.
Environmental comfort and safety research	Many studies optimize one environmental variable or transfer algorithms from non-residential settings. Observational housing studies identify associations but cannot establish the causal effect of a specific retrofit. Li et al. [12], for example, relied partly on self-report and could not examine detailed interior features such as grab bars and slip-resistant flooring.	Single-factor evidence offers limited guidance when safety, accessibility, comfort, and independence compete for priority. The present model places these outcomes in one hierarchy and applies dimensional balance constraints. It evaluates alignment with user ratings, but it does not claim to estimate causal health effects of individual modifications.

Table 2. *Cont.*

Research Stream	Critical Methodological and Practical Limitation	Response and Retained Scope
Home modification outcomes and implementation	Outcome evidence is heterogeneous in intervention content, measurement tools, participant characteristics, and follow-up. Qualitative studies provide rich user meanings but often involve small samples [35], while systematic evidence identifies limited objective measurement, long-term follow-up, personalization, and cost-effectiveness research [37]. Implementation is also constrained by affordability and access: Langdon et al. [88] found that nearly half of Ontario households needing disability-related adaptations lacked at least some of the required modifications.	Evidence that a modification is valued or beneficial does not by itself determine which intervention should be funded first under constrained resources. The present model provides a transparent priority-ranking and feasible-weight structure for current functional needs. Monetary cost, funding eligibility, construction duration, and long-term outcomes are not optimized in the present model and are explicitly retained as limitations and future extensions.
Previous AHP-PSO decision models	Existing combinations commonly use AHP to produce expert weights before PSO solves a downstream allocation problem, or use PSO to repair inconsistent or incomplete comparison matrices. Other applications concern products, suppliers, nutrition, or environmental-resource evaluation rather than dwelling-level aging-in-place adaptation.	User evidence may therefore be absent from the iterative search, and an algorithmically optimal solution may remain poorly aligned with residential experience. In the present study, sample-aggregated resident preferences enter both initialization (response-intensity correction, θ_{ij}) and iteration (preference intensity δ_i and guidance factor φ), with adaptive inertia and feasibility and balance constraints. Performance is tested against PSO, GA, and DE rather than inferred from convergence alone.

3. Research Design

3.1. Data Sources and Preprocessing

Figure 1 presents the complete mixed-method research framework and the analytical workflow of the group preference-informed AHP–PSO model. The empirical phase began with site selection, participant recruitment, questionnaire administration, and explanatory interviews. Data were collected from April to June 2024 using a cross-sectional mixed-method design. A multistage non-probability sampling strategy combined maximum-variation purposive site selection with community-based convenience recruitment [89]. At the first stage, Beijing in North China, Fushun in Northeast China, and Shanghai in East China were selected to capture contextual variation in population aging, climatic conditions, urban development, housing stock, and the maturity of age-friendly home modification practice. Beijing represented a northern high-density metropolis, where 4.948 million permanent residents were aged 60 years or older in 2023, accounting for 22.6% of the population. Fushun represented a cold-climate old industrial city with a comparatively old residential stock and 683,600 registered residents aged 60 years or older in 2023, accounting for 35.0% of its registered population. Shanghai represented a high-density eastern metropolis with an established citywide home modification policy environment; 5.8155 million permanent residents were aged 60 years or older in 2020, accounting for 23.4% of the population [90–92]. These cities were selected to provide contrasting residential contexts for model development and evaluation, rather than to constitute a statistically representative sample of all Chinese regions.

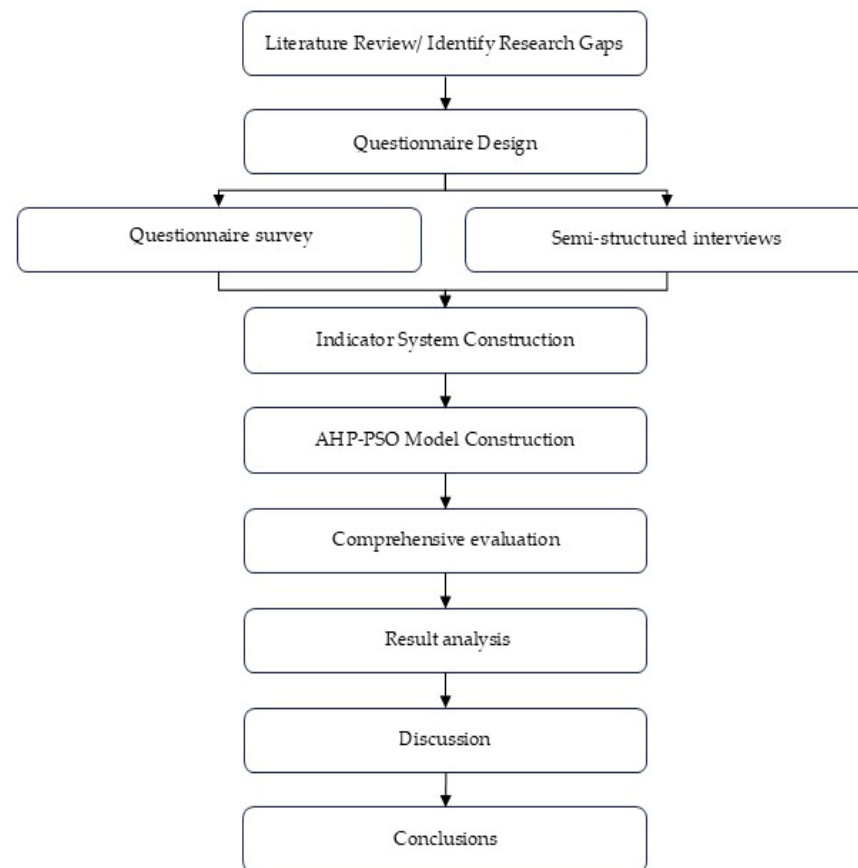


Figure 1. Research framework flowchart (source: by the authors).

At the second stage, urban communities within each city were selected purposively in collaboration with local community organizations. Site selection was based on four criteria: (1) a substantial resident population aged 60 years or older; (2) the presence of existing multi-story housing with observable age-friendly adaptation needs; (3) variation in dwelling age, housing type, and prior modification status; and (4) feasibility of field access and community cooperation. Within participating communities, eligible older residents were recruited through community-based convenience sampling. Inclusion criteria were: being aged 60 years or older; living in a privately owned dwelling or a long-term rental used as the primary residence for at least 6 months; having direct familiarity with the dwelling's daily use and modification needs; being able to understand the questionnaire and provide informed consent; and participating voluntarily. Residents living in nursing homes or other institutional settings, temporary residents, proxy respondents, and persons unable to complete the questionnaire with adequate comprehension were excluded.

A total of 600 questionnaires were distributed across the participating communities. Of these, 543 questionnaires met the eligibility, completeness, and internal-consistency criteria and were retained, yielding an effective response rate of 90.5%. The sample was analyzed as a pooled model-development dataset because questionnaire allocation was not proportional to the population of each city and the sampling design was non-probabilistic; the data were therefore not used to estimate city-level prevalence or to make formal interregional comparisons. The qualitative component was designed as an explanatory and content-validation strand linked to the questionnaire. Twenty older questionnaire participants who agreed to follow-up contact were purposively selected to provide variation in region, dwelling type, housing condition, and modification experience. Five professionals were purposively recruited on the basis of direct involvement in the planning, design, implementation, or community management of age-friendly home mod-

ifications. The interviews examined how the questionnaire items related to daily residential experience, whether the four functional domains and 12 indicators adequately represented the problem, which trade-offs and implementation constraints affected modification priorities, and how the model-generated deficiencies should be interpreted. The interview narratives were not used to estimate prevalence or converted into numerical weights. The same five professionals subsequently completed a separate, standardized AHP pairwise-comparison task.

Questionnaire preprocessing followed a fixed sequence: case-level screening, restricted item-level imputation, variable encoding, fixed-endpoint normalization, and derivation of the AHP-PSO inputs. Of the 600 questionnaires distributed, 57 (9.5%) were removed because they failed at least one eligibility, completeness, or logical-consistency criterion, leaving 543 questionnaires (90.5%) in the analytic dataset. For screening purposes, extensive missingness referred to the absence of a complete adequacy or importance rating block, or to missing responses distributed across multiple functional domains; such questionnaires were excluded. Minor missingness referred only to an isolated blank item in an otherwise eligible and interpretable questionnaire. Eligibility variables and the overall dwelling evaluation item were required to be complete.

For an isolated missing response, item-mean substitution was performed separately within the corresponding rating block: the blank response was replaced by the arithmetic mean of the observed responses to the same item among the retained questionnaires. This method was selected because the AHP-PSO model requires a complete 12-dimensional input vector and its group-level inputs are derived from item means. When restricted to isolated omissions, item-mean substitution preserves the location of the item mean and avoids excluding an otherwise usable questionnaire because of a single blank response. Because mean substitution can reduce item variance, it was not used when a complete block or multiple functional domains were affected. Imputation was completed on the original 1–5 response scale before any normalization or aggregation.

