Simulating decision-makers' behaviour in risk management problems using prospect theory

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Abstract. Risk management plays a crucial role in multi-criteria decision analysis, as decision-makers must balance the attractiveness of alternatives with the uncertainty and risk associated with their selection. behavioural aspects such as sensitivity to gains and losses and loss aversion significantly influence how risk is perceived and processed, yet their impact on the stability of decision-support outcomes remains insufficiently explored. This study provides a systematic analysis of recommendation robustness under structured behavioural perturbations using the Risk-Informed Decision Making (RIDM) method. A large-scale simulation framework is proposed to model decision-makers' behavior through systematic modifications of prospect-theory parameters representing gain sensitivity, loss sensitivity, and loss aversion. Three complementary experimental approaches are considered: directional behavioural profiles reflecting rational, emotional, and asymmetric attitudes; unequal responsiveness of risk parameters; and isolated single-parameter modifications. The experiments examine how changes in risk perception affect local ranking stability, measured as one-position shifts in the ordering of alternatives. The results indicate that asymmetric and gain-oriented behaviors lead to less stable rankings, requiring smaller behavioural changes to alter outcomes, while more balanced profiles exhibit higher robustness. These findings provide behavioural insight into the sensitivity of RIDM-based recommendations and support their interpretation in risk-aware decision-support applications.

Keywords: risk management · multi-criteria decision analysis · prospect theory · RIDM method

1 Introduction

Decision-makers facing Multi-Criteria Decision Analysis (MCDA) problems frequently rely on various analytical tools to support their choices [15]. With rapid technological development in recent years, a wide range of decision support techniques has emerged to address increasingly complex decision environments [5, 7]. A key challenge in such problems is the rational handling of both the attractiveness and the risk associated with selecting particular decision alternatives [11].

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Appropriately accounting for risk, in line with a decision-maker's preferences and risk aversion, can lead to more informed, justified, and expectation-consistent decisions [9, 10]. One theoretical framework that enables a nuanced representation of decision-makers' attitudes toward risk is prospect theory, which captures behavioral responses to gains and losses and allows for asymmetric risk perception [6, 8].

Supporting decision-makers in managing risk within multi-criteria decision problems is an important area of development for decision support systems [13]. One recently proposed approach addressing this challenge is the Risk-Informed Decision Making (RIDM) method. RIDM extends traditional MCDA assessments by complementing attractiveness-based evaluations with an explicit assessment of the risk-taking tendencies associated with selecting particular alternatives. In this way, RIDM brings a second evaluation dimension, enabling decision-makers to balance attractiveness and risk when forming final recommendations. The method is grounded in prospect theory and employs its value function, parameterized by α, β, and λ, which jointly represent the decision-maker's attitudes toward risk, gains, and losses [14]. Additionally, decision-makers specify neutral reference points for each criterion, representing performance levels at which neither gains nor losses are perceived.

Reliable recommendations regarding the risk-taking tendencies associated with alternatives depend strongly on accurate specification of these parameters. However, despite their importance, the effects of modifying them, reflecting changes in the decision-maker's risk preferences and attitudes, have not yet been systematically examined. In practice, decisions under risk often change not because of new data, but due to shifts in the perception of gains, losses, and risks. Many decision support methods, however, assume stable managerial preferences and overlook the resilience of recommendations to behavioral fluctuations. This motivates research into the sensitivity of decision outcomes to changes in decision-makers' behavior and justifies the present study, which investigates how variations in RIDM parameters affect the stability of resulting recommendations.

To address this objective, the study proposes a simulation-based experiment that evaluates how changes in decision-maker parameters influence RIDM outcomes. The key novelty lies in the systematic analysis of recommendation robustness under structured behavioural perturbations. The experiments rely on synthetically generated decision problems and simulated representations of decision-makers' risk attitudes, allowing systematic control of the prospect-theory-based parameters α, β, and λ. The simulation framework is organized into three complementary experimental approaches. The first approach examines directional attitudes toward gains and losses, represented by four decision-maker profiles: rational, emotional, gain-oriented, and loss-aversion-oriented. These profiles are implemented through coherent and asymmetric perturbations of the parameters α and β, capturing both theoretically consistent behaviors and departures from symmetry between gains and losses. The second approach focuses on parameter responsiveness, considering scenarios in which α and β change at unequal rates,

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reflecting differences in how quickly specific aspects of risk perception evolve. The third approach investigates single-parameter modifications, analyzing cases in which only one of the parameters α or β is altered while the remaining parameters are held constant.

