

## Article

# A Perceived-Value-Informed, Segment-Level Assessment of Mountain Greenway Suitability Across Physical-Activity Scenarios: Evidence from Wugong Mountain, China

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## Abstract

Mountain-greenway planning requires approaches that account for heterogeneous user needs, trail safety, experiential quality, and limited maintenance capacity. Taking the Shenzi Village–Longshan Village section of Wugong Mountain as a case, this study develops a perceived-value-informed, segment-level, scenario-based framework for assessing mountain greenway suitability. COROS PACE 3 FIT trajectories, field observations, and researcher-based environmental interpretation were used to construct eight indicators for ten segments. Entropy weights characterize within-sample variation, while the Potential Suitability Value (PSV) integrates environmental conditions with a priori utility rules for low-, moderate-, and high-activity scenarios. Ranking sensitivity was examined through utility-function sampling, fixed-endpoint comparisons, equal-weight comparisons, leave-one-segment-out reweighting, weight perturbation, and indicator-deletion analysis. Shade, exposure, movement difficulty, and cumulative ascent exhibited relatively high differentiation within the present sample. S10 ranked among the top three under all three scenarios in both the baseline entropy-weight and leave-one-segment-out schemes, but fell to fourth under the high-activity scenario with equal weights. The low-activity rankings of S5 and S8 were jointly affected by the span and internal spacing of the utility functions, whereas the high-activity advantage of S6 depended structurally on the treatment of risk indicators. By identifying segments with inadequate environmental support, elevated safety pressure, or parameter-sensitive rankings, the framework can inform targeted field verification, maintenance prioritization, and risk communication. It is a scenario-based suitability and planning-support tool, not an assessment of sustainability outcomes. Ecological disturbance, environmental carrying capacity, community benefits, social equity, long-term maintenance costs, resource efficiency, and actual user perceptions were not measured and require separate indicators and external validation.



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**Keywords:** mountain greenway; perceived value; segment-level suitability; physical-activity-volume scenario; uncertainty analysis; planning decision support

## 1. Introduction

Greenways are linear open spaces that support walking, running, cycling, and hiking and lie at the intersection of landscape planning, outdoor recreation, and public health [1,2]. In mountain destinations, planning additionally requires the reconciliation of recreational access, user safety, experiential quality, limited maintenance capacity, and the avoidance

of unnecessary or spatially indiscriminate intervention. These considerations may inform sustainability-oriented decisions, but they do not by themselves constitute a measurement of ecological, social, or economic sustainability outcomes. Existing studies have applied subjective evaluation, spatial analysis, and multisource data to examine jogging supportiveness [3], greenway service effectiveness [4], and route-selection suitability [5]. User-oriented evaluation can draw on two complementary forms of evidence. Direct measures of perception, satisfaction, and behavior provide individual-level empirical evidence, whereas combinations of objective environmental conditions and decision rules support planning-oriented scenario inference. This study adopts the latter approach and defines its outputs as model-based estimates of potential perceived value.

Adjacent mountain-greenway segments may differ substantially in cumulative ascent, surface stability, exposure, wayfinding demand, shade, and rest support. Previous research indicates that terrain, surface conditions, difficulty, environmental attractiveness, and motivation are associated with hikers' route choices [6]. A single route-level composite score may obscure such local heterogeneity and cannot readily reveal how evaluation outcomes change when assumptions about physical activity vary. This study therefore represents path load, environmental support, and experiential conditions at the segment level and examines changes in relative suitability across physical-activity-volume scenarios.

Perceived value provides the principal theoretical lens and is operationalized here as a potential-value structure supported by objective environmental attributes [7]. The benefit-sacrifice trade-off is used to organize indicators and interpret model outputs: shade, rest facilities, and an appropriate level of challenge represent potential benefits or environmental support, whereas cumulative ascent, movement difficulty, exposure, wayfinding demand, poor surface conditions, and noise represent potential costs whose utility may vary or remain fixed across scenarios. Segments constitute the evaluation units, entropy weights describe variation among the ten segments, and scenario-specific utility functions transform path-load levels under low-, moderate-, and high-activity assumptions. Parameter perturbations and a risk-cost counterfactual are then used to examine ranking sensitivity. The study addresses three questions: (1) how can segment-level path load, environmental support, and experiential conditions be integrated within the benefit-sacrifice structure of perceived value; (2) how does potential perceived value vary across the three predefined scenarios; and (3) how do measured route attributes and model rules respectively shape the assessment results? The principal contribution is a reproducible and auditable proxy-assessment procedure that provides a structured basis for subsequent user-based calibration and validation. The segment-level framework supports differentiated planning by locating where safety checks, environmental-support improvements, or further evidence are most needed, enabling limited planning and maintenance resources to be directed toward specific problems rather than applied uniformly across a mountain route. This is a potential contribution to sustainability-oriented planning rather than an evaluation of sustainability performance.

## 2. Literature Review and Conceptual Framework

### 2.1. Greenways, Physical Activity and User-Oriented Reviews

Existing studies provide different types of precedents for user-led greenway evaluations. Liu et al. combined subjective scoring, semantic difference scale, semantic segmentation, and machine learning to investigate jogging supportiveness [3]; Peng et al. combined service efficiency and service effect [4]; Lu and Wu integrated spatial resources, accessibility, and public demand in the selection line [5]. Other studies have addressed greenway exposure, vitality, visual characteristics, and activity behavior [8–13]. These studies have shown that user sensitivity can be characterized by direct perception of data, behav-

ioral trajectories, or demand proxies. This study further focuses on the segmented scale of mountain paths and estimates the potential perceived value supported by objective environmental conditions through explicit situational rules; the correspondence between true aesthetics, satisfaction, and preferences belongs to the follow-up validity test.

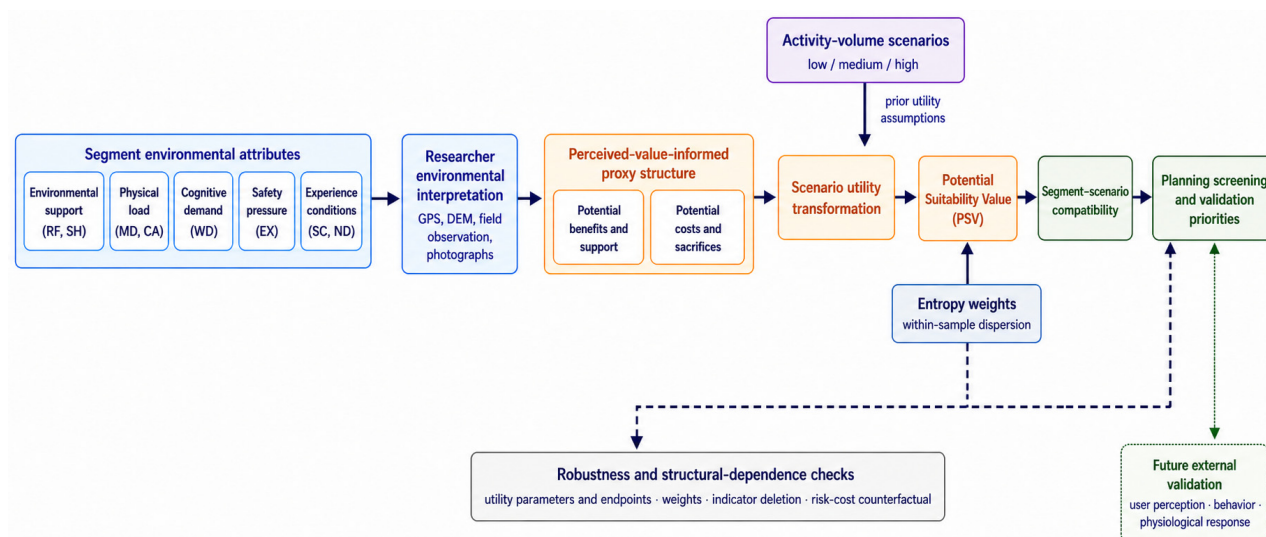
## 2.2. Hiking Path Preferences, Path Load and Environmental Support

Hiking suitability involves physical load, navigation, safety, environmental support, and experiences. Molokáč et al. found that route selection is related to slope, terrain ups and downs, pavement, difficulty, natural landscape, environmental attraction, and motivation [6]. Accordingly, this study classified cumulative ascent and movement difficulty as physical needs, pathfinding as cognitive needs, exposure as safety stress, shade and rest facilities as environmental support, and surface condition and noise as experiential conditions. This classification is used to establish a structured evaluation dimension, and there may be a certain conceptual overlap between the dimensions.

## 2.3. Perceived-Value-Informed Scenario Suitability

Perceived value is usually understood as the overall assessment formed by the subject after comparing the benefits obtained with the costs or sacrifices paid [7]. This paper transforms this theoretical relationship into a proxy evaluation structure at the segment level: environmental support and experience opportunities represent potential benefits, and physical load, cognitive needs, and safety stress represent potential sacrifices; the value direction of the same load indicator can change with the preset physical-activity-volume scenario. “Perceived-value-informed” refers specifically to the guiding role of perceived value theory in the organization of indicators, utility transformation, and interpretation of results. Suitability is thus defined as the degree of compatibility of potential perceived value between segment conditions and preset user scenarios. The three scenarios represent the analytical hypothesis of the level of physical activity, technical ability, risk tolerance, and challenge preference as independent constructs to be tested in subsequent user studies. In the benchmark model, all four path loads are involved in scenario utility conversion; environmental exposure and wayfinding demands are also fixed as costs in a fixed-cost treatment of risk indicators. This distinction is used to identify the reliance of benchmark ranking on risk-related scoring rules.

Figure 1 summarizes the guiding role of perceived value theory in the organization of indicators, the transformation of scenario utility, and the interpretation of results. The segment-level environmental attributes are formed by the researcher-based environmental interpretation supported by COROS PACE 3 FIT trajectory records, field observations, and photos, and are organized under a potential benefit–sacrifice proxy structure. The activity scenario enters the scenario transformation through a priori utility assumptions, and the entropy weight enters the PSV calculation according to the within-sample dispersion of 10 segments. PSV characterizes the degree of potential suitability compatibility between segment conditions and preset activity scenarios. Utility parameters and endpoints, weights, indicator-deletion analysis, and risk-cost counterfactual are used to test model robustness and structural dependence, and the results serve to plan screening and subsequent verification priorities; real user perception, behavior, and physiological responses belong to the future external validity test.