Variable encoding and normalization were then applied consistently. Survey city, age group, sex, housing tenure, dwelling type, floor, previous modification status, mobility-aid use, and living arrangement were assigned numeric category codes for data management and descriptive analysis only; these background variables were not included in the optimization vector. Valid ratings retained their original integer codes from 1 to 5, no items were reverse-coded, and zero was not used as a missing-value code. Each rating was mapped to $[0, 1]$ using the fixed transformation $z = (x - 1)/4$, so that response categories 1, 2, 3, 4, and 5 became 0, 0.25, 0.50, 0.75, and 1.00, respectively. A fixed-anchor transformation was used instead of sample-dependent minimum-maximum scaling or z-standardization so that the substantive meaning of each response category remained identical across samples and replications. After normalization, the indicator adequacy means s_i , importance means q_i , response-intensity coefficients θ_{ij} , preference-intensity terms δ_i , and dimension-balance coefficients β_j were calculated. Interview material remained a separate qualitative dataset and was not encoded or normalized as questionnaire observations.

3.2. Indicator System Construction

3.2.1. Questionnaire Item Development and Source Basis

The questionnaire and indicator system were developed by drawing on a traceable source pool and synthesizing key elements extracted from a literature review. Candidate concepts were extracted from studies addressing age-friendly housing, person-environment accessibility, home modification, residential fall risks, and user-reported outcomes [12,34,35,37,55,67,72]. The extraction unit was a specific dwelling feature or spatial condition that could be observed or rated by residents, could potentially be modified,

and was directly relevant to safety, accessibility, independent daily activity, or environmental comfort. Preliminary non-participant observations during site familiarization were used to check whether the literature-derived concepts covered recurrent conditions in entrances, internal routes, bathrooms, kitchens, lighting, emergency response provision, thermal and acoustic conditions, and furniture use. The resulting candidate concepts were then subjected to the staged selection and consultation protocol.

3.2.2. Measurement Scale and Variable Construction

The questionnaire contained a background-information section and two parallel rating blocks for the same 12 residential features. Current dwelling adequacy was measured using a five-point Likert-type scale ranging from 1 (very inadequate or not provided) to 5 (fully adequate). Perceived importance was measured using a five-point Likert-type scale ranging from 1 (not important) to 5 (very important). Higher values consistently indicated better current provision or greater perceived importance, and no items were reverse-coded. An additional five-point overall evaluation item measured how well the current dwelling supported safe and independent aging in place.

For variable construction, adequacy responses were coded ADQ1-ADQ12, importance responses IMP1-IMP12, and the overall dwelling evaluation OA1. After the restricted item-mean substitution, raw 1–5 ratings were converted to $[0, 1]$ using $z = (x - 1)/4$; thus, $1 = 0$, $2 = 0.25$, $3 = 0.50$, $4 = 0.75$, and $5 = 1.00$. This fixed-endpoint conversion preserves the original scale anchors and does not depend on the observed sample minimum, maximum, mean, or standard deviation. The mean normalized adequacy score for indicator i was used as the observed residential-performance value s_i , while the corresponding mean normalized importance score q_i represented group-level user preference. Relative differences between q_i and q_j generated the AHP response-intensity coefficient θ_{ij} , constrained to $[-0.2, 0.2]$; indicator-specific preference intensity δ_i was defined relative to the overall item mean and entered the PSO update. Criterion-level importance means generated the dimension-balance coefficient β_j . OA1 was normalized using the same fixed transformation and served as the user-reported criterion in the prediction-error assessment.

3.2.3. Instrument Review and Measurement-Quality Procedures

Measurement quality was addressed through instrument development, administration, and analytical procedures. Content and face validity were supported by source traceability, preliminary site observation, review by older residents for comprehensibility and lived relevance, and structured consultation with professionals. The professionals reviewed relevance to dwelling-level functional adaptability, technical clarity, non-redundancy, actionability, cross-context applicability, and allocation to a primary domain. The current-dwelling-adequacy and perceived-importance blocks used identical item statements, standardized five-point response anchors, consistent score direction, and no reverse-coded items.

To assess internal consistency, we calculated Cronbach's α separately for the 12-item adequacy block and the 12-item importance block using IBM SPSS Statistics 26.0. The adequacy block yielded $\alpha = 0.89$, and the importance block yielded $\alpha = 0.91$, both exceeding the conventional threshold of 0.70, indicating high internal reliability.

3.2.4. Staged Indicator Development, Expert Review, and Final Confirmation

To reduce discretionary selection and make the indicator-development process reproducible, the study used five sequential stages with explicit decision criteria.

Stage 1—Construct definition and literature-derived candidate generation. The construct was bounded to modifiable physical or operational characteristics of the dwelling and its immediate access route. Candidate concepts were retained for screening when they

were directly relevant to at least one of four provisional functions: risk control, spatial access, independent performance of daily activities, or sustained environmental usability. Community-level services, personal health characteristics, and post-intervention outcomes were outside the indicator boundary.

Stage 2—Candidate consolidation and preliminary observation. Literature-derived terms referring to the same functional target were grouped in a traceability worksheet. Concepts were merged when they described components of one intervention or one user task, separated when they represented distinct modification decisions, and reworded when technical terminology was unlikely to be clear to older respondents. Preliminary observations were used to check contextual relevance but did not generate numerical weights. Duplicate wording, non-modifiable attributes, public or neighborhood conditions, and implementation constraints such as cost, tenure, family agreement, construction disruption, property-management support, and maintenance were excluded from the dwelling-function indicator set.

Stage 3—Questionnaire operationalization and resident evidence. The consolidated concepts were expressed as 12 observable residential statements and administered in parallel adequacy and importance blocks. Questionnaire evidence was used to confirm that residents could evaluate the features consistently and to generate the performance and preference variables. Indicators were not deleted merely because they received a lower mean score, because each item represented a non-interchangeable component of the formative functional adaptability index.

Stage 4—Older-resident review, interview analysis, and structured professional consultation. The follow-up interviews with 20 older adults examined clarity, lived relevance, missing content, overlap, and priority trade-offs. The five professionals reviewed the candidate set using six criteria: relevance to the defined construct, clarity, non-redundancy, actionability through home modification, applicability across the three urban contexts, and defensible allocation to one primary domain. Ambiguous wording was refined; overlapping components were integrated; and contextual implementation conditions were retained for interpretation rather than converted into model indicators. These five professionals subsequently served as the AHP panel, but their interview statements and their pairwise-comparison judgments were collected and analyzed as separate evidence streams.

Stage 5—Final confirmation and model entry. A candidate was retained when it had a documented literature basis, fell within the dwelling-level construct boundary, represented a distinct and potentially actionable function, was understandable to resident reviewers, and had no unresolved duplication or domain-allocation concern after consultation. The final system contained four criterion dimensions and 12 indicators. Table 3 records the item-level audit trail, including the consolidated content, principal source basis, and final retention rationale.

Table 3. Indicator-development audit trail and final decision rationale.

Code	Candidate Content and Decision	Principal Source Basis	Final Retention/Exclusion Rationale
I1	Slip-resistant materials/treatments across wet and circulation areas; retained as a stand-alone safety item.	Li et al. [12]; Luciano et al. [32]; Cha [37]	Direct fall-risk relevance; observable, modifiable.
I2	Lighting at entrances, routes, bathrooms, and stairs; wording consolidated around safe daytime/night-time visibility.	Luciano et al. [32]; Jang et al. [70]; Cha [37]	Distinct visibility function with a clear residential intervention pathway.

Table 3. Cont.