The analysis focuses on local ranking disturbances, examining how sensitive specific positions in the ranking are to parameter changes. In particular, the study quantifies the mean magnitude of parameter modifications required to induce a one-position shift (upward or downward) for a given alternative in the ranking. This perspective enables a direct interpretation of stability in terms of decision-maker behaviour: how substantial a change in risk perception or preference structure is necessary to achieve a desired change in the ranking outcome. In this way, the study directly operationalizes and measures recommendation robustness within the RIDM framework, linking behavioural parameter changes to observable effects on ranking stability. By examining how local ranking changes emerge under structured perturbations, the proposed approach provides new insights into the interdependencies between behavioural parameters and the robustness of recommendations, strengthening the interpretability and practical applicability of RIDM as a risk-aware decision support tool.

The rest of the paper is organized as follows. Section 2 presents the preliminaries of the RIDM method. Section 3 describes the methodology used to perform simulation experiments. Section 4 shows the results of those experiments, including different behaviors of decision-makers. Finally, Section 5 draws conclusions from the research and indicates future directions

2 Preliminaries

2.1 The Risk-Informed Decision Making method

The RIDM method incorporates a behavioural perspective into multi-criteria evaluation by focusing on decision-makers' risk attitudes. It assesses how alternatives relate to neutral reference points and whether they induce risk-seeking or risk-averse behaviour, complementing traditional MCDA with a two-dimensional analysis of attractiveness and behavioural response. The approach is grounded in prospect theory, particularly the evaluation of outcomes relative to reference points and the asymmetric perception of gains and losses. Following Audia and Greve [2], risk is interpreted as attitudes toward deviations from aspiration levels rather than the likelihood of adverse outcomes. Thus, RIDM captures behavioural responses to known outcomes and is especially useful in contexts where such effects influence decision-making.

Decision problem formulation The RIDM method builds on standard MCDA input data. When used alongside MCDA methods, it directly adopts the set of alternatives, the set of criteria, the performance values from the decision matrix, and the criteria weights, acting as a complementary extension without requiring data modification. When applied independently, the same elements must be

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defined explicitly. In both cases, these inputs form the basis for the behavioural analysis conducted within the RIDM framework.

Definition of neutral reference points In the context of the RIDM method, neutral reference points represent criterion-specific performance levels at which decision-makers perceive neither gains nor losses. They provide a behavioural baseline that defines the threshold between outcomes that are likely to trigger risk-averse responses and those that may encourage risk-seeking behavior, thus serving as a key element in assessing risk-taking tendencies. The vector of neutral reference points is defined as (1):

$$P = [p_1, p_2, \dots, p_j, \dots, p_n], \quad j = 1, \dots, n, \tag{1}$$

where r_j denotes the neutral performance level for criterion C_j.

Behavioural value transformation To capture the asymmetric perception of gains and losses in RIDM, each performance value x_{ij} is transformed relative to the neutral reference point p_j for criterion C_j using value functions inspired by prospect theory. It reflects behavioural responses to deviations from the neutral performance level, enabling evaluation of risk-taking tendencies at the criterion level.

Two types of criterion-specific value functions are applied depending on the preference direction of the criterion:

- Increasing value function (for criteria where higher values lead to gains and smaller to losses) as (2:

$$v(x_{ij}) = \begin{cases} (x_{ij} - p_j)^{\alpha}, & x_{ij} \geq p_j, \\ -\lambda(-(x_{ij} - p_j))^{\beta}, & x_{ij} < p_j, \end{cases} \tag{2}$$

- Decreasing value function (for criteria where lower values lead to gains and higher to losses) as (3):

$$v(x_{ij}) = \begin{cases} (-(x_{ij} - p_j))^{\alpha}, & x_{ij} \leq p_j, \\ -\lambda((x_{ij} - p_j))^{\beta}, & x_{ij} > p_j. \end{cases} \tag{3}$$