**Figure 1.** Perceived-value-informed mountain greenway segmented suitability scenario assessment framework.

### 3. Materials and Methods

#### 3.1. Study Area

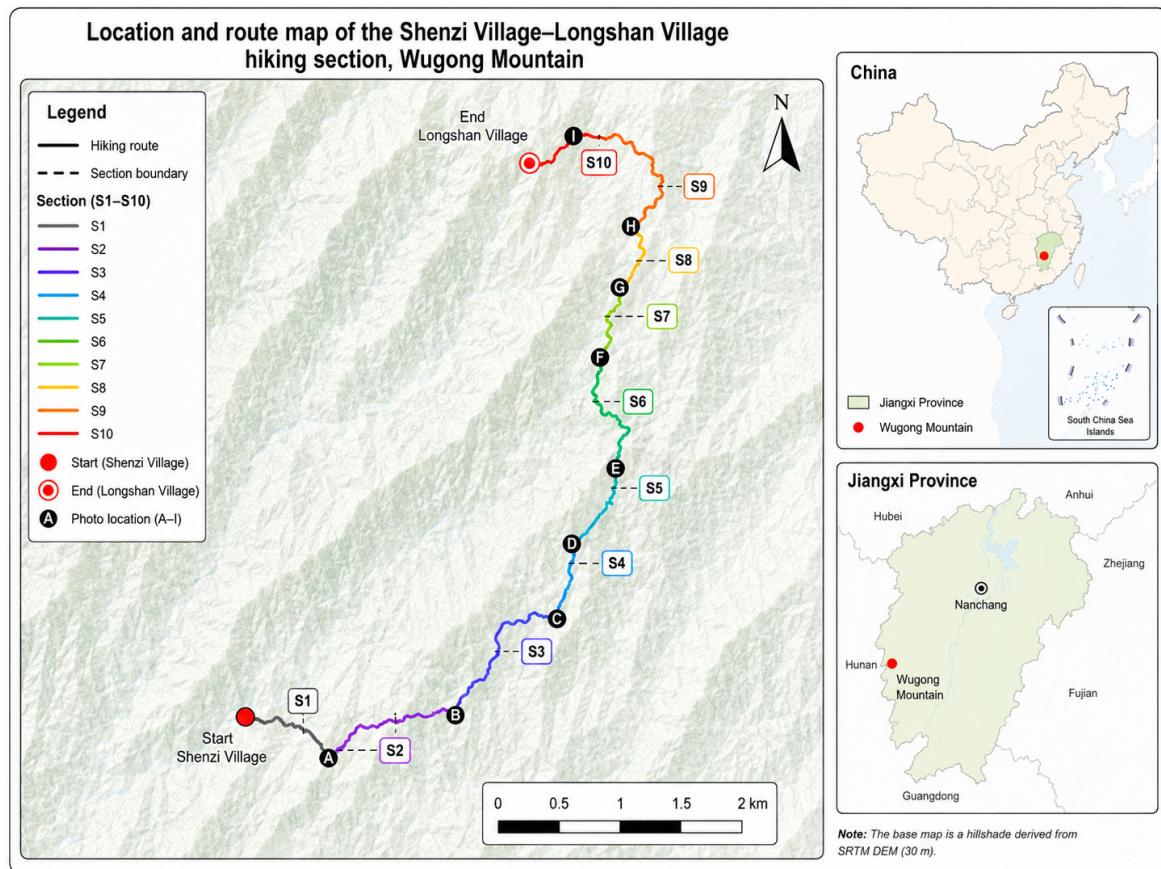
Located in Pingxiang City and the northern section of the Luoxiao Mountains in western Jiangxi Province, Wugong Mountain is a representative mountain outdoor recreation destination in southern China. Alpine meadows, sea-of-clouds sunrise, ridge traversal, and camping activities form a distinct hiking characteristic, and tent festivals and cross-country events also show its stable outdoor recreation function. Figure 2 shows the location of Wugong Mountain in China and Jiangxi Province, as well as the spatial environment of the Shenzi Village–Longshan Village hiking section. According to the line direction shown in Figure 2, each consecutive segment is numbered S1–S10 in turn, and the segment number is also used for index summary, entropy weight calculation, and PSV result expression.

In this study, 10 consecutive segments were used as the analysis unit. Segmentation also considers spatial continuity, relative homogeneity of terrain, and operability of on-site data acquisition: identification of slope trends, dominant pavement, ridge, or forest landscape units along the line, as well as locations of variation in major forks and landscape nodes, and formation of segments with relatively consistent internal conditions between adjacent points of variation. This method is similar to the idea of Avila Callau et al. [14] to improve the operability of on-site collection and inter-section through near-equal-length sections, while retaining the location where the terrain and path conditions have changed significantly as the boundary. The segmented boundary is jointly determined by the terrain interpretation and the field investigation, so it has a certain investigator judgment component. Indicator aggregation, entropy weights, and rankings are conditional on this spatial division, and different boundary settings may produce variable spatial unit effects; this paper regards segmented scales as one of the sources of uncertainty in the results.

#### 3.2. Data Sources and Processing

Route geometry and elevation data were obtained from FIT files recorded in hiking mode by a COROS PACE 3 sports watch (COROS PACE 3; COROS Wearables, Inc., Irvine, CA, USA). The two field recordings were conducted on 5–6 April 2026 and 9 May 2026 and contained 20,556 and 19,481 valid coordinate points, respectively; the median effective sampling interval was 1 s. Trajectory coordinates were used to identify route direction, spatial nodes, segment lengths, and geographic positions. Cumulative ascent was derived

from the elevation recorded in the FIT trajectories (Table 1). Each trajectory was clipped according to the predefined S1–S10 boundaries. Within each segment, positive elevation increments between successive points were summed in recording order and divided by segment length to obtain cumulative ascent per unit distance (m/km). Thus, both trajectory positioning and cumulative ascent were derived from the same watch records; no separate DEM elevation data were used in this calculation.



**Figure 2.** Wugong Mountain: Shenzi Village–Longshan Village hiking section location, route, and section.

**Table 1.** Data sources, processing, and analytical uses.

| Data Type                    | Sources of Data Used                                           | Main Content                                                     | Analytical Uses                                                              |
|------------------------------|----------------------------------------------------------------|------------------------------------------------------------------|------------------------------------------------------------------------------|
| GPS track                    | COROS PACE 3 FIT trajectory and site inspection                | Lines, nodes, segment lengths, and spatial locations             | Determine the line and the spatial basis of S1–S10                           |
| Fit trajectory elevation     | COROS PACE 3 FIT trajectory recording                          | Segmented height sequence and positive elevation increment       | Calculate cumulative ascent and physical load per unit distance step by step |
| Field investigations         | Exploration, photos, and observation                           | Facilities, shade, pavement, wayfinding, exposure, and noise     | Quantify support, load, and experience                                       |
| Environmental interpretation | Photos of the scene and interpretation of the line environment | Forests, meadows, ridges, cliffs, entrances, and landscape nodes | Interpreting exposure, shade, pathfinding, and experience revenue            |

Two experts with relevant professional qualifications and field-survey experience jointly participated in both route recordings and environmental surveys. Weather conditions were sunny during the first survey and overcast with light rain during the second. Movement difficulty, wayfinding difficulty, and environmental exposure correspond respectively to the MIDE dimensions of difficulty of movement, orientation on the route, and severity of the environment, each assessed on an ascending five-level scale (Table 2). The experts jointly interpreted each segment using the operational MIDE descriptions presented in Table 3 and cross-checked the classifications against geolocated photographs and contextual route information. Cumulative ascent was calculated independently from FIT-recorded elevation and was not included among these three field-interpreted MIDE dimensions. Interobserver agreement coefficients could not be calculated because the retained data comprised jointly agreed records rather than two independent sets of ratings. The nine photographs in Figure 3 document representative route environments and support field interpretation. Although computer-vision studies have used image-feature extraction for environmental assessment [3,15], the present study did not calculate semantic-segmentation, visual-attention, or esthetic-prediction metrics. The photographs therefore serve as descriptive evidence, while PSV organizes potential environmental benefits and costs through perceived-value theory and represents scenario differences through rule-based utility functions.



**Figure 3.** Representative landscape of Wugong Mountain: Shenzi Village–Longshan Village hiking trail (A–I) (The Chinese text on the signposts in panels (F,H) indicates local place names and directional information; “发云界之颠” in panel (H) means “Summit Above the Clouds”).

**Table 2.** Evaluation index system for segmented suitability of mountain greenways.

| Criterion Level       | Specifications         | Definition                                                                              | Data Sources and Measurements                                               | RATIONALE                                                                    |
|-----------------------|------------------------|-----------------------------------------------------------------------------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------------|
| Comfortable support   | Rest facilities        | Seat and rest-point support for physical recovery and rhythm adjustment                 | Field survey; number or grade                                               | Facility & Functional Value                                                  |
|                       | Shade condition        | Stable vegetation shade that relieves heat load and supports continuous walking comfort | On-site inspection; proportion to segment length                            | Environmental support and comfort                                            |
| Path load             | Movement difficulty    | Pavement Flatness, Walking Stability and Motion Resistance                              | MIDE Movement Difficulty; Interpretation by Two Experts; Level 1–5          | MIDE Mobility Difficulty Dimension [14]                                      |
|                       | Wayfinding difficulty  | Path continuity, identification clarity, and cognitive navigation needs                 | MIDE route orientation; joint interpretation by two experts; levels 1–5     | MIDE Routing Orientation Dimension [14]                                      |
|                       | Environmental exposure | Open ridges, steep cliffs, fall risks and safety pressures from weather exposure        | MIDE environmental severity; joint interpretation by two experts; level 1–5 | MIDE Environmental Severity Dimension [14]                                   |
|                       | Cumulative ascent      | Continuous physical load due to positive elevation change                               | COROS PACE 3 FIT track record elevation segmented positive increment; m/km  | Physical needs; weight interpretation limited to differences within the case |
| Experience conditions | Surface condition      | The impact of hard paving on gait impact, stability, and nature experience              | On-site inspection; proportion to segment length                            | Surface condition affects the aesthetic and walking experience               |
|                       | Noise/quietness        | Impact of traffic or mechanical noise on quietness, pace, and recovery experience       | On-site interpretation; levels 1–5                                          | Ambiance and rewards                                                         |