Code	Candidate Content and Decision	Principal Source Basis	Final Retention/Exclusion Rationale
I3	Emergency call buttons, alarm systems, and accessible evacuation provision merged as emergency response capacity.	Jang et al. [70]; Ainsworth et al. [35]; Cha [37]	Components serve one urgent-response function and were integrated to avoid fragmentation.
I4	Level access/ramps, handrails, and door width merged as entrance/exit accessibility.	Iwarsson et al. [71]; Luciano et al. [32]; Ptak-Wojciechowska et al. [27]	Components jointly determine transition across the dwelling threshold.
I5	Internal route width, surface smoothness, and step-free continuity retained as internal circulation.	Iwarsson et al. [71]; Fänge & Iwarsson [72]; Luciano et al. [32]	Distinct from entrance access and directly relevant to walking and wheelchair movement.
I6	Bathroom/toilet door width, grab bars, and turning space merged as restroom accessibility.	Iwarsson et al. [71]; Schorderet et al. [34]; Luciano et al. [32]	Components support one high-risk daily task and one spatial modification zone.
I7	Bedroom and living-room arrangement merged around independent movement and routine activity.	Fänge & Iwarsson [72]; Ainsworth et al. [35]; Schorderet et al. [34]	Captures room-layout support for daily independence without duplicating circulation width.
I8	Worktop, sink, and stove height/position merged as kitchen operation convenience.	Schorderet et al. [34]; Ainsworth et al. [35]; Cha [37]	Components form one task-specific operability construct and require coordinated redesign.
I9	Switches, outlets, curtains, windows, and gas valves merged as facility operability.	Luciano et al. [32]; Ptak-Wojciechowska et al. [27]; Cha [37]	Shared reach-and-control function; integration avoids multiple narrowly defined control items.
I10	Natural lighting and ventilation merged as basic environmental quality.	Luciano et al. [32]; Montacchini et al. [93]; Cha [37]	Closely linked passive environmental conditions that residents can evaluate directly.
I11	Temperature stability and external-noise insulation merged as thermal/acoustic control.	Luciano et al. [32]; Montacchini et al. [93]; Ainsworth et al. [35]	Both depend substantially on building-envelope performance and sustained comfort.
I12	Beds, chairs, and storage ergonomics merged as furniture adaptability.	Ainsworth et al. [35]; Schorderet et al. [34]; Cha [37]	Person-furniture fit involving posture, reach, transfer, and mobility.

The confirmed indicators were organized into a three-level evaluation system. The target level was Home Renovation Spatial Function Adaptability (G). The criterion level comprised Safety Assurance (C1), Spatial Accessibility (C2), Living Independence (C3), and Environmental Comfort (C4), with three formative and non-interchangeable indicators assigned to each dimension. Safety Assurance and Spatial Accessibility represent fundamental risk-control and barrier-free requirements, whereas Living Independence and Environmental Comfort represent support for autonomous daily activity and sustained residential use. The final operational definitions are presented in Table 4.

Table 4. Final indicator system.

Criterion Layer	Indicator Layer	Description
Safety Assurance (C1)	Anti-slip Measures (I1)	Coverage of slip-resistant flooring materials or designs in areas such as bathrooms, kitchens, and hallways.
	Lighting & Visibility (I2)	Whether illumination in indoor/outdoor main pathways, bathrooms, and staircases meets the nighttime activity needs of the elderly.
	Emergency Rescue Facilities (I3)	Installation of emergency call buttons, alarm systems, and barrier-free evacuation routes.
Spatial Accessibility (C2)	Barrier-Free Entrance/Exit (I4)	Presence of ramps, handrails, and wheelchair-accessible door widths at entryways.
	Indoor Pathway Width & Smoothness (I5)	Whether main indoor pathways accommodate wheelchair passage with level, step-free surfaces.
	Restroom Accessibility (I6)	Restroom door width, handrail placement, and turning space compliance with barrier-free requirements.
Independent Living (C3)	Bedroom & Living Room Layout (I7)	Whether spatial flow promotes independence in daily activities among older adults.
	Kitchen Operation Convenience (I8)	Counter height and sink/stove positions aligned with ergonomics and habits of older adults.
	Facility Operability (I9)	Accessibility of switches, outlets, curtains, and gas valves for elderly users.
Environmental Comfort (C4)	Natural Lighting & Ventilation (I10)	Adequacy of daylight and window-to-wall ratio in living/sleeping areas.
	Temperature & Soundproofing (I11)	Stability of indoor temperature and noise insulation against external disturbances.
	Ergonomic Furniture Adaptability (I12)	Suitability of beds, chairs, and storage units for posture and mobility needs of older adults.

3.2.5. Qualitative Interview

The interviews served four linked purposes. First, they clarified how older respondents understood and experienced the 12 questionnaire features in relation to daily routines. Second, they assessed the substantive coverage and clarity of the four functional domains: Safety Assurance, Spatial Accessibility, Living Independence, and Environmental Comfort. Third, they elicited priority trade-offs and implementation conditions that could not be represented adequately by five-point ratings alone. Fourth, they supplied contextual explanations for the indicator rankings and dwelling-level deficiencies generated by the AHP-PSO model. The guide contained 14 main questions. After questions on participant and housing context and overall functional adaptability, questions were organized around safety, entry and internal circulation, independent daily activities, environmental comfort, priority interventions, commonly inadequate features, implementation barriers, differences between user preferences and professional recommendations, completeness of the indicator system, contextual variation, and intervention sequencing. Older participants were asked to draw on their current dwelling and routines, whereas professionals were asked to draw on general planning, design, implementation, or community-management experience.

Interview notes were anonymized and analyzed using hybrid framework analysis. A deductive coding matrix was constructed from the questionnaire's four dimensions and 12 indicators, together with cross-cutting categories for overall adaptability, priority and

trade-offs, user-professional alignment, implementation feasibility, contextual variation, and intervention sequencing. Within this structure, inductive codes were retained for experiences or constraints that were not anticipated by the questionnaire. Relevant text segments were coded, summarized by participant group and housing context, and compared across cases to identify convergence, divergence, and exceptions between older residents and professionals.

Qualitative findings were integrated with the research model through a documented three-stage process. At the measurement stage, interview evidence was used to check the interpretation, overlap, and practical relevance of the four domains and 12 indicators and to refine their operational descriptions for model application. At the variable-selection stage, only themes that represented dwelling-level functional adaptability and corresponded to the predefined construct were retained as model indicators; contextual factors such as cost, tenure, family agreement, property-management support, construction disruption, and maintenance were not converted into numerical weights because they represented implementation conditions rather than residential-function variables. At the interpretation stage, these contextual themes were used to explain the questionnaire/model patterns and the practical feasibility of priority interventions. Numerical AHP weights, PSO preference terms, adaptability scores, and rankings remained derived from expert judgments and questionnaire responses.

The integration of qualitative evidence is confined to the pre-model development phase and the post-model interpretation phase, while the core computational pipeline remains exclusively driven by the quantitative questionnaire data and expert pairwise judgments.

3.3. AHP-PSO Model Construction

The framework begins with AHP-based weight determination, incorporating questionnaire-based corrections into expert judgments to balance professional knowledge and sample-aggregated resident priorities. Subsequently, the conventional PSO process is employed with sample-aggregated preference factors and adaptive parameter settings to refine indicator weights and improve the applicability of the evaluation results. The PSO procedure incorporates an adaptive inertia weight and sample-aggregated preference factor within the conventional PSO framework to refine the indicator weights according to group-level residential adaptation priorities. Finally, a composite adaptability function incorporating a weight dispersion penalty term and criterion-level balance coefficients is established, enabling quantitative evaluation and grading of home renovation solutions while improving the interpretability and practical applicability of the model.

3.3.1. AHP Weight Determination

The conventional AHP method constructs judgment matrices through expert scoring and obtains weights using the eigenvector method. Because relying solely on expert judgment may introduce disciplinary or professional bias, the study first established a transparent expert-comparison procedure and then applied a limited questionnaire-based correction. The expert panel and evaluation protocol were as follows.

Five professionals constituted the AHP expert panel. Purposive expert selection was used because the task required substantive knowledge of age-friendly residential environments rather than statistical representation. Eligibility required direct project-level experience in at least one of the following areas: residential architecture or interior/spatial design; barrier-free and accessibility design; aging-friendly home modification; renovation planning or implementation; or community-based management of older-adult housing. Experts also had to be familiar with existing urban dwellings and older residents' functional requirements and be able to evaluate the complete four-dimension, 12-indicator

hierarchy. The panel collectively covered planning, design, accessibility, implementation, and community-management perspectives. Professional seniority was not used to assign differential voting weights; each expert contributed equally to the group judgment.

Before evaluation, each expert received the hierarchy, operational definitions for all criteria and indicators, and standardized written instructions. The common decision question was: relative to the overall objective of supporting safe and independent aging in place, how much more does one criterion or indicator contribute than the other? Experts were instructed to consider four aspects consistently: the severity of safety or functional consequences if the feature was inadequate; the frequency with which the feature affected everyday residential activities; the breadth of older residents likely to be affected; and the urgency and actionability of the feature within home modification. Relative importance was judged independently using Saaty's 1–9 scale: 1 indicated equal importance; 3, moderate importance; 5, strong importance; 7, very strong importance; and 9, extreme importance, with 2, 4, 6, and 8 used as intermediate values and reciprocal values used for the reverse comparison. Each expert completed 18 unique comparisons: six comparisons among the four criterion dimensions and three comparisons within each of the four three-indicator groups. Independent completion was used to reduce group-dominance and conformity effects.

Each expert's judgments were first converted into a positive reciprocal comparison matrix. The five individual matrices were then aggregated element by element using the geometric mean, so that every expert contributed equally while the reciprocal structure of the AHP matrix was preserved. For each aggregated criterion- or indicator-level matrix, the priority weights were obtained from the principal right eigenvector and normalized so that their sum equaled one. Matrix consistency was evaluated using the conventional maximum-eigenvalue, consistency-index, and consistency-ratio procedure. Only matrices with $CR < 0.10$ were accepted. This sequence—independent comparison, geometric-mean aggregation, eigenvector normalization, and consistency testing—was applied before the questionnaire-based response-intensity correction was introduced.