**Table 3.** Indicator quantification and five-level grading criteria.

| Criterion Layer       | Code | Measurement Method                                                                   | Level 1                             | Level 2                                         | Level 3                                                | Level 4                                                   | Level 5                                       | Interpretation                                        |
|-----------------------|------|--------------------------------------------------------------------------------------|-------------------------------------|-------------------------------------------------|--------------------------------------------------------|-----------------------------------------------------------|-----------------------------------------------|-------------------------------------------------------|
| Environmental support | RF   | Number or density within the segment                                                 | None                                | Very few                                        | Few                                                    | Relatively adequate                                       | Adequate and evenly distributed               | Higher levels indicate stronger environmental support |
|                       | SH   | Shaded length/total segment length                                                   | 0–20%                               | 21–40%                                          | 41–60%                                                 | 61–80%                                                    | 81–100%                                       | Higher levels indicate stronger shade provision       |
| Path load             | MD   | MIDE difficulty of movement; joint interpretation by two experts                     | Travel on an even surface           | Travel on paths with different surface types    | Travel on steps or uneven terrain                      | Hand support or negotiation of terrain obstacles required | Continuous hand support required for movement | Higher levels indicate greater movement cost          |
|                       | WD   | MIDE orientation on the route; joint interpretation by two experts                   | Route and junctions clearly defined | Path alignment and markers clearly identifiable | Geographic features and orientation must be identified | Navigation away from the established path required        | Obstacles require detours                     | Higher levels indicate greater cognitive demand       |
|                       | EX   | MIDE severity of the environment; joint interpretation by two experts                | Limited environmental risk factors  | More than one risk factor                       | Several risk factors                                   | Numerous risk factors                                     | A large number of risk factors                | Higher levels indicate greater safety pressure        |
|                       | CA   | Positive elevation increments within each FIT trajectory segment, normalized as m/km | ≤25                                 | 26–74                                           | 75–124                                                 | 125–174                                                   | ≥175                                          | Higher levels indicate greater physical load          |

Table 3. Cont.

| Criterion Layer         | Code | Measurement Method                                        | Level 1                                    | Level 2                         | Level 3                                       | Level 4                                   | Level 5                                                 | Interpretation                                                                   |
|-------------------------|------|-----------------------------------------------------------|--------------------------------------------|---------------------------------|-----------------------------------------------|-------------------------------------------|---------------------------------------------------------|----------------------------------------------------------------------------------|
| Experiential conditions | SC   | Hard-surfaced length/total length, adjusted for stability | Highly hardened or weak natural experience | High proportion of hard surface | Relatively balanced hard and natural surfaces | High proportion of stable natural surface | Strong natural experience with generally stable passage | Balances stability and natural experience; interpretation should remain cautious |
|                         | ND   | Field interpretation and identification of sound sources  | Pronounced strong disturbance              | Clearly audible noise           | Moderate disturbance                          | Weak noise                                | Quiet environment                                       | Higher levels indicate quieter conditions and are treated as a benefit indicator |

### 3.3. Hiker Scenarios Based on Physical-Activity Level

The WHO recommendations for weekly moderate- to vigorous-intensity physical activity [16] provide an external reference for defining the low-, moderate-, and high-activity scenarios. For operational purposes, activity volume is expressed as moderate-intensity-equivalent minutes, with 1 min of vigorous-intensity activity treated as equivalent to 2 min of moderate-intensity activity. The low-activity scenario corresponds to <150 min/week, the moderate-activity scenario to 150–300 min/week, and the high-activity scenario to >300 min/week. These scenarios are used to examine how assumptions about activity volume affect model outputs. As ascent tolerance, technical competence, risk attitude, and preference for challenge are conceptually distinct, subsequent research should calibrate them using physiological measures, skill scales, and user surveys. Activity grouping and load-utility transformation are therefore treated as separate modeling levels: weekly activity minutes define the scenario labels, whereas Table 4 specifies the assumed attribute utilities under each scenario. Their correspondence is an explicit hypothesis to be tested; the WHO thresholds themselves do not provide quantitative conversion coefficients for ascent tolerance, technical skill, or risk preference.

**Table 4.** A priori benchmark utility scores for path-load classes under three activity scenarios.

| Path Load Rating (MD, WD, EX, CA) | Low-Activity Scenario | Moderate-Activity Scenario | High-Activity Scenario |
|-----------------------------------|-----------------------|----------------------------|------------------------|
| $\leq 2$                          | 1.5                   | 0.5                        | 0                      |
| $2 < \text{level} \leq 3$         | 1.0                   | 1.5                        | 0.5                    |
| $3 < \text{level} \leq 4$         | 0.5                   | 1.0                        | 1.0                    |
| $> 4$                             | 0                     | 0.5                        | 1.5                    |

### 3.4. Construction of Indicator System

Candidate indicators were grouped into physical load (cumulative ascent and movement difficulty), cognitive demand (wayfinding difficulty), safety pressure (environmental exposure), environmental support (rest facilities and shade), and experiential conditions (surface condition and noise) [5,6,14,17–23]. Field grading of MD, WD, and EX follows the MIDE framework applied by Ávila Callau et al. [14] to greenway-segment assessment and corresponds, respectively, to difficulty of movement, orientation on the route, and severity of the environment. Through ascending five-level operational descriptions, MIDE converts technical and safety conditions into comparable ordinal categories based on movement requirements, wayfinding demands, and the number or combination of environmental risk factors. CA was calculated independently from FIT-recorded elevation as an indicator of physical load. The grouping reflects each indicator's principal role in the perceived-value structure, although movement difficulty shares some stability information with surface condition, and cumulative ascent may covary with movement difficulty. To examine potential redundancy, Spearman correlations were calculated from the benefit-oriented five-level matrix, and indicator-deletion analysis was conducted by removing each indicator in turn and renormalizing the remaining weights.

### 3.5. Indicator Quantification and Grading

Indicators were quantified using either continuous measurement or five-level ordinal interpretation. MD, WD, and EX follow the three MIDE dimensions used in the reference study [14]. MD increases from travel on an even surface to continuous movement requiring hand support; WD increases from clearly identifiable routes and junctions to situations requiring navigation beyond an established path; and EX increases with the number and combination of environmental risk factors. CA was obtained by summing positive elevation increments within each segment and converting the result to m/km using elevation

recorded in the COROS PACE 3 FIT trajectories. The remaining indicators were expressed as continuous values or five-level ordinal ratings based on field records. To incorporate different data types into a common model, all indicators were converted to five-level scores and subsequently mapped to a common [0, 1.5] utility scale. Because five-level discretization entails within-class information loss and discontinuities at category thresholds, the resulting threshold effects are treated as a source of uncertainty.

### 3.6. Standardization of Indicators and Entropy Weight

The evaluation matrix comprised benefit-oriented five-level scores  $q_{ij}$  for 10 segments ( $i = 1, \dots, 10$ ) and 8 indicators ( $j = 1, \dots, 8$ ). For the benefit indicators—rest facilities (RF), shade condition (SH), surface condition (SC), and noise/quietness (ND)—the normalized score was  $z_{ij} = 1.5(q_{ij} - 1)/4$ , producing environmental-support and experiential contributions that remained constant across scenarios. For movement difficulty (MD), wayfinding difficulty (WD), environmental exposure (EX), and cumulative ascent (CA), the load level was  $L_{ij} = 6 - q_{ij}$ , and the corresponding scenario utility was assigned according to Table 4. Appendix A provides the indicator matrices, numerical-consistency tests, and calculation examples.

Calculations used unrounded values. For each indicator  $j$ ,  $p_{ij}$  denotes the proportion of segment  $i$ ,  $e_j$  denotes information entropy,  $d_j$  denotes the coefficient of difference, and  $w_j$  denotes the normalized entropy weight. Because all  $q_{ij}$  values were positive,  $p_{ij}$  was well defined; for a constant indicator column,  $d_j$  was set to 0. The entropy-weight calculation and utility conversion served distinct purposes: the former quantified within-sample differentiation in the benefit-oriented five-level matrix, whereas the latter produced fixed contributions for benefit indicators and scenario-dependent contributions for path-load indicators.

$$p_{ij} = \frac{q_{ij}}{\sum_{i=1}^n q_{ij}} \quad (1)$$

$$e_j = -k \sum_{i=1}^n p_{ij} \ln p_{ij} \quad (2)$$

$$d_j = 1 - e_j \quad (3)$$

$$w_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (4)$$

where  $p_{ij}$  is the proportion of segment  $i$  for indicator  $j$ ,  $e_j$  is the information entropy,  $d_j$  is the coefficient of difference,  $w_j$  is the normalized weight,  $m = 10$ , and  $n = 8$ . The input  $q_{ij}$  corresponds to the benefit-oriented five-level score.

### 3.7. PSV Calculation and Perceived Value Proxy Interpretation

PSV is a segmented-situational compatibility proxy index guided by perceived value theory. Higher values indicate that the potential benefits and environmental support provided by the segments have a higher combined value relative to the potential costs under the current metric, entropy weight, and value conversion rules. Its empirical meaning is limited to the potential perceived value derived from the combination of objective conditions and the rules of a priori scenarios. True perceived value, satisfaction, behavioral intent, and line selection constitute the reference variables for the index's subsequent external validity tests.

Table 4 is an a priori, normative benchmark matrix rather than an empirical estimate of hikers' utilities. Its purpose is to encode three deliberately contrasting hypotheses about how path load may contribute to scenario-based suitability: a monotonically decreasing function for the low-activity scenario, a single-peaked function for the moderate-activity

scenario, and a monotonically increasing function for the high-activity scenario. The upper bound of 1.5 was selected to match the common [0, 1.5] scale used for the benefit indicators, while 0 represents the lower bound and 0.5 increments provide a simple, transparent ordinal contrast across the four load classes. Consequently, the values 0, 0.5, 1.0, and 1.5 do not represent measured physiological thresholds, expert-consensus weights, pilot-survey estimates, or population preference intensities; an alternative common scale such as 0–2 would change the magnitude of path-load contributions relative to the fixed benefit contributions unless all model components were rescaled consistently. The directional assignment has a structural precedent in the differential-assignment approach reported in [14]. However, that precedent does not empirically validate the numerical entries used here. The baseline matrix was retained as an interpretable reference case so that its implications could be compared consistently with the sampled utility functions, fixed-endpoint controls, and risk-cost counterfactual. Accordingly, the baseline PSVs should be read as conditional model outputs under this stated coding convention, not as uniquely justified or behaviorally calibrated utilities. Empirical calibration using expert elicitation, pilot surveys, physiological measurements, or observed route choices remains necessary before the matrix can be interpreted as representing actual hikers.

PSV is calculated as a weighted sum:

$$PSV_i^g = \sum_{j=1}^m w_j a_{ij}^g \quad (5)$$

Among them,  $PSV_i^g$  is the Potential Suitability Value (PSV) of segment  $i$  under scenario  $g$ ;  $w_j$  is the entropy weight of index  $j$ ; and  $a_{ij}^g$  is the normalized value or scenario utility score on the common [0, 1.5] scale,  $m = 8$ . For example, the third level cumulative ascent is 1.5 in the moderate-activity scenario, which is multiplied by the climbing weight of 0.1297. This contribution is about 0.1946, and then it is added to the remaining 7 contributions. Together, scenario utility and weights determine the contribution of each indicator to the composite index.

PSV adopts a linear additive model to summarize the scenario utility of the path load and the weighted contribution of environmental support and experience conditions. The utility scores of MD, WD, EX, and CA vary with the physical-activity-volume scenario according to Table 4; RF, SH, SC, and ND use a fixed normalized score. Fixed-cost treatment of risk indicators sets WD and EX as the low-load adaptation function of Table 4 in all three scenarios, allowing only the utility scores of MD and CA to vary with the scenario to identify the impact of the risk-related assignment on ranking. Neither the baseline model nor the fixed-cost treatment of risk indicators included an interaction between risk and physical ability. The fixed-cost comparison maintains a linear compensation structure, and the lower risk utility may still be offset by other environmental benefits. Therefore, the comparison is used to identify the ranking effect of risk allocation and does not assume the function of safety threshold determination or non-passable segment exclusion.

Therefore, the PSV should be interpreted as a potential gain-sacrificing composite index conditioned by rules under the perceived value theory. A high score indicates that the coded segmentation condition has a high potential value compatibility in a preset activity scenario, but does not mean that real hikers necessarily form the same perception, preference, selection, or completion behavior.

### 3.8. Model Scope and Interpretive Boundaries

The scope of application of the model is determined by 10-segment spatial division, entropy weight in the sample, and a priori scenario parameters. The PSV of each segment is used to compare the relative differences under the same indicator system and parame-

ter conditions. Segmented boundary changes may change the aggregation of indicators, index threshold changes may change the distribution of grades, and scenario matrix changes may change the direction and amplitude of physical load. Therefore, spatial partitioning, discretization, and parameter setting together constitute the main source of model uncertainty, and the research conclusions are limited to the indicator system, segmented scale, and scenario rules defined in Tables 2–4.

### 3.9. Sensitivity Analysis of the Scenario Utility Matrix

With reference to the uncertainty utility function study [24] and the Monte Carlo ranking acceptability evaluation method [24], this study tested the parameter sensitivity of Table 4 under the conditions of a fixed segmented matrix and entropy weight. First, four load-sharing utility functions were sampled, and then each load index was sampled independently as a structural extension. Independent sampling between the three physical-activity-volume scenarios; low- and high-activity scenarios do not impose mirror constraints; the same indicator level in the same simulation uses consistent utility values in all segments.

Each candidate utility set was generated from a four-dimensional random vector on  $[0, 1.5]$ . Rejection sampling was used: candidate vectors that violated the shape constraints were rejected. Let  $u_k^s$  denote the utility for load class  $k \in \{1, 2, 3, 4\}$  under scenario  $s \in \{L, M, H\}$ . The low-activity scenario satisfied  $u_1^L \geq u_2^L \geq u_3^L \geq u_4^L$ ; the moderate-activity scenario satisfied  $u_2^M \geq u_1^M$ ,  $u_2^M \geq u_3^M$ , and  $u_3^M \geq u_4^M$ ; and the high-activity scenario satisfied  $u_1^H \leq u_2^H \leq u_3^H \leq u_4^H$ . Candidate distributions were uniform, scaled Beta(0.5, 0.5), and scaled Beta(2, 2). These constraints and distributions are analytical settings for conditional exploration of the parameter space and are not interpreted as observed preference distributions.

Two parameter sharing modes and three candidate distributions were combined to form six sets of tests, each with 100,000 valid simulations. The random seeds of the sharing method are 20260830, 20260831, and 20260832 in order; the independent methods are 20260930, 20260931, and 20260932. An additional 100,000 independent replicates were performed using 20260840 and 20260940 for the two uniform sampling methods, respectively. PSV and ranking are not rounded for each calculation, and the average ranks are assigned to exact ties. The report ranks median, 2.5–97.5% simulation quantile intervals, top three frequencies, and Spearman's correlation coefficient with baseline model ranking. The quantile interval represents the parameter analog variation, the confidence interval of the non-user population; the frequency is reported as a continuous amount, and no arbitrary robustness pass threshold is set.

Structural controls included scenario-difference contraction and a risk-cost counterfactual. For contraction,  $\mu$  denoted the mean utility across the three benchmark scenarios, whereas  $\lambda$  denoted the contraction coefficient and took values 0, 0.25, 0.50, 0.75, and 1; contracted utilities were defined as  $u(\lambda) = \mu + \lambda[u - \mu]$ . For the risk-cost counterfactual, EX and WD were fixed to the benchmark low-load utility function in all three scenarios. The input indicators and entropy weights remained unchanged in both controls. These tests illustrated how utility span, scenario-differentiation intensity, and risk-related rules affected rankings; they did not replace empirical calibration of the relationship between physical-activity volume and load preference.

Fixed-endpoint controls use utility vectors paired with free-span samples. The low- and high-activity scenarios are ordered by four independent uniform random numbers, and the moderate-activity scenario satisfies the single-peak constraint in Section 3.9 using rejection sampling; the resulting vectors are first linearly normalized according to their minimum and maximum values, and then mapped to the baseline utility intervals of each

scenario:  $[0, 1.5]$  for low- and high-activity scenarios and  $[0.5, 1.5]$  for moderate-activity scenarios. Thus, the upper and lower bounds of the reference and the direction of the function are maintained, and the change in the position of the internal nodes is examined. The normalized node distribution is induced by the above transformation and is not interpreted as a uniform distribution in the endpoint constraint space. The shared and independent indicator modes were run 100,000 times, and the random seeds were 2026083111 and 2026083112, respectively; the results before and after the same vector transformation were matched and compared to identify the contribution of the utility span change.

### 3.10. Weighted Stability and Indicator Redundancy Test

Three controls were used to assess weight stability. First, the eight indicators were assigned equal weights ( $1/8$  each), while the benchmark utility function was held constant. Second, each segment was omitted in turn, entropy weights were recalculated from the remaining nine segments using the normalization coefficient  $1/\ln(9)$ , and the resulting weights were then applied to the fixed 10-segment evaluation matrix to isolate the effect of sample composition on weight estimation. This leave-one-segment-out design was used for influence diagnosis rather than predictive validation of the omitted segment. Finally, each benchmark weight was multiplied by an independent uniform random multiplier and then renormalized to sum to 1. Multiplier ranges of  $[0.9, 1.1]$  and  $[0.8, 1.2]$  were tested in 100,000 simulations each, using random seeds 2026083101 and 2026083102, respectively. These perturbation ranges were stress-test settings, not confidence intervals for the weight estimates.

Indicator redundancy was assessed by calculating Spearman rank correlations from the  $10 \times 8$  benefit-oriented five-level matrix, with average ranks assigned to exact ties. Each of the eight indicators was then deleted in turn; the deleted indicator's weight was set to 0, the remaining weights were proportionally renormalized, and the benchmark utility function was held constant. Correlation coefficients, segment rankings, and key ranking relationships were reported for each control relative to the benchmark ranking. Deterministic controls were summarized by minimum and maximum ranks, whereas stochastic simulations were summarized by quantile intervals and top-three frequencies. Correlation and deletion effects were used to examine within-sample information overlap, not to justify automatic indicator removal or infer a population-level structure.

## 4. Results

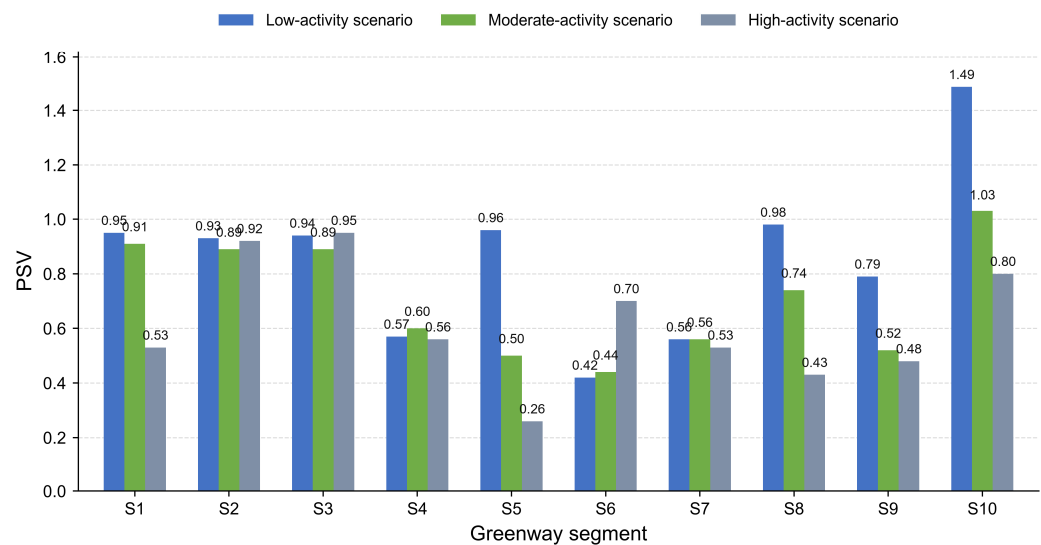
### 4.1. Segmented Suitability Under Different Physical-Activity-Volume Scenarios

Figure 4 and Table 5 reports the PSV under the baseline scenario, with the values retained to two decimal places for display. All rankings and related analyses were calculated without rounding, and the average ranks were assigned to exact ties. The same display value only indicates that it is indistinguishable at the current display accuracy; the sensitivity of the segmentation rank is evaluated according to the parameter and weight test in Section 4.4.

In the low-activity scenario, S10 (1.49), S8 (0.98), and S5 (0.96) ranked in the top three in the baseline model, with similar scores for S1 (0.95), S3 (0.94), and S2 (0.93). This ranking is formed by a combination of environmental support contributions and decreasing load utility. Whether S5 and S8 enter the top three changes with the utility span and internal spacing setting, and their reference positions should be explained in combination with the parameter distribution.