First, construct the judgment matrix $A = (a_{ij})_{n \times n}$, where a_{ij} represents the relative importance of the i -th criterion (or indicator) compared with the j -th criterion (or indicator). To incorporate older residents' preferences, the expert comparison is adjusted using the response-intensity coefficient θ_{ij} , as shown in Equation (1).

$$a_{ij}^* = a_{ij}(1 + \theta_{ij}) \quad (1)$$

The response-intensity coefficient θ_{ij} is derived from the normalized mean importance scores q_i and q_j obtained from the questionnaire. Specifically, $\theta_{ij} = 0.2 \times \frac{q_i - q_j}{q_i + q_j}$, which reflects the relative preference for indicator i over indicator j among older residents. This formulation bounds θ_{ij} within $[-0.2, 0.2]$ and treats the two indicators symmetrically.

The $[-0.2, 0.2]$ range was selected to allow questionnaire evidence to make bounded adjustments to expert judgments without overriding the professional AHP structure. A larger range (e.g., ± 0.5) would risk allowing sample-aggregated resident preferences to dominate expert knowledge, whereas a smaller range (e.g., ± 0.1) would render the user correction inconsequential. The ± 0.2 bound was determined through pilot testing as the maximum adjustment that preserved the original expert ranking order while meaningfully reflecting sample-level preference patterns.

The revised matrix A^* is constructed as $a_{ij}^* = a_{ij}(1 + \theta_{ij})$ for $i < j$ and $a_{ji}^* = \frac{1}{a_{ij}^*}$ for $i > j$. This construction strictly preserves the reciprocal property $a_{ij}^* \times a_{ji}^* = 1$, while all diagonal elements remain equal to 1.

Second, normalize the revised matrix A^* to obtain the initial weight vector $w = (w_1, w_2, \dots, w_n)$. The conventional geometric-mean eigenvector approximation is given in Equation (2).

$$w_i = \frac{\left(\prod_{j=1}^n a_{ij}^* \right)^{1/n}}{\sum_{k=1}^n \left(\prod_{j=1}^n a_{kj}^* \right)^{1/n}} \quad (2)$$

Finally, consistency was evaluated using the conventional AHP consistency ratio. The revised judgment matrix was accepted only when $CR < 0.10$. Sample-aggregated preference information was incorporated through the response-intensity correction before the consistency test and was not used to relax the conventional threshold.

3.3.2. PSO Mechanism

After obtaining the initial weights derived from AHP, this study introduces a Particle Swarm Optimization (PSO) algorithm to mitigate potential biases caused by expert subjectivity and enhance the sensitivity of weight allocation to practical home modification needs. Within the conventional PSO framework, this study incorporates questionnaire-derived statistical characteristics into the fitness evaluation process to better reflect residential adaptation priorities. Furthermore, the algorithm introduces adaptive inertia weight and sample-derived group-preference guidance factors into the update rules, enabling iterative optimization of multidimensional indicator weights. The detailed optimization steps are as follows:

First, the weight vector $w = (w_1, w_2, \dots, w_n)$ is treated as the particle position, with each particle representing a candidate weight-allocation scheme. Using the mean questionnaire adequacy score s_i for each indicator, the fitness function is defined in Equation (3).

$$F(w) = \sum_{i=1}^n w_i s_i - \lambda \sigma(w) \quad (3)$$

where $-\lambda \sigma(w)$ represents the weight dispersion penalty term, which is used to prevent excessive dispersion or concentration of indicator weights during optimization. The interpretation and purpose of the fitness function require clarification. The fitness function $F(w) = \sum_i (w_i s_i) - \lambda \sigma(w)$ serves two related purposes.

First, the term $\sum_i (w_i s_i)$ represents the weighted mean adequacy of the dwelling under the candidate weight vector w . A higher value indicates better performance across the 12 indicators under the specified weighting scheme. The second term, $-\lambda \sigma(w)$, penalizes excessive dispersion in the weights, thereby discouraging any single indicator from dominating the evaluation. The balancing parameter λ controls the trade-off between weighted adequacy and weight dispersion.

Second, the fitness function does not directly predict renovation outcomes. Instead, it identifies an optimized weighting structure for evaluating current dwelling conditions. The resulting global vector w^* is subsequently combined with β_j and renormalized to obtain the final effective vector used in Section 3.3.3, Equation (7), to calculate the adaptability score S for each dwelling and identify priority deficiencies for intervention.

Third, the optimization process seeks the weight vector w that maximizes $F(w)$, under the assumption that higher weighted adequacy should correspond to higher overall user evaluations.

In addition, regarding position and velocity updates, this study adopts an adaptive inertia weight $\omega(t)$, dynamically adjusted based on the iteration count:

$$\omega(t) = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \frac{t}{T} + \phi \delta_i \quad (4)$$

where $\omega_{\max}$ and $\omega_{\min}$ are the initial and minimum inertia weights, respectively; t is the current iteration; T is the maximum number of iterations; δ_i denotes the questionnaire-derived preference intensity for indicator i ; and ϕ is the sample-level preference guidance factor.

Finally, to ensure result reproducibility and reasonableness, the optimization process imposes non-negativity and normalization constraints on the weights:

$$w_i \geq 0, \quad \sum_{i=1}^n w_i = 1 \quad (5)$$

After the stopping criterion is reached, the feasible particle with the highest fitness value $F(w)$ is retained as the final optimized weight vector.

3.3.3. Integrated Evaluation Mechanism

After obtaining the weight coefficients determined by AHP and optimized through PSO, they are applied to the comprehensive evaluation of aging-friendly home modifications to achieve quantitative assessment of functional adaptability for different solutions. The integrated evaluation mechanism developed in this study follows a logical framework of “indicator scoring $\rightarrow$ weight optimization $\rightarrow$ comprehensive adaptability assessment”. By establishing a weighted comprehensive evaluation function, it enables objective judgment of the quality of modification solutions. The specific steps are as follows:

First, the 12 indicators provide normalized dwelling-level scores s_{hi} . Equation (6) defines the pre-balance PSO score using the global vector w^* , where $\sum_i w_i^* = 1$.

$$F^* = \sum_{i=1}^n w_i^* S_i \quad (6)$$

where F_h^* is the pre-balance PSO score for dwelling h and w_i^* is the global PSO-optimized weight for indicator i .

To distinguish the four sequential weight representations used in the model, the weight-transformation pathway is defined as follows.

First, the expert-only AHP vector w^E contains global indicator priorities obtained by multiplying each criterion priority by the corresponding within-criterion local priority; $\sum_i w_i^E = 1$.

Second, questionnaire-derived response-intensity coefficients θ_{ij} are applied to the pairwise comparisons, producing the user-corrected global AHP vector $w(0)$, which is renormalized to $\sum_i w_i(0) = 1$ and used to initialize PSO.

Third, PSO searches the 12-dimensional continuous weight space using Equation (3), subject to $w_i^* \geq 0$ and $\sum_i w_i^* = 1$, to obtain the global optimized vector w^* .

Fourth, the criterion coefficients β_j are applied once to the PSO vector, and the products are renormalized across all 12 indicators. This preserves the within-criterion PSO ratios while producing the final global effective vector used for dwelling-level scoring. Table 5 summarizes the parameter roles.

Table 5. Summary of parameters, sources, roles, and constraints.

Parameter	Source	Role	Constraint/Range
s_i	Questionnaire (ADQ)	Indicator-level adequacy score	[0, 1]
q_i	Questionnaire (IMP)	Indicator-level importance score	[0, 1]
θ_{ij}	Derived from q_i and q_j	Bounded correction to AHP comparisons	[−0.2, 0.2]
$w(0)$	Expert AHP vector w^E adjusted by θ_{ij}	User-corrected global starting weights for PSO	$\sum_i w_i = 1, w_i \geq 0, CR < 0.10$
w^*	PSO (initialized with $w(0)$)	PSO-optimized global weights before β_j adjustment	$\sum_i w_i = 1, w_i \geq 0$
δ_i	Questionnaire (IMP relative to mean)	Preference intensity guiding PSO search	Real number
ϕ	Preset parameter	Sample-level preference guidance factor in PSO update	[0, 1]
β_j	Questionnaire (dimension-level importance means)	Dimensional balance adjustment coefficient	$\sum_j \beta_j = 1; \beta_j > 0$
$F(w)$	Fitness function $\sum_i (s_i \cdot w_i) - \lambda \cdot \sigma(w)$	PSO objective (maximized)	—
S	$\sum_i (w_{\text{eff},i} \cdot s_{hi})$, with $w_{\text{eff},i}$ normalized after β_j	Final adaptability score for each dwelling	[0, 1], classified into four levels

For final scoring, the normalized criterion coefficients β_j adjust the four domain contributions, after which the 12 products are renormalized to obtain the final effective global weights:

$$\begin{aligned}\tilde{w}_i &= \frac{\beta_{g(i)} w_i^*}{\sum_{k=1}^{12} \beta_{g(k)} w_k^*}, \\ S_h &= \sum_{i=1}^{12} \tilde{w}_i s_{hi}, \quad \sum_{i=1}^{12} \tilde{w}_i = 1\end{aligned}\quad (7)$$

Here, $g(i)$ maps indicator i to its criterion. The normalized coefficients were $\beta = (0.24377, 0.24640, 0.25281, 0.25702)$ for C1–C4, respectively. The final effective vector w_{eff} , rather than the pre-adjustment vector w^* , was used to calculate every dwelling-level adaptability score.