In the moderate-activity scenario, S10 (1.03), S1 (0.91), S3 (0.89), and S2 (0.89) ranked high. The S5 score dropped to 0.50, reflecting that the moderate scenario utility rule gives a low adaptation value to extremely low body load; this result describes the value conversion

process in the model, and its corresponding relationship with real preferences needs to be verified by user data.



**Figure 4.** Comparison of PSV in 10 segments across three physical-activity scenarios.

**Table 5.** PSV results in 10 segments across three physical-activity scenarios.

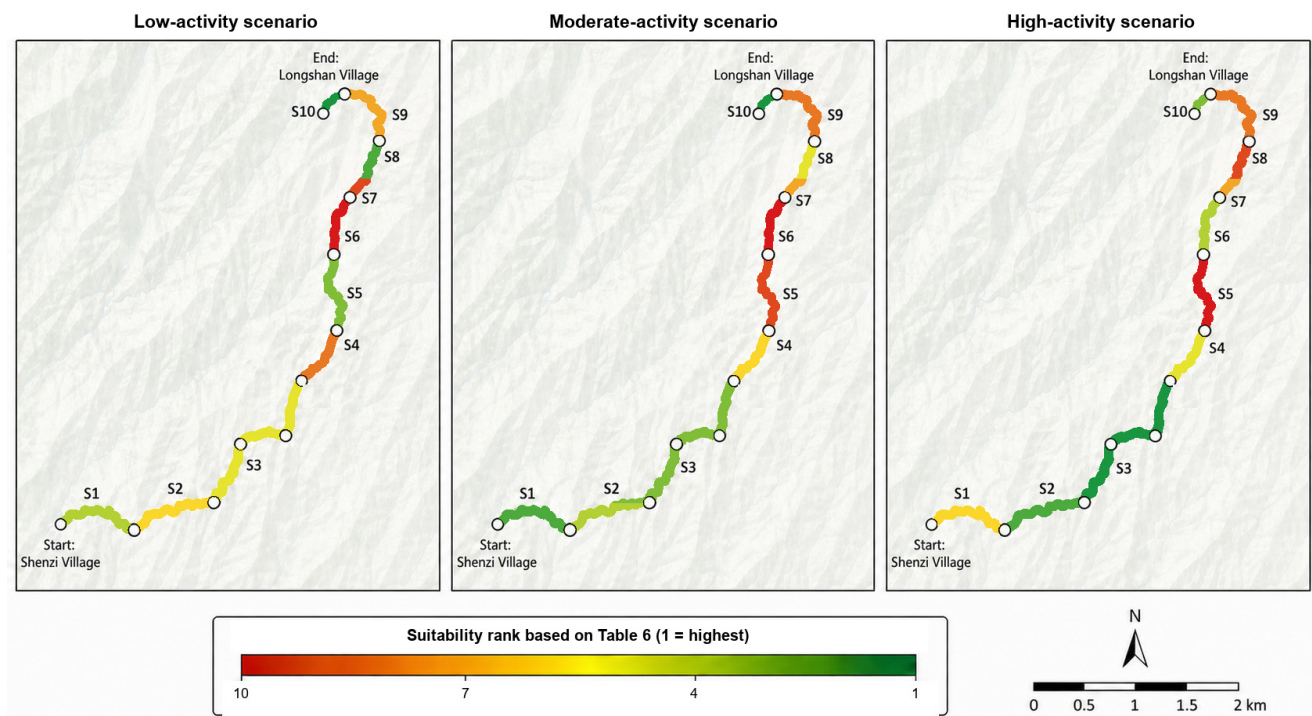
| Segment | Low-Activity Scenario PSV | Moderate-Activity Scenario PSV | High-Activity Scenario PSV |
|---------|---------------------------|--------------------------------|----------------------------|
| S1      | 0.95                      | 0.91                           | 0.53                       |
| S2      | 0.93                      | 0.89                           | 0.92                       |
| S3      | 0.94                      | 0.89                           | 0.95                       |
| S4      | 0.57                      | 0.60                           | 0.56                       |
| S5      | 0.96                      | 0.50                           | 0.26                       |
| S6      | 0.42                      | 0.44                           | 0.70                       |
| S7      | 0.56                      | 0.56                           | 0.53                       |
| S8      | 0.98                      | 0.74                           | 0.43                       |
| S9      | 0.79                      | 0.52                           | 0.48                       |
| S10     | 1.49                      | 1.03                           | 0.80                       |

In the high-activity scenario, the model compatibility of S3 (0.95), S2 (0.92), S10 (0.80), and S6 (0.70) is higher. This change is consistent with the scenario transition rules for path loads in Table 4, where the assignment of exposure and pathfinding is further tested by fixed-cost treatment of risk indicators. Therefore, this result reflects the response of the model under the established rules, and its correspondence with the actual preferences of highly active hikers needs to be tested with empirical data.

#### 4.2. Spatial Differentiation and Scenario Compatibility Types of Segmented Suitability

In the benchmark model (Figure 5), S10 ranked in the top three in all three scenarios, showing a wide range of scenario compatibility. It maintains this position in the leave-one-segment-out reweighting test; under equal-weight control, the high-activity scenario drops to 4th place. Therefore, the cross-scenario advantage of S10 reflects the combined effect of its environmental support combination and weighting method.

S8 and S5 rank higher in the benchmark low-activity scenario than in the high-activity scenario, showing a relatively favorable response to the low-load utility hypothesis. The fine ranking of the two segments in the low-activity scenario is sensitive to the span and node position of the utility function, and is therefore classified as a parameter-sensitive segment. This type is used to prioritize environmental inspections and model calibrations.



**Figure 5.** Spatial distribution of segmented suitability under the three physical-activity scenarios.

The relative positions of S1, S2, and S3 rose in the benchmark and high-activity scenario, where S2 and S3 remained in the top three in the high-activity scenario with equal weight, one estimate, and two sets of local weight perturbation. S6 showed a clear cross-scenario ranking improvement, but its high-activity scenario ranking dropped from 4th to 8th in the fixed-cost treatment of risk indicators, belonging to the risk assignment sensitive segment. The above induction is based on the response of the model and the comparison results, and does not constitute a judgment of the technical capability or the level of the public line.

S4, S7, and S9 are in the middle-low position in the baseline model, with small differences in some scores. The evaluation of such segments should be combined with specific indicators and the range of change in rank, so as to avoid deriving stable advantages and disadvantages from a single benchmark rank.

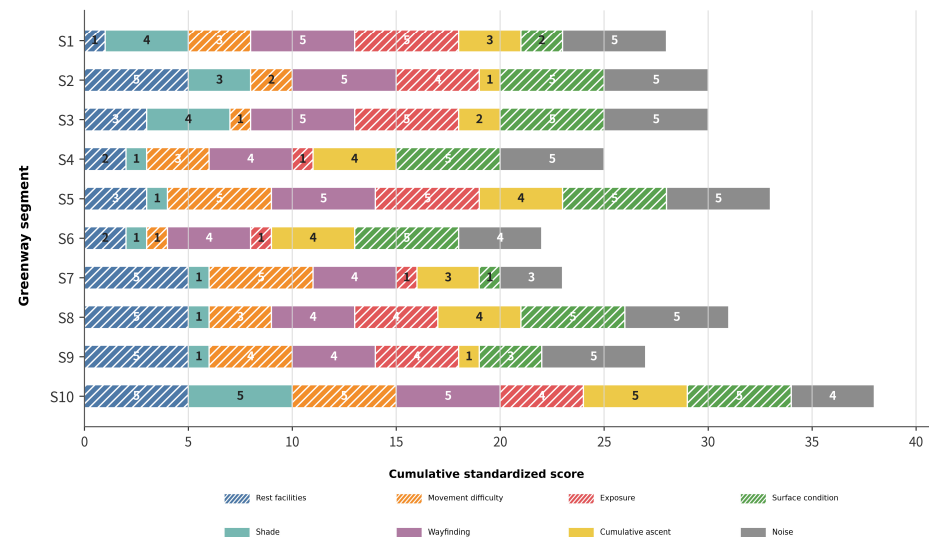
In the moderate-activity scenario, both S3 and S2 are displayed as 0.89, and S1 and S7 are displayed as 0.53 under the high-activity scenario; the unrounded results still have a sequential order. Table 6 expresses the calculation order of the benchmark, and the ranking interval of the parameter simulation and the ranking range of the deterministic control respectively reflect their conditional changes.

**Table 6.** Segmented suitability ranking under different physical-activity scenarios.

| Scenarios                  | Segment Ranking                                  |
|----------------------------|--------------------------------------------------|
| Low-activity scenario      | S10 > S8 > S5 > S1 > S3 > S2 > S9 > S4 > S7 > S6 |
| Moderate-activity scenario | S10 > S1 > S3 > S2 > S8 > S4 > S7 > S9 > S5 > S6 |
| High-activity scenario     | S3 > S2 > S10 > S6 > S4 > S1 > S7 > S9 > S8 > S5 |

#### 4.3. Segmentation Indicator Characteristics and Composition of Suitability Differences

Figure 6 shows that 10 segments have different combinations of indicators. Some segments are strongly supported by shade and rest facilities, while others have larger cumulative ascent, movement difficulty, or environmental exposure. The line conditions are composed of multiple types of potential costs and benefits, showing obvious spatial heterogeneity.



**Figure 6.** Standardized index composition of 10 greenway segments.

Shade, exposure, movement difficulty, and cumulative ascent achieved higher entropy weight in the 10-segment benchmark protocol, indicating that these indicators had a large degree of discretization between sample segments. This result describes the degree of discrimination within the sample; the lower weights of pathfinding and noise correspond to the smaller variation in the two along the line. The entropy-weight structure is affected by the segmentation boundary and sample composition, so Table 7 reflects the difference structure under the segmentation condition of the line.