Finally, to enhance result interpretability, the comprehensive adaptability is classified into four levels: low adaptability, moderate adaptability, relatively high adaptability, and high adaptability.

The comprehensive adaptability score S ranges from 0 to 1 because each normalized indicator score s_{hi} lies in [0, 1] and the final effective weights satisfy $w_{\text{eff},i} \geq 0$ and $\sum_i w_{\text{eff},i} = 1$. The four adaptability levels are defined through equal-interval partitioning of the [0, 1] range, as shown in Table 6.

The equal-interval partitioning method was selected for three reasons. First, it provides a transparent and easily interpretable classification that does not depend on the distribution of the sample, allowing consistent application across different datasets and contexts. Second, it aligns with the conventional interpretation of normalized scores in multi-criteria evaluation studies, where [0, 0.25), [0.25, 0.50), [0.50, 0.75), and [0.75, 1.00] are commonly used to represent poor, fair, good, and excellent performance levels, respectively [35,37]. Third, it facilitates communication with policymakers and practitioners by using intuitive percentage-based thresholds (e.g., “below 25%” indicates severe deficiency).

Table 6. Adaptability level classification criteria.

Adaptability Level	Score Range	Interpretation
Low	$0 \leq S < 0.25$	Multiple critical functional deficiencies exist; urgent intervention is required.
Moderate	$0.25 \leq S < 0.50$	Some functional deficiencies exist; targeted improvements are recommended.
Relatively High	$0.50 \leq S < 0.75$	Most functional requirements are met; minor refinements may be beneficial.
High	$0.75 \leq S \leq 1.00$	All functional requirements are well satisfied; no immediate intervention is required.

S denotes the comprehensive adaptability score, normalized to the interval $[0, 1]$.

3.4. Comprehensive Evaluation

To comprehensively assess the applicability and effectiveness of the AHP-PSO hybrid optimization model for aging-friendly home modifications, this study selects the following evaluation metrics from four aspects: prediction accuracy, functional adaptation rationality, dimensional balance, and robustness:

MAE, Mean Absolute Error

MAE measures the deviation between the model's predicted comprehensive adaptation scores and actual evaluations from elderly users. A lower value indicates better alignment between model predictions and actual needs. The formula is as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

In this study, y_i represents the user's normalized overall evaluation of dwelling i (OA1), and $\hat{y}_i$ represents the model-predicted comprehensive adaptability score. MAE therefore quantifies the agreement between the model output and users' overall dwelling evaluations.

FDR, Functional Deviation Ratio

FDR measures the degree of difference between adaptation scores of functional indicators and sample-level resident priorities, reflecting whether the model results truly align with elderly living scenarios. The formula is as follows:

$$FDR = \frac{1}{m} \sum_{j=1}^m \left| \frac{s_j - \hat{s}_j}{s_j} \right| \quad (9)$$

where s_j represents the user-expected score for indicator j , $\hat{s}_j$ is the model-estimated adaptation score for that indicator, and m is the number of indicators.

DBR, Dimensional Balance Ratio

DBR measures the balance among the four criterion layers in final weight allocation. Excessive or insufficient weight in any dimension may lead to imbalanced overall adaptation evaluation. The formula is as follows:

$$DBR = 1 - \frac{\sigma(W_c)}{\mu(W_c)} \quad (10)$$

where W_c is the weight vector of the four criterion layers, $\sigma(\cdot)$ is the standard deviation, and $\mu(\cdot)$ is the mean.

FSR, Feasible Solution Ratio

FSR measures the proportion of feasible solutions generated by the model under non-negative weight and normalization constraints, reflecting the model's robustness and stability. The formula is as follows:

$$FSR = \frac{N_f}{N} \quad (11)$$

where N_f is the number of solutions satisfying all constraints and N is the total number of generated solutions.

4. Results

4.1. Experimental Setup

To ensure the scientific validity of model training and validation, the dataset was divided into training, validation, and test sets after preprocessing. The allocation ratio was set at 70% for training, 15% for validation, and 15% for testing to achieve balanced parameter optimization and generalization performance evaluation. The experimental platform ran on a Windows 11 operating system with the following hardware configuration: Intel Core i7-12700 processor, 16 GB of RAM, and an NVIDIA RTX 3060 graphics card. This ensured computational efficiency during multiple iterations of optimization and matrix operations. For the software environment, the experiment was implemented on the Python 3.10 platform, primarily utilizing NumPy (version 1.26.4), SciPy (version 1.11.4), scikit-learn (version 1.3.0), and Matplotlib (version 3.8.2) for data processing, weight calculation, and result visualization. Regarding parameter configuration: the particle swarm size was set to 50, with a maximum of 500 iterations and an inertia weight range within [0.4, 0.9], and both learning factors c_1 and c_2 were set to 2.0.

4.2. Sample Characteristics of Participants and Dwellings

To characterize the empirical sample and clarify the background distribution of the surveyed population, this section presents the demographic and dwelling-related characteristics of the 543 valid respondents. As summarized in Table 7, the participants were recruited from three regions of China, including North China, Northeast China, and East China, covering diverse urban residential contexts. The sample characteristics include region, age group, sex, housing tenure, dwelling type, floor level, previous modification experience, mobility-aid use, and living arrangement.

Table 7. Demographic and dwelling characteristics of participants (n = 543).

Variable	Category	n	Percentage (%)
Region	Beijing	186	34.3
	Fushun	162	29.8
	Shanghai	195	35.9
Age group	60–69 years	224	41.3
	70–79 years	202	37.2
	≥80 years	117	21.5
Sex	Male	267	49.2
	Female	276	50.8

Table 7. *Cont.*

Variable	Category	n	Percentage (%)
Housing tenure	Owner-occupied housing	486	89.5
	Rental housing	57	10.5
Dwelling type	Apartment building	471	86.7
	Other residential types	72	13.3
Floor level	Low floor (1st–3rd floor)	182	33.5
	Middle floor (4th–6th floor)	218	40.1
	High floor (>6th floor)	143	26.4
Previous modification	Yes	156	28.7
	No	387	71.3
Mobility-aid use	Yes	98	18
	No	445	82
Living arrangement	Living alone	126	23.2
	Living with spouse	214	39.4
	Living with family members	203	37.4

4.3. AHP Weight Analysis

In the initial AHP phase, the independent pairwise-comparison matrices completed by the five experts were combined using the element-wise geometric mean. The priority vector was derived from the principal right eigenvector of the aggregated matrix and normalized to obtain the criterion weights. The aggregate expert matrix satisfied the prespecified consistency requirement ($CR = 0.056$). Questionnaire-derived response-intensity coefficients were subsequently used to make bounded adjustments to comparison relationships that differed from older residents' group-level importance ratings. The corrected matrix yielded $CR = 0.072$, which remained below the 0.10 threshold. These results indicate acceptable consistency in the group-comparison structure before and after the sample-level preference correction; they do not represent a separate test of individual-expert reliability. The corresponding user-corrected group pairwise-comparison matrices at the criterion and indicator levels are provided in Tables S1–S5 of the Supplementary Materials.

Table 8 reports the complete global weight-transformation pathway from the expert AHP vector to the β -adjusted final effective vector. The expert AHP criterion shares were $C1 = 0.35200$, $C2 = 0.29600$, $C3 = 0.21100$, and $C4 = 0.14100$; after questionnaire correction, they became 0.34100, 0.28700, 0.22100, and 0.15100, respectively. PSO redistributed the criterion shares to 0.28600, 0.26300, 0.23700, and 0.21400. After applying β_j and renormalizing, the final effective shares were 0.27950, 0.25979, 0.24020, and 0.22051, yielding $DBR = 0.912$. Safety Assurance and Spatial Accessibility therefore remained the two largest final contributors, while the dispersion penalty and criterion adjustment reduced concentration across the four domains.

At the user-corrected AHP stage, the within-C1 local weights for I1, I2, and I3 were 0.416, 0.382, and 0.202, corresponding to global weights of 0.14186, 0.13026, and 0.06888. Their final effective weights were 0.11264, 0.10481, and 0.06205, respectively. Across all 12 indicators, the final effective weights ranged from 0.06205 to 0.11264 and summed to 1.00000.