**Table 7.** Information entropy, coefficient of difference, and entropy weight of each evaluation index.

| Specifications         | Information Entropy | Coefficient of Difference | Entropy Weight | Interpreted                                                  |
|------------------------|---------------------|---------------------------|----------------|--------------------------------------------------------------|
| Rest facilities        | 0.9579              | 0.0421                    | 0.1243         | In-case variance; indicates restoration support in the model |
| Shade condition        | 0.8996              | 0.1004                    | 0.2968         | Biggest source of difference in this 10-part sample          |
| Movement difficulty    | 0.9492              | 0.0508                    | 0.1500         | In-case differences in investigator grading exercise needs   |
| Wayfinding difficulty  | 0.9973              | 0.0027                    | 0.0079         | Small variation between sample segments                      |
| Environmental exposure | 0.9398              | 0.0602                    | 0.1779         | Difference in safety pressure between segments in this case  |
| Cumulative ascent      | 0.9561              | 0.0439                    | 0.1297         | In-case differences in Dem Body Load                         |
| surface condition      | 0.9665              | 0.0335                    | 0.0990         | Intra-case variance; overlaps with motion stability section  |
| Noise/quietness        | 0.9951              | 0.0049                    | 0.0144         | There is less variation within this line                     |

Within the perceived value framework, shade differences characterize underlying environmental support, and exposure, movement difficulty, and cumulative ascent differences characterize safety stress or physical needs. Relevant literature supports the correlation of these conditions in greenway evaluation [3,4]; entropy weight in this paper further quantifies their relative dispersion in the current 10 segments.

#### 4.4. Robustness of Suitability Evaluation Results

Under the shared utility function and uniform sampling conditions, the median Spearman correlation coefficients between the low-, moderate-, and high-activity scenarios and the baseline ranking were 0.806, 0.891, and 0.927, respectively. S10 enters the top three in

all three scenarios simultaneously 99.88% of the time. The S5 low-activity scenario ranked better than the high-activity scenario at 100.00%, and the S6 high-activity scenario ranked better than the low-activity scenario at 100.00%. The stability of these relationships is conditional on preserving the preset function orientation. The detailed ranking distributions and top-three frequencies are presented in Table 8.

**Table 8.** Shared utility function, ranking distribution under uniform sampling, and top three frequencies.

| Segment | Low-Activity Scenario: Median Rank [Interval]; Top-Three Frequency | Moderate-Activity Scenario: Median Rank [Interval]; Top-Three Frequency | High-Activity Scenario: Median Rank [Interval]; Top-Three Frequency |
|---------|--------------------------------------------------------------------|-------------------------------------------------------------------------|---------------------------------------------------------------------|
| S1      | 4 [2, 6]; 16.32%                                                   | 4 [2, 4]; 37.12%                                                        | 5 [4, 8]; 0.00%                                                     |
| S2      | 3 [3, 6]; 76.88%                                                   | 3 [2, 5]; 66.49%                                                        | 3 [2, 3]; 100.00%                                                   |
| S3      | 2 [2, 5]; 87.29%                                                   | 2 [1, 4]; 91.48%                                                        | 1 [1, 2]; 100.00%                                                   |
| S4      | 8 [8, 8]; 0.00%                                                    | 7 [6, 8]; 0.00%                                                         | 6 [5, 8]; 0.00%                                                     |
| S5      | 6 [2, 6]; 4.83%                                                    | 7 [6, 10]; 0.00%                                                        | 10 [9, 10]; 0.00%                                                   |
| S6      | 10 [10, 10]; 0.00%                                                 | 10 [8, 10]; 0.00%                                                       | 4 [4, 7]; 0.00%                                                     |
| S7      | 9 [9, 9]; 0.00%                                                    | 9 [7, 9]; 0.00%                                                         | 8 [7, 10]; 0.00%                                                    |
| S8      | 5 [2, 5]; 14.68%                                                   | 5 [3, 5]; 5.03%                                                         | 8 [5, 9]; 0.00%                                                     |
| S9      | 7 [7, 7]; 0.00%                                                    | 7 [6, 9]; 0.00%                                                         | 7 [5, 9]; 0.00%                                                     |
| S10     | 1 [1, 1]; 100.00%                                                  | 1 [1, 3]; 99.88%                                                        | 2 [1, 3]; 100.00%                                                   |

The stability of the specific ranking is weaker than the direction of change across some scenarios. In the low-activity scenario, the frequency of S5 and S8 entering the top three was 4.83% and 14.68%, respectively, in the shared uniform sample, indicating that its benchmarks 3 and 2 are more sensitive to free-span parameter setting. Under shared sampling, the top three frequencies of S5 varied from 0.39% to 14.51% with the candidate distribution, and S8 varied from 2.64% to 32.99%. Therefore, the relative change direction of S5 and S8 between different scenarios and whether they steadily enter the top three should be explained separately. The effects of sampling distribution and parameter sharing are summarized in Table 9.

**Table 9.** Effects of sampling distribution and parameter sharing on ranking statistics.

| Parameter Method | Candidate Distribution | Median $\rho$ : Low-/Moderate-/High-Activity | S10 Top Three in All Three Scenarios/% | S5 Low-Activity Scenario Better/% | S6 High-Activity Scenario Better/% |
|------------------|------------------------|----------------------------------------------|----------------------------------------|-----------------------------------|------------------------------------|
| Share            | Evenly                 | 0.806/0.891/0.927                            | 99.88                                  | 100.00                            | 100.00                             |
| Share            | Beta(0.5, 0.5)         | 0.818/0.903/0.952                            | 98.08                                  | 99.99                             | 100.00                             |
| Share            | Beta(2, 2)             | 0.782/0.891/0.830                            | 100.00                                 | 100.00                            | 100.00                             |
| Independent      | Evenly                 | 0.794/0.891/0.915                            | 100.00                                 | 100.00                            | 100.00                             |
| Independent      | Beta(0.5, 0.5)         | 0.818/0.891/0.939                            | 99.92                                  | 100.00                            | 99.99                              |
| Independent      | Beta(2, 2)             | 0.782/0.879/0.830                            | 100.00                                 | 100.00                            | 99.99                              |

In the six groups of tests, the maximum difference between the top three frequencies obtained by the first 50,000 and all 100,000 simulations was 0.239 percentage points; the maximum difference between the independent repeat and the main run of the two uniform samples was 0.131 and 0.122 percentage points, respectively. The above differences show that the simulation frequency has good numerical stability; the uncertainty of model settings caused by sampling distribution and function constraints still needs to be considered independently.

Scenario differential contraction shows that when  $\lambda = 0$ , the three scenarios have the same ordering, which is an algebraic result of the shared utility function. As  $\lambda$  increases from 0.25 to 1, S6 ranked 7th, 5th, 4th, and 4th in the high-activity scenario, indicating that the improvement in its ranking depends on the intensity of differentiation among scenarios. Fixed-cost treatment of risk indicators further reduces the ranking of the S6 high-activity scenario from 4th to 8th, while S3, S2, and S10 still occupy the top three positions in the

scenario. Some of the advantages of S6 are therefore related to the scenario assignment of EX and WD, and should not be attributed to the climb and the challenge gain of movement difficulty. The segment rankings under the benchmark and fixed-cost treatment of risk indicators are presented in Table 10.

**Table 10.** Segment ranking under benchmark and fixed-cost treatment of risk indicators.

| Segment | Benchmark<br>Low-Activity | Benchmark<br>Moderate-Activity | Benchmark<br>High-Activity | Control<br>Low-Activity | Control<br>Moderate-Activity | Control<br>High-Activity |
|---------|---------------------------|--------------------------------|----------------------------|-------------------------|------------------------------|--------------------------|
| S1      | 4                         | 2                              | 6                          | 4                       | 2                            | 4                        |
| S2      | 6                         | 4                              | 2                          | 6                       | 4                            | 2                        |
| S3      | 5                         | 3                              | 1                          | 5                       | 3                            | 1                        |
| S4      | 8                         | 6                              | 5                          | 8                       | 8                            | 9                        |
| S5      | 3                         | 9                              | 10                         | 3                       | 7                            | 7                        |
| S6      | 10                        | 10                             | 4                          | 10                      | 10                           | 8                        |
| S7      | 9                         | 7                              | 7                          | 9                       | 9                            | 10                       |
| S8      | 2                         | 5                              | 9                          | 2                       | 5                            | 6                        |
| S9      | 7                         | 8                              | 8                          | 7                       | 6                            | 5                        |
| S10     | 1                         | 1                              | 3                          | 1                       | 1                            | 3                        |

After fixing the benchmark endpoint, the median low-, moderate-, and high-activity scenario rank correlation coefficients of the shared utility function were 0.952/0.915/0.976, and the frequencies of S5 and S8 entering the top three in the low-activity scenario were 41.70% and 72.12%, respectively; the corresponding frequencies of independent index methods were 44.25% and 64.88%. The paired free-span sampling results and fixed-endpoint results of the two groups are shown in Table A6. After the fixed endpoint, the frequency of the top three in S5 and S8 rises, indicating that the change in the magnitude of utility contribution in free-span sampling is one of the sources of its ranking sensitivity; the frequency after the fixed endpoint is still not completely stable, and the internal spacing also affects the specific ranking. The top three frequencies for the first 50,000 vs. all 100,000 shared and independent fixed endpoint simulations differed the most by 0.242 and 0.258 percentage points, respectively.

The low-, moderate-, and high-activity scenario correlation coefficients of the equal-weight comparison and benchmark ranking were 0.915/0.815/0.867, respectively, and the ranking of S10 changed to 1, 2, and 4, indicating that its top three positions across scenarios depended on the weighting method. The three scenario correlation coefficients ranged from 0.758 to 1.000, 0.939 to 1.000, and 0.927 to 0.988, respectively; S10 maintained the top three of the three scenarios in the 10 sets of leave-one-segment-out weights. The range of shade weights in the leave-one-segment-out weights was 0.2658–0.3222, rest facilities was 0.0761–0.1471, and surface condition was 0.0477–0.1193. See Tables A4 and A5 for weight change and segment ranking.

When the weight multiplier is disturbed and normalized in the range of  $\pm 10\%$  and  $\pm 20\%$ , the frequency of S10 entering the top three in the three scenarios at the same time is 99.96% and 91.10%, respectively. S2 and S3 remained in the top three in the high-activity scenario under equal weighting, leave-one-segment-out reweighting, and both levels of local weight perturbation. The high correlation between the overall ranking and the local ranking changes can occur at the same time, so it is necessary to explain the evaluation stability in combination with the results at the segmentation level (Table A7).

The index correlation matrix showed that the Spearman coefficients of SH and WD were 0.787, WD and EX were 0.775; MD and SC, MD and CA, and MD and EX were  $-0.376$ ,  $0.307$ , and  $0.000$ , respectively (Table A3). These coefficients are based on the benefit-oriented five-level matrix and describe the covariance relationship in the sample, without excluding the overlap at the conceptual level. After deleting the MD, S3 dropped from position 1 to position 3 in the high-activity scenario and S6 from position 4 to position 6; after deleting the SC, both remained in positions 1 and 4, respectively. Deleting SH lowered the S10 high-

activity scenario to 8th place, showing that its advantages are dependent on the shade contribution; deleting WD did not change the baseline ordering of the three scenarios, which is consistent with its lower weight, but this does not mean that the navigation conditions lack management significance.

## 5. Discussion

### 5.1. Ranking from Lines to Contextualized Suitability

The findings comprise two related forms of evidence. First, segment-level data reveal route heterogeneity, including variation in shade, exposure, movement difficulty, and cumulative ascent across the ten segments. Second, the perceived-value-informed scenario matrix produces model responses: rankings change as the assumed benefit–sacrifice relationship varies across physical-activity scenarios. The first form of evidence is grounded in observed route conditions, whereas the second reflects a theory-informed utility structure. Together, they show both that route conditions are spatially heterogeneous and that the proxy model can make the evaluative consequences of alternative planning assumptions explicit. Actual hikers’ perceptions remain the appropriate target for subsequent empirical validation.

### 5.2. Path Loads as Costs, Capacity Needs and Challenge Benefits

Shade, exposure, movement difficulty, and cumulative ascent displayed relatively high dispersion across the ten segments, consistent with the importance assigned to shade, terrain, surface conditions, difficulty, and risk in related studies [6,18–20,25,26]. Entropy weights quantify information variation within this particular sample and are jointly influenced by sample size, segment boundaries, ordinal grading, and correlations among indicators. Indicators with large weights are therefore interpreted as strong sources of spatial differentiation in this case, rather than as universally dominant or causal factors.

The scenario ranking reflects the path load utility logic set in Table 4. Physical ability, skill level, risk tolerance, and challenge preference have independent conceptual connotations [6,14,19,21,22,26,27]. The ranking relationship maintained in the constrained sampling reflects the parameter stability in the direction of the given function. The high-activity scenario of S6 in the fixed-cost treatment of risk indicators dropped from 4th to 8th place, indicating that its benchmark advantage is structurally dependent on the contextualized assignment of exposure and pathfinding. The results require that physical challenges be interpreted separately from safety costs, avoiding direct equation of risk exposure with sustainable recreational gains. Real suitability still needs to be verified by actual selection, completion rate, heart rate, step speed, and user rating [3,28].

This study is theoretically positioned as a perceived-value-informed, conditional multi-criteria decision-making framework. The framework preserves the core proposition that benefit–sacrifice trade-offs and attribute values depend on user conditions, and forms a computable underlying value structure with objective environmental characteristics and rules set by researchers. The results of existing outdoor recreation studies on motivation, cognitive evaluation, recreational benefits, local attachments, and behavioral intentions [26,28–31] provide a variable basis for subsequent verification. In the future, the convergence and predictive validity between PSV and real perceived value can be tested using the Perceived Benefit, Perceived Cost, Overall Value, Perceived Difficulty, and Behavioral Intent Scale.

### 5.3. Planning Implications for Mountain Greenway Management

For mountain greenway management, segment indicators and robustness results can be used together to screen for inadequate environmental support, elevated safety pressure,

and ranking-sensitive segments. Facilities and maintenance checks can then be directed to specific indicators, while composite scores can be used to compare the consequences of alternative evaluation rules. S6 is sensitive to the treatment of risk-related indicators and therefore warrants priority verification of exposure and wayfinding conditions; S5 and S8 are sensitive to utility parameters and warrant user-based calibration before public recommendation. This approach may support more targeted use of limited survey and maintenance resources. It does not, however, evaluate sustainability itself: ecological disturbance, environmental carrying capacity, community benefits, social equity, long-term maintenance costs, and resource efficiency were outside the model. Whether the proposed prioritization improves any of these outcomes must be tested with dedicated indicators and longitudinal implementation data.

#### 5.4. Limitations and Future Research

Uncertainty in this study arises from spatial segmentation, indicator measurement, utility specification, weighting structure, and external validity. The ten segment boundaries were established through terrain interpretation and field investigation; alternative boundaries could simultaneously alter indicator aggregation, entropy weights, and rankings. MD, WD, and EX follow five-level MIDE operational descriptions, but category assignment still requires expert judgment. The other five-level thresholds and the experts' jointly agreed field records likewise introduce discretization and judgment uncertainty. Because two independent rating sets were not retained, weighted Cohen's kappa or intraclass correlation coefficients could not be calculated. Weather also differed between surveys—sunny during the first and overcast with light rain during the second—which may have affected surface stability, perceived shade, environmental exposure, and noise conditions. Cumulative ascent was calculated segment by segment from watch-recorded FIT elevation and may therefore be affected by watch elevation error, trajectory drift, and proprietary device processing. The baseline utility matrix is a normative coding convention and was not derived from expert consensus, pilot surveys, physiological measurements, or observed choices; the sensitivity analyses characterize dependence on alternative admissible parameters but do not validate the baseline values. The utility analyses covered free-span and fixed-endpoint sampling; the weighting analyses covered equal weights, leave-one-segment-out reweighting, and local perturbation; and indicator-deletion analysis examined structural dependence. These procedures diagnose individual sources of uncertainty but do not jointly propagate uncertainty in boundaries, measurement error, thresholds, and parameters. Moreover, the correlation matrix is based on only ten segments and cannot establish a stable population correlation structure. The framework also excludes ecological disturbance, environmental carrying capacity, community benefits, social equity, long-term maintenance costs, and resource efficiency; it therefore assesses scenario-based suitability rather than sustainability performance. Independent evidence is required to calibrate actual perceptions, preferences, completion behavior, safety thresholds, and any claimed ecological, social, or economic outcomes.

## 6. Conclusions

This study developed a perceived-value-informed, segment-level, multi-criteria, and scenario-based framework for assessing mountain greenway suitability by integrating COROS PACE 3 FIT trajectories, field observations, researcher-based environmental interpretation, entropy weights, and PSV calculations. The method organizes segment attributes through a benefit–sacrifice structure while distinguishing measured route conditions, within-sample weights, predefined scenario rules, and actual user perceptions. The baseline utility matrix provides a transparent reference convention rather than an empir-

ically calibrated representation of hikers' utilities. This separation makes the origins, assumptions, and limitations of the proxy outputs explicit and auditable.

Shade, exposure, movement difficulty, and cumulative ascent showed relatively high within-sample differentiation in the 10-segment Wugong Mountain benchmark analysis. S10 remained among the top three segments across all three activity scenarios under the benchmark and leave-one-segment-out weighting schemes; however, its high-activity ranking fell to fourth under equal weighting and was sensitive to deletion of the shade indicator. S2 and S3 remained in the top three under the high-activity scenario across equal weighting, leave-one-segment-out reweighting, and both levels of local weight perturbation. These differences reflect the combined effects of segment conditions, indicator composition, scenario assumptions, and weighting methods.

The perceived-value framework provides a structured representation for scenario comparisons of environmental benefits and costs. The fixed-endpoint test shows that the ranking sensitivity of S5 and S8 involves both utility span and internal spacing, while the fixed-cost treatment of risk indicators shows that the benchmark advantage of S6 depends on risk-related assignment. Suitability assessments should therefore report benchmark results, sensitivity ranges, and key indicator dependencies together and should be followed by segment-level and user-based validation. The framework can inform targeted field verification, maintenance prioritization, and risk communication, but it does not demonstrate improvements in sustainability. Ecological disturbance, environmental carrying capacity, long-term maintenance costs, resource efficiency, community benefits, social equity, and users' actual perceived value remain separate outcomes that must be evaluated with independent indicators and longitudinal data before implementation.

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## Appendix A. Indicator Matrix, Examples of Numerical Consistency Testing and Calculation

Table A1 summarizes the  $10 \times 8$  benefit-oriented five-level coding matrix corresponding to the segmentation index, containing a total of 80 scores. The matrix is used for entropy weight calculation, benchmark model calculation, and scenario parameter sensitivity analysis. After calculating the index weight by column and calculating the index weight, the eight entropy weights obtained are consistent with the four-decimal results in Table 7. The four path loads are determined according to  $L_{ij} = 6 - q_{ij}$  and assigned to scenarios, and the remaining indicators are calculated according to  $z_{ij} = 1.5 (q_{ij} - 1)/4$  to calculate the fixed utility. The numerical consistency test is based on the illustrated five-level coding and reporting scores. The scope of evidence is limited to the computational consistency at

the coded data level, and does not cover the empirical validity of continuous observation errors and scoring rules.

**Table A1.** 10-segment benefit-oriented five-level index matrix.

| Segment | RF | SH | MD | WD | EX | CA | SC | ND |
|---------|----|----|----|----|----|----|----|----|
| S1      | 1  | 4  | 3  | 5  | 5  | 3  | 2  | 5  |
| S2      | 5  | 3  | 2  | 5  | 4  | 1  | 5  | 5  |
| S3      | 3  | 4  | 1  | 5  | 5  | 2  | 5  | 5  |
| S4      | 2  | 1  | 3  | 4  | 1  | 4  | 5  | 5  |
| S5      | 3  | 1  | 5  | 5  | 5  | 4  | 5  | 5  |
| S6      | 2  | 1  | 1  | 4  | 1  | 4  | 5  | 4  |
| S7      | 5  | 1  | 5  | 4  | 1  | 3  | 1  | 3  |
| S8      | 5  | 1  | 3  | 4  | 4  | 4  | 5  | 5  |
| S9      | 5  | 1  | 4  | 4  | 4  | 1  | 3  | 5  |
| S10     | 5  | 5  | 5  | 5  | 4  | 5  | 5  | 4  |

**Table A2.** Comparison of consistency between PSV report values and model-calculated values.

| Segment | Reported (Low) | Reported (Moderate) | Reported (High) | Calculated (Low) | Calculated (Moderate) | Calculated (High) |
|---------|----------------|---------------------|-----------------|------------------|-----------------------|-------------------|
| S1      | 0.9511         | 0.9051              | 0.5325          | 0.951103         | 0.905064              | 0.532475          |
| S2      | 0.9329         | 0.8869              | 0.9236          | 0.932935         | 0.886895              | 0.923638          |
| S3      | 0.9409         | 0.8948              | 0.9519          | 0.940850         | 0.894811              | 0.951857          |
| S4      | 0.5731         | 0.5995              | 0.5586          | 0.573145         | 0.599485              | 0.558627          |
| S5      | 0.9616         | 0.4961              | 0.2634          | 0.961637         | 0.496115              | 0.263354          |
| S6      | 0.4177         | 0.4441              | 0.7032          | 0.417747         | 0.444087              | 0.703188          |
| S7      | 0.5638         | 0.5597              | 0.5290          | 0.563827         | 0.559711              | 0.529005          |
| S8      | 0.9799         | 0.7393              | 0.4316          | 0.979866         | 0.739313              | 0.431562          |
| S9      | 0.7861         | 0.5151              | 0.4769          | 0.786112         | 0.515103              | 0.476856          |
| S10     | 1.4946         | 1.0291              | 0.7963          | 1.494581         | 1.029059              | 0.796298          |

The maximum absolute difference between the calculated values of 30 models and the reported value to four decimal places is 0.000050137, of which 29 results are consistent when expressed to four decimal places. The calculated value of S3 in the low-activity scenario is 0.940849863, and the corresponding reported value is 0.9409, which is slightly more than half a unit of measurement with four decimal places of precision. Existing coded data is not sufficient to determine the specific source of the discrepancy and therefore does not directly attribute it to rounding. The sensitivity analysis was calculated using an unrounded model, and all benchmark rankings were consistent with the report ranking.