Table 8. Traceable transformation from expert AHP weights to final effective global indicator weights.

Indicator	Expert AHP (Global)	User-Corrected AHP (Global)	PSO-Optimized w^* (Global)	Final Effective Weight After β_j (Global)
I1 Anti-slip Measures (C1)	0.14960	0.14186	0.11526	0.11264
I2 Lighting & Visibility (C1)	0.13200	0.13026	0.10725	0.10481
I3 Emergency Rescue Facilities (C1)	0.07040	0.06888	0.06349	0.06205
C1 subtotal (Safety Assurance)	0.35200	0.34100	0.28600	0.27950
I4 Barrier-Free Entrance/Exit (C2)	0.12284	0.11509	0.10231	0.10106
I5 Indoor Pathway Width & Smoothness (C2)	0.10508	0.10561	0.09363	0.09249
I6 Restroom Accessibility (C2)	0.06808	0.06630	0.06706	0.06624
C2 subtotal (Spatial Accessibility)	0.29600	0.28700	0.26300	0.25979
I7 Bedroom & Living Room Layout (C3)	0.07702	0.08442	0.08556	0.08672
I8 Kitchen Operation Convenience (C3)	0.07807	0.07868	0.08674	0.08791
I9 Facility Operability (C3)	0.05591	0.05790	0.06470	0.06557
C3 subtotal (Independent Living)	0.21100	0.22100	0.23700	0.24020
I10 Natural Lighting & Ventilation (C4)	0.05499	0.06161	0.08025	0.08269
I11 Temperature & Soundproofing (C4)	0.05076	0.05240	0.07319	0.07542
I12 Ergonomic Furniture Adaptability (C4)	0.03525	0.03699	0.06056	0.06240
C4 subtotal (Environmental Comfort)	0.14100	0.15100	0.21400	0.22051

4.4. Model Performance Analysis

4.4.1. Convergence Analysis

Under identical parameter conditions (population size = 50, maximum iterations = 500), the convergence performance of the AHP-PSO model was compared with standard PSO. As shown in Figure 2, both algorithms demonstrated increasing fitness values with iterations, indicating continuous solution quality improvement. The standard PSO exhibited rapid initial convergence but entered stagnation around the 120th iteration, with fitness values fluctuating around 0.87, demonstrating premature convergence characteristics. In contrast, the AHP-PSO model maintained stronger global search capability during early stages and reached stable convergence after 200 iterations. Its fitness curve showed smoother progression with minor fluctuations, ultimately converging to approximately 0.91. These results confirm that the adaptive inertia weight adjustment and sample-level preference guidance mechanism effectively enhanced convergence stability, preventing the algorithm from trapping in local optima. Consequently, the proposed approach provides more reliable weight optimization results for subsequent fitness evaluation.

4.4.2. Parameter Sensitivity Analysis

Parameter sensitivity was examined by varying the principal PSO settings while keeping the data partition and evaluation procedure unchanged. The results showed that parameter changes affected convergence behavior more strongly than prediction accuracy: conservative settings slowed convergence, whereas overly aggressive settings increased oscillation and computational cost without materially improving MAE. The adopted configuration provided the most stable balance between convergence efficiency and predictive performance, indicating that the main findings were not dependent on a single arbitrary parameter choice.

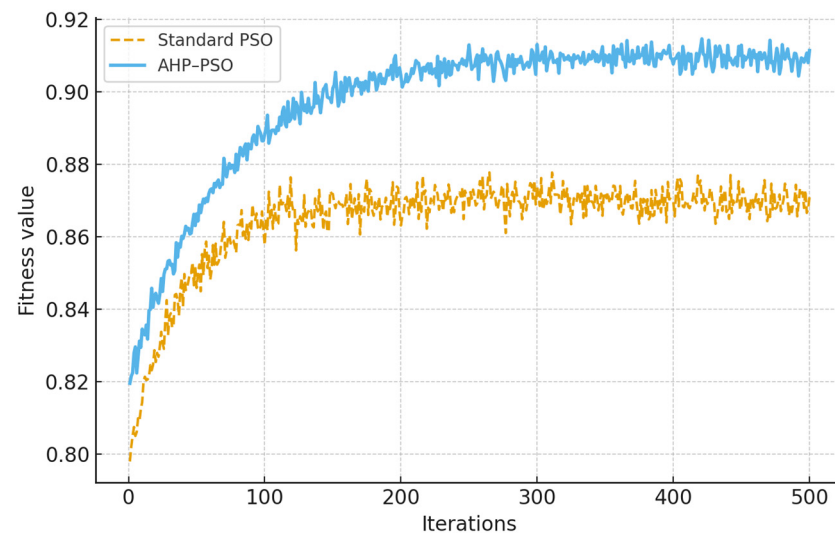


Figure 2. Convergence curves of the AHP-PSO and standard PSO models (source: by the authors).

4.4.3. Comparison with Other Models

To validate the comprehensive performance advantages of AHP-PSO in aging-friendly home modification functional adaptation problems, this study selected PSO, GA, and DE as comparative algorithms. As a typical swarm intelligence algorithm driven by velocity and position iteration, PSO exhibits advantages of fast convergence and simple implementation. Its selection enables direct demonstration of AHP-PSO's improvements in search efficiency and stability. GA, serving as a classical evolutionary algorithm, achieves global optimization through selection, crossover, and mutation mechanisms. Its widespread application in multi-criteria decision optimization makes it an important benchmark for evaluating AHP-PSO's diversity maintenance and convergence quality. DE, as a representative evolutionary optimization method driven by differential mutation and selection mechanisms, demonstrates strong global exploration capability and convergence accuracy in continuous optimization problems. Its inclusion further highlights AHP-PSO's comprehensive advantages in weight optimization and fitness evaluation.

As shown in Table 9, AHP-PSO demonstrates significant advantages across all four metrics. Regarding prediction accuracy and functional rationality, AHP-PSO evidently outperforms comparative algorithms, achieving MAE and FDR values of 0.121 and 0.136, respectively—substantially lower than those of PSO and GA. PSO's weight allocation primarily relies on random initialization and iterative search, making it prone to premature convergence and resulting in deviation between predictions and sample-level resident priorities. In contrast, AHP-PSO incorporates expert judgments and pooled-sample questionnaire adjustments during initial phases, establishing structured and realistic foundations for weight distribution from the outset. Subsequent PSO-based global optimization further refines these weights, reducing subjective bias. This synergistic combination of dual-source information fusion and optimization iteration enables AHP-PSO to achieve optimal results in both MAE and FDR metrics, generating predictions that better align with sample-level resident priorities.

In terms of dimensional balance and robustness, the AHP-PSO approach also demonstrates remarkable advantages. It achieves a DBR value of 0.912, showing significant improvement over PSO's 0.873 and GA's 0.881. Moreover, its feasible solution ratio (FSR) reaches 94.8%, surpassing DE's 91.5%. These results indicate that AHP-PSO not only obtains higher-quality solutions during optimization but also maintains balanced weight distribution and solution stability. This superiority stems from two key design features in AHP-PSO. First, the incorporation of a weight dispersion penalty term in the fitness

function constrains excessive concentration of optimized weights during the search process, preventing individual indicators from dominating the overall evaluation structure. Second, additional non-negativity and normalization constraints enhance the feasible solution ratio, making the results more aligned with real-world application requirements. The combined effect of these mechanisms ensures robust performance across both performance metrics and solution feasibility.

Table 9. Comparative results.

Model	MAE	FDR	DBR	FSR
PSO	0.148	0.162	0.873	88.7%
GA	0.139	0.154	0.881	90.2%
DE	0.133	0.149	0.889	91.5%
AHP-PSO	0.121	0.136	0.912	94.8%

MAE = mean absolute error (lower is better); FDR = functional deviation ratio (lower is better); DBR = dimensional balance ratio (higher is better); and FSR = feasible solution ratio (higher is better). MAE assesses prediction error, FDR assesses alignment with sample-level resident priorities, DBR assesses balance across the four criterion dimensions, and FSR denotes the percentage of generated solutions satisfying the model constraints.

4.4.4. Ablation Study

To quantify the individual contribution of each core mechanism within the proposed AHP-PSO framework, we conducted a series of ablation experiments by systematically removing or disabling one component at a time. Four variants were constructed as follows:

- Variant 1 (*w/o* AHP-init): The AHP-derived prior weight vector is replaced by random initialization, while adaptive inertia, sample-level preference guidance, and the dispersion penalty term ($-\lambda\sigma(w)$) are retained. This variant evaluates the benefit of AHP-based initialization.
- Variant 2 (*w/o* Adapt): The adaptive inertia weight mechanism is replaced with a fixed inertia coefficient ($\omega = 0.7$), while all other components remain unchanged. This variant assesses the effectiveness of adaptive exploration–exploitation transition.
- Variant 3 (*w/o* User): The questionnaire-derived preference-intensity term (δ_i) and sample-level guidance factor (φ) are removed from the velocity update equation; only the fitness function (with the dispersion penalty) guides the search. This variant isolates the marginal benefit of incorporating sample-aggregated older-resident-preference information.
- Variant 4 (*w/o* Balance): The dispersion penalty term $-\lambda\sigma(w)$ is removed from the fitness function (Equation (3)), while all other components (including AHP initialization, adaptive inertia, and sample-level preference guidance) are retained. This variant is used to test whether penalizing weight dispersion during optimization is necessary for achieving both predictive accuracy and dimensional balance.

The full model (with all components) serves as the baseline. All variants were run with the same population size (50), maximum iterations (500), and data split as the main experiment. Table 10 reports the performance of each variant across the four evaluation metrics.

The ablation results reveal several important findings. First, removing the sample-level preference guidance (V3) causes the largest degradation in prediction accuracy (MAE increases from 0.121 to 0.138) and functional rationality (FDR rises to 0.153), confirming that incorporating sample-aggregated older-resident stated preferences is the most critical factor for aligning model outputs with sample-level resident priorities. Second, disabling AHP initialization (V1) also leads to noticeable performance decline, indicating that the

expert-informed starting point provides a structured prior that accelerates convergence and prevents inferior local optima. Third, the adaptive inertia mechanism (V2) contributes to stability and convergence efficiency; removing it moderately worsens all metrics. Fourth, deactivating the dimensional-balance constraint (V4) primarily affects DBR, which drops to 0.876, whereas MAE (0.124), FDR (0.139), and FSR (94.2%) remain comparatively close to the full-model values; this confirms that the balance coefficient specifically prevents any single functional domain from dominating the evaluation. Overall, the full model consistently outperforms all ablated variants across all four metrics, providing strong empirical evidence that each component plays a non-redundant role and that their synergistic combination is essential for achieving the reported improvements.

Table 10. Results of ablation experiments.

Model Variant	MAE ↓	FDR ↓	DBR ↑	FSR ↑
Full Model (AHP-PSO)	0.121	0.136	0.912	94.8%
V1 (<i>w/o</i> AHP-init)	0.134	0.148	0.895	92.1%
V2 (<i>w/o</i> Adapt)	0.129	0.142	0.903	93.5%
V3 (<i>w/o</i> User)	0.138	0.153	0.887	91.8%
V4 (<i>w/o</i> Balance)	0.124	0.139	0.876	94.2%

Arrows indicate the preferred direction of each metric: ↓ means lower values indicate better performance, and ↑ means higher values indicate better performance.

4.5. Functional Adaptation Results for Renovated Spaces

4.5.1. Distribution of Comprehensive Adaptation Levels

The classification thresholds defined in Section 3.3.3 were applied to the adaptability scores of the 543 sampled dwellings. For each dwelling, the comprehensive adaptability score S was calculated using Equation (7), and the dwelling was assigned to one of the four levels according to the score ranges in Table 6.

The four intervals are: Low Adaptation, $0 \leq S < 0.25$; Moderate Adaptation, $0.25 \leq S < 0.50$; Relatively High Adaptation, $0.50 \leq S < 0.75$; High Adaptation, $0.75 \leq S \leq 1.00$.

To assess the sensitivity of the classification results to the selected thresholds, the three boundary values were shifted by 0.05. The tested sets were {0.20, 0.45, 0.70}, {0.25, 0.50, 0.75} (original), and {0.30, 0.55, 0.80}. The resulting category proportions are presented in Table 11.

Table 11. Sensitivity analysis of classification thresholds.

Threshold Set	Low Adaptation (%)	Moderate Adaptation (%)	Relatively High Adaptation (%)	High Adaptation (%)
{0.20, 0.45, 0.70}	7.3	26.8	41.2	24.7
{0.25, 0.50, 0.75} (original)	8.1	28.4	39.6	23.9
{0.30, 0.55, 0.80}	9.0	30.1	37.8	23.1

The original threshold set was {0.25, 0.50, 0.75}. Values represent the percentage of the 543 sampled dwellings assigned to each adaptability category.

The sensitivity analysis shows that the overall classification pattern remains stable across the three threshold sets. The maximum deviation from the original classification is 1.8 percentage points, observed for the Relatively High Adaptation category under the {0.30, 0.55, 0.80} set. The original equal-interval thresholds {0.25, 0.50, 0.75} were retained for the main analysis because of their interpretability.

Figure 3 presents the overall distribution of adaptation levels based on calculations for 543 samples. Significant variations exist in the proportion of samples across different levels. Notably, the combined percentage of “High Adaptation” and “Relatively High Adaptation” exceeds 60%, indicating that most renovated dwellings can effectively meet seniors’ safety and independence needs in daily life. Such residences typically feature well-designed accessibility features at entrances/exits, anti-slip flooring, and optimized lighting visibility, collectively reducing fall risks while enhancing indoor mobility convenience.

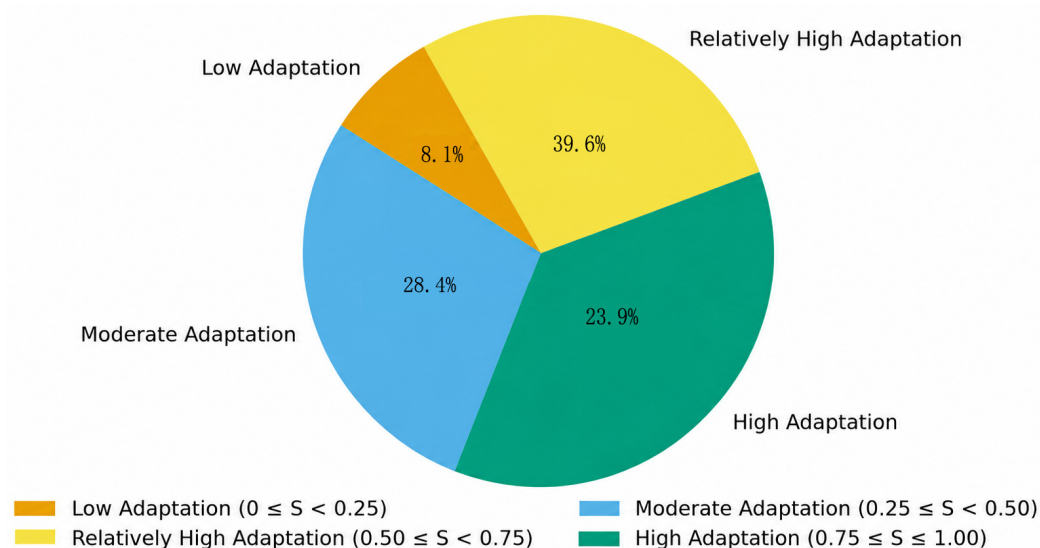


Figure 3. Distribution of comprehensive adaptability levels across the 543 sampled dwellings (source: by the authors).

Approximately 30% of samples demonstrate “Moderate Adaptation” levels, primarily due to incomplete alignment between some functional details and elderly users’ habits—for instance, inappropriate kitchen counter heights or suboptimal ergonomic furniture arrangements. While these deficiencies do not compromise overall safety, they introduce minor inconveniences during daily use. Samples with “Low Adaptation” account for less than 10% and are predominantly found in older multi-story apartments lacking emergency response systems. These dwellings exhibit critical shortcomings in spatial accessibility and safety provisions, urgently requiring prioritized improvements—such as wheelchair-accessible pathways, emergency call systems, and lighting upgrades. These results validate the AHP-PSO model’s efficacy in comprehensive adaptation grading by simultaneously capturing aggregate performance and revealing structural distinctions between different adaptation tiers.

4.5.2. Identification of Key Shortcomings

The qualitative framework analysis was used at this stage to interpret, rather than calculate, the indicator rankings. Statements relevant to the lower-scoring indicators are organized under implementation cost, structural constraints, property management and service support, user acceptance and awareness, household-specific modification needs, and maintenance. These themes provide the contextual basis for interpreting I3, I8, I11, and I12; the indicator means and rankings themselves are derived from the questionnaire data and AHP-PSO model.

Significant disparities exist in the average scores across different indicators, as shown in Figure 4. Overall, anti-slip measures (I1), lighting visibility (I2), and entrance/exit accessibility (I4) scored the highest. These improvements belong to low-cost, easy-to-implement foundational modifications, and their requirements are clearly defined in policies and industry standards. As a result, they have achieved high adoption rates in actual renova-

tion projects. For example, laying anti-slip flooring and installing supplementary lighting in bathrooms and corridors are both mature technologies that yield immediate benefits, explaining their strong performance across the samples.