Taking S10 as an example, the  $q$  of RF, SH, and SC are all 5, and the ND is 4, so the non-contextual part is  $1.5 (w_{RF} + w_{SH} + w_{SC}) + 1.125w_{ND} = 0.796297800$ . The benefit-oriented scores MD, WD, EX, and CA of the four loads are 5, 5, 4, and 5, respectively, corresponding to load classes 1, 1, 2, and 1, all of which fall into the first grade group in Table 4; the sum of the four weights is 0.465522405. Therefore, the PSV of low-, moderate-, and high-activity scenarios is  $0.796297800 + 1.5 \times 0.465522405 = 1.494581408$ ,  $0.796297800 + 0.5 \times 0.465522405 = 1.029059005$  and  $0.796297800$ , respectively.

The weight calculation and utility function sampling characterize the evaluation structure and scenario parameters, respectively. The top three frequencies are conditional on the input matrix, sampling distribution, and function constraints, and a simulation frequency close to 100% indicates the ordering stability in the corresponding parameter space. The relationship between scoring direction and actual perceived value, risk attitudes, and challenge preferences is a separate empirical validity issue.

## Appendix B. Weighting, Indicator Structure and Utility Endpoint Comparison

**Table A3.** Spearman correlation matrix of benefit-oriented five-level indicators ( $n = 10$ ).

| Specifications | RF     | SH     | MD     | WD     | EX     | CA     | SC     | ND     |
|----------------|--------|--------|--------|--------|--------|--------|--------|--------|
| RF             | 1.000  | −0.037 | 0.402  | −0.112 | −0.145 | −0.179 | −0.040 | −0.205 |
| SH             | −0.037 | 1.000  | −0.120 | 0.787  | 0.508  | −0.032 | 0.084  | 0.013  |
| MD             | 0.402  | −0.120 | 1.000  | 0.000  | 0.000  | 0.307  | −0.376 | −0.289 |
| WD             | −0.112 | 0.787  | 0.000  | 1.000  | 0.775  | −0.072 | 0.214  | 0.258  |
| EX             | −0.145 | 0.508  | 0.000  | 0.775  | 1.000  | −0.210 | 0.055  | 0.583  |
| CA             | −0.179 | −0.032 | 0.307  | −0.072 | −0.210 | 1.000  | 0.418  | −0.362 |
| SC             | −0.040 | 0.084  | −0.376 | 0.214  | 0.055  | 0.418  | 1.000  | 0.249  |
| ND             | −0.205 | 0.013  | −0.289 | 0.258  | 0.583  | −0.362 | 0.249  | 1.000  |

**Table A4.** Scope of benchmark entropy weight and revaluation weight of the reserved segment.

| Specifications | Benchmark Weight | Leave-One-Segment-Out Minimum | Leave-One-Segment-Out Maximum |
|----------------|------------------|-------------------------------|-------------------------------|
| RF             | 0.1243           | 0.0761                        | 0.1471                        |
| SH             | 0.2968           | 0.2658                        | 0.3222                        |
| MD             | 0.1500           | 0.1075                        | 0.1708                        |
| WD             | 0.0079           | 0.0073                        | 0.0085                        |
| EX             | 0.1779           | 0.1379                        | 0.2001                        |
| CA             | 0.1297           | 0.0862                        | 0.1586                        |
| SC             | 0.0990           | 0.0477                        | 0.1193                        |
| ND             | 0.0144           | 0.0056                        | 0.0161                        |

**Table A5.** Segment ranking of deterministic controls (low-/moderate-/high-activity scenarios for each cell in turn).

| Segment | Base    | Equal Weights | Leave-One-Segment-Out Rank Range | Delete MD | Delete SC |
|---------|---------|---------------|----------------------------------|-----------|-----------|
| S1      | 4/2/6   | 7/5/9         | 2–6/2–4/5–7                      | 5/4/8     | 2/2/6     |
| S2      | 6/4/2   | 4/1/1         | 2–6/2–4/2–2                      | 3/3/2     | 6/4/2     |
| S3      | 5/3/1   | 5/4/2         | 2–6/2–4/1–1                      | 2/2/3     | 5/3/1     |
| S4      | 8/6/5   | 8/6/5         | 8–9/6–7/5–8                      | 8/9/5     | 9/7/7     |
| S5      | 3/9/10  | 3/7.5/10      | 3–6/8–9/10–10                    | 6/8/10    | 4/9/10    |
| S6      | 10/10/4 | 10/10/3       | 10–10/10–10/4–4                  | 9/10/6    | 10/10/4   |
| S7      | 9/7/7   | 9/9/8         | 8–9/6–8/6–8                      | 10/6/4    | 8/6/5     |
| S8      | 2/5/9   | 2/3/7         | 2–5/5–5/8–9                      | 4/5/9     | 3/5/9     |
| S9      | 7/8/8   | 6/7.5/6       | 7–7/7–9/6–9                      | 7/7/7     | 7/8/8     |
| S10     | 1/1/3   | 1/2/4         | 1–1/1–1/3–3                      | 1/1/1     | 1/1/3     |

Note: The range is 10 groups, with one weight applied to the minimum-maximum ranking after fixing the 10-segment matrix; the average ranking is used for exact ties.

**Table A6.** Pairing free span vs. fixed datum endpoint sampling results (100,000 per group).

| Parameter Method           | Median $\rho$<br>(Low-/Moderate-/High-Activity) | S5 Low-Activity Scenario<br>Top Three/% | S8 Low-Activity Scenario<br>Top Three/% | S10 Top Three in All<br>Three Scenarios/% |
|----------------------------|-------------------------------------------------|-----------------------------------------|-----------------------------------------|-------------------------------------------|
| Sharing; free span         | 0.806/0.891/0.927                               | 4.70                                    | 14.46                                   | 99.88                                     |
| Sharing; fixed endpoints   | 0.952/0.915/0.976                               | 41.70                                   | 72.12                                   | 99.87                                     |
| Independence; free span    | 0.794/0.891/0.915                               | 1.79                                    | 12.88                                   | 100.00                                    |
| Standalone; fixed endpoint | 0.927/0.903/0.964                               | 44.25                                   | 64.88                                   | 100.00                                    |

Note: The fixed endpoints for low- and high-activity scenarios are 0 and 1.5, and the moderate-activity scenario is 0.5 and 1.5. The free span and fixed endpoints use the same batch of candidate vectors to maintain the function direction and peak position of each scenario; the frequency represents the proportion of occurrence under the corresponding simulation conditions.

**Table A7.** Segment rank distribution of local weight perturbation (low-/moderate-/high-activity scenarios for each cell in turn).

| Segment | ±10%: Median Rank [Interval]     | ±10%: Top Three/%   | ±20%: Median Rank [Interval]     | ±20%: Top Three/%   |
|---------|----------------------------------|---------------------|----------------------------------|---------------------|
| S1      | 4 [2, 6]/2 [2, 4]/6 [5, 7]       | 28.22/89.47/0.00    | 4 [2, 6]/2 [2, 4]/6 [5, 8]       | 33.83/77.78/0.00    |
| S2      | 6 [4, 6]/4 [2, 4]/2 [2, 2]       | 0.29/28.16/100.00   | 5 [3, 6]/4 [2, 4]/2 [1, 2]       | 7.25/44.94/100.00   |
| S3      | 5 [3, 6]/3 [2, 4]/1 [1, 1]       | 11.27/82.37/100.00  | 5 [2, 6]/3 [2, 4]/1 [1, 2]       | 27.08/77.29/100.00  |
| S4      | 8 [8, 9]/6 [6, 6]/5 [5, 6]       | 0.00/0.00/0.00      | 8 [8, 9]/6 [6, 7]/5 [5, 7]       | 0.00/0.00/0.00      |
| S5      | 3 [3, 6]/9 [9, 9]/10 [10, 10]    | 63.48/0.00/0.00     | 3 [2, 6]/9 [8, 9]/10 [10, 10]    | 55.06/0.00/0.00     |
| S6      | 10 [10, 10]/10 [10, 10]/4 [4, 4] | 0.00/0.00/0.04      | 10 [10, 10]/10 [10, 10]/4 [3, 4] | 0.00/0.00/8.90      |
| S7      | 9 [8, 9]/7 [7, 7]/7 [6, 7]       | 0.00/0.00/0.00      | 9 [8, 9]/7 [6, 7]/6 [5, 8]       | 0.00/0.00/0.00      |
| S8      | 2 [2, 4]/5 [5, 5]/9 [9, 9]       | 96.74/0.00/0.00     | 2 [2, 5]/5 [5, 5]/9 [8, 9]       | 76.78/0.00/0.00     |
| S9      | 7 [7, 7]/8 [8, 8]/8 [8, 8]       | 0.00/0.00/0.00      | 7 [7, 7]/8 [8, 9]/8 [6, 9]       | 0.00/0.00/0.00      |
| S10     | 1 [1, 1]/1 [1, 1]/3 [3, 3]       | 100.00/100.00/99.96 | 1 [1, 1]/1 [1, 1]/3 [3, 4]       | 100.00/100.00/91.10 |

Note: ±10% and ±20% refer to the independent weight multiplier range before normalization; the interval is the 2.5–97.5% simulation quantile. The benchmark matrix and utility function remain fixed for each set of 100,000 simulations.

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