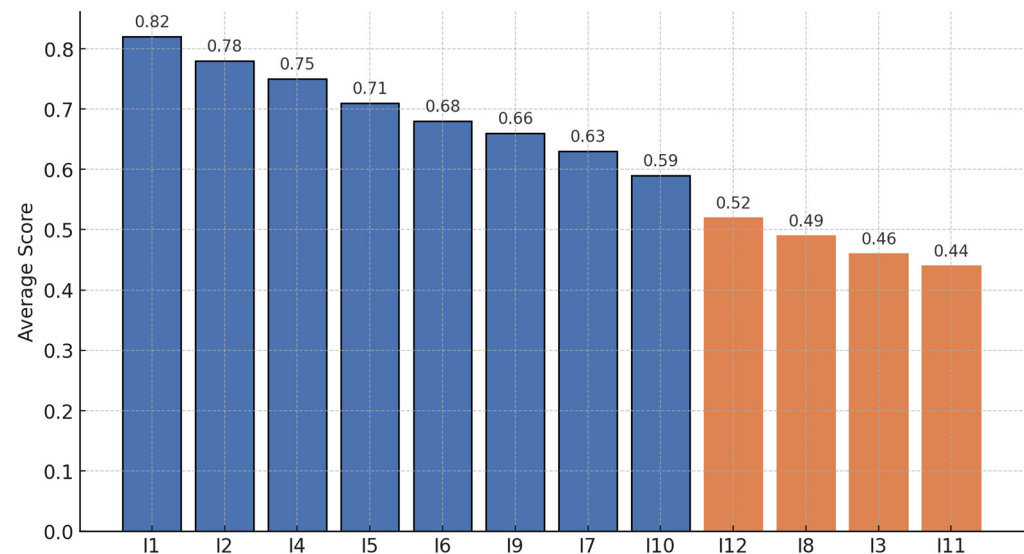


Figure 4. Ranking of mean indicator scores (source: by the authors).

In contrast, emergency rescue facilities (I3), kitchen operation convenience (I8), temperature and sound insulation control (I11), and furniture adaptability (I12) received lower average scores and therefore represented priority shortcomings in the sampled dwellings. The interview themes suggested that emergency response provision was constrained by installation and maintenance costs, limited service or property-management support, and uneven resident acceptance. For kitchen operation and furniture adaptability, participants' accounts emphasized the mismatch between standardized products and individual stature, mobility, reach, and established routines, together with the additional cost and disruption associated with household-specific redesign. These qualitative explanations were used to contextualize the numerical pattern and did not modify the scores.

For environmental comfort, the interview material linked the lower performance of temperature and sound insulation control (I11) to building-envelope and structural constraints in older housing. Improvements often require coordinated work on walls, doors, windows, ventilation, and external interfaces rather than a single interior adjustment. Participants also raised construction duration, disruption, technical coordination, and affordability as practical barriers. These themes help explain why environmental-comfort interventions may remain difficult to implement even when they are rated as important.

To summarize, the ranking of average indicator scores not only reveals the performance levels of various functional aspects but also reflects common patterns in aging-friendly renovations: measures that are easy to implement and strongly policy-driven (e.g., anti-slip features, lighting, barrier-free access) tend to score higher, while those requiring personalized design, substantial investment, or dependent on building physical conditions (e.g., emergency rescue, kitchen convenience, furniture adaptability and sound/temperature control) remain practical shortcomings in renovations.

5. Discussion

The performance of the proposed AHP–PSO model should be interpreted within the present dataset and optimization setting. Compared with PSO, GA, and DE benchmarks, the proposed framework achieved lower MAE and FDR values and higher DBR and FSR

values, indicating better consistency with resident evaluations and more balanced weight allocation under the defined constraints. However, these results do not imply universal superiority of AHP–PSO over other optimization algorithms, as performance is influenced by problem characteristics, parameter settings, and objective formulation.

The disclosed final effective vector shows that Safety Assurance (criterion share = 0.27950) and Spatial Accessibility (0.25979) remained the largest contributors, followed by Independent Living (0.24020) and Environmental Comfort (0.22051). At the indicator level, I1 (0.11264), I2 (0.10481), and I4 (0.10106) had the largest final effective weights. These weights quantify contribution to the adaptability score and should be distinguished from the observed adequacy scores in Figure 4. The pattern suggests that risk reduction and barrier removal remained prominent while the optimization and β adjustment produced a more balanced four-domain allocation.

The difference between the present findings and those reported by Valderrama-Ulloa et al. [94] is particularly noteworthy. Their study identified autonomy as the dominant criterion, whereas the current model assigned higher priorities to safety and accessibility. This divergence can be explained by differences in research context and indicator definition. Valderrama-Ulloa et al. focused on inclusive housing evaluation across multiple disability groups, where autonomy represented a broad concept related to independent living. In contrast, the present study examined modification priorities in occupied urban dwellings, where fall risks, emergency limitations, and retrofit feasibility directly influence intervention decisions. Therefore, the different weighting patterns reflect contextual variation rather than inconsistent conclusions.

A similar distinction is observed when comparing the results with Ptak-Wojciechowska et al. [27]. Their expert-based framework emphasized overall housing functionality and accessibility, whereas the current study introduced sample-aggregated resident preferences into both AHP adjustment and PSO refinement. This difference indicates that weighting outcomes are affected not only by housing objectives but also by who participates in the decision process. Likewise, Gaglione et al. [95] investigated accessibility at the neighborhood scale, focusing on pedestrian networks and service availability, while this study concentrated on indoor residential conditions. These studies address different levels of aging-friendly environments and should therefore be considered complementary rather than competing perspectives.

The theoretical contribution of this study does not arise from the combination of AHP and PSO itself, as previous research has applied similar hybrid strategies in various decision-making contexts [28,44,45,48,73–78]. Instead, the contribution lies in incorporating the older-resident sample's aggregated preferences directly into the weighting process. Pooled resident information modifies the initial AHP structure and guides subsequent PSO-based refinement, while dimensional balance constraints prevent optimization results from being dominated by a single functional aspect. This provides a sample-informed group-level decision framework for residential adaptation assessment.

From a practical perspective, the proposed framework can support the identification and prioritization of common renovation needs at community and program levels. However, the optimized weights should not be regarded as individualized renovation prescriptions. Household-level decisions still require professional assessment of functional ability, daily routines, economic conditions, structural constraints, and resident preferences. The model provides a quantitative reference for prioritization but should work together with on-site evaluation and participatory decision-making.

Several limitations should be acknowledged. First, the current indicator system mainly focuses on physical and functional characteristics of housing, while psychological perception, cultural preferences, and social factors require further integration. Second, the

sample was collected from selected urban communities in Beijing, Fushun, and Shanghai through a non-probabilistic design, which limits direct generalization to other regions and housing contexts. Third, the optimized weights represent group-level preferences rather than individual priorities. Future studies should develop participant-specific model extensions, validate them longitudinally, and assess economic feasibility before individual-level application.

6. Conclusions

This study developed an AHP–PSO integrated decision-support model for assessing functional adaptation needs in aging-in-place home modifications. The framework combines expert knowledge with sample-aggregated older-resident preference information to refine indicator weights and evaluate dwelling-level adaptation conditions based on empirical data from 543 valid questionnaires.

The proposed model achieved improved consistency with resident evaluations compared with PSO, GA, and DE benchmarks, obtaining an MAE of 0.121, an FDR of 0.136, a DBR of 0.912, and an FSR of 94.8%. These results indicate that integrating sample-aggregated resident-preference information into the weighting process can reduce evaluation deviation and improve the balance of functional priorities under the defined optimization conditions.

The final effective criterion shares were 0.27950 for Safety Assurance, 0.25979 for Spatial Accessibility, 0.24020 for Independent Living, and 0.22051 for Environmental Comfort. The largest final indicator weights were assigned to anti-slip measures (I1 = 0.11264), lighting and visibility (I2 = 0.10481), and barrier-free entrance/exit accessibility (I4 = 0.10106). The application analysis separately identified emergency response facilities, kitchen operation convenience, thermal and acoustic conditions, and furniture adaptability as the main observed deficiencies, distinguishing model weighting priority from current dwelling adequacy.

The proposed framework provides a quantitative approach for identifying priority adaptation needs at the residential assessment level. However, the optimized weights represent group-level preferences rather than individualized renovation solutions. The current model also does not incorporate renovation costs, construction feasibility, long-term adaptation outcomes, or broader psychosocial factors. Future studies should validate the framework using more diverse residential samples and develop and validate participant-specific extensions while integrating economic considerations to improve its applicability.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18178893/s1>. Table S1. The criterion-level group comparison matrix (C1–C4); Table S2. The Safety Assurance group comparison matrix (C1: I1–I3); Table S3. The Spatial Accessibility group comparison (C2: I4–I6); Table S4. The Independent Living group comparison matrix (C3: I7–I9); Table S5. The Environmental Comfort group comparison matrix (C4: I10–I12).

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