The parameters α and β control the sensitivity to gains and losses, respectively, while λ captures decision-makers' loss aversion. Applying these transformations to all elements of the decision matrix X produces the behavioural value matrix V defined as (4):

$$\mathbf{V} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1j} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2j} & \cdots & v_{2n} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ v_{i1} & v_{i2} & \cdots & v_{ij} & \cdots & v_{in} \\ \vdots & \vdots & \dots & \vdots & \dots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mj} & \cdots & v_{mn} \end{bmatrix} \tag{4}$$

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where each entry v_{ij} quantifies the potential risk-taking or risk-averse response of decision-makers to deviations from the neutral reference point at the criterion level.

Behavioural value standardization To ensure comparability across criteria, values in the behavioral matrix V are standardized using absolute maximum scaling [3]. For each criterion C_j, all values are divided by the maximum absolute value in the column, standardizing gains and losses to $[-1, 1]$ while preserving their relative magnitudes. Formally, the standardized value $\bar{v}_{ij}$ is given by (5):

$$\bar{v}_{ij} = \frac{v_{ij}}{\max |v_j|}, \quad i = 1, \ldots, m, \quad j = 1, \ldots, n. \tag{5}$$

Aggregation and construction of risk-taking tendency indicator The normalized values are aggregated across criteria to obtain an overall indicator of risk-taking tendency for each alternative with (6):

$$R_i = \sum_{j=1}^{n} \bar{v}_{ij} \cdot w_j, \tag{6}$$

where w_j denotes the weight of criterion C_j. The resulting measure R_i reflects the extent to which a given alternative may be associated with potential risk-seeking or risk-averse tendencies relative to the defined neutral reference points.

3 Methodology

This section presents a simulation-based methodology for modeling decision-makers' behavior in risk management using the RIDM method to evaluate the risk of selecting alternatives in MCDA problems. The main objective is to assess the stability of RIDM-based recommendations, focusing on local ranking shifts at specific positions.

The approach examines how changes in decision-makers' preferences and risk attitudes, represented by RIDM's prospect-theory parameters, affect rankings. It quantifies the parameter modifications needed to induce one-position promotions or demotions, providing a behavioural interpretation of ranking stability. The methodology combines simulated decision-makers with varying risk attitudes, synthetic decision problems, and controlled incremental parameter perturbations.

3.1 Decision-makers behavior

The simulation experiment considers several decision-maker profiles reflecting different risk attitudes as described by prospect theory [13], including (a) rational, (b) emotional, (c) gain-oriented, and (d) loss-aversion-oriented types. It also models parameter changes with unequal rates or single-parameter modifications.

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All profiles are represented through controlled variations of RIDM parameters α, β, and λ, capturing sensitivities to gains, losses, and loss aversion.

A baseline decision-maker is generated by sampling the parameters $(\alpha_0, \beta_0, \lambda_0)$ from predefined distributions. The gain-related parameter α_0 is drawn from a uniform distribution as (7):

$$\alpha_0 \sim \mathcal{U}(0.6, 1.0). \tag{7}$$

The loss-related parameter β_0 is sampled in relation to α_0 with (8):

$$\beta_0 = \alpha_0 + \varepsilon, \qquad \varepsilon \sim \mathcal{N}(0, 0.05), \tag{8}$$

and clipped to the interval $[0.5, 1.2]$ to ensure behavioural credibilty. The loss-aversion parameter λ_0 is drawn from (9)

$$\lambda_0 \sim \mathcal{U}(1.5, 3.0), \tag{9}$$

and adjusted to account for interdependence with gain sensitivity with (10):

$$\lambda_0 \leftarrow \max\bigl(\lambda_0 \cdot \bigl(1 - 0.3(\alpha_0 - 0.8)\bigr),\, 1.0\bigr)\,. \tag{10}$$

This adjustment reflects a stylized behavioural assumption that higher sensitivity to gains is typically associated with lower relative loss aversion. While this relationship is model-driven rather than empirically derived, it ensures consistency between parameters and prevents unrealistic combinations of high gain sensitivity and strong loss aversion.

To model changes in decision-makers' attitudes, controlled perturbations of the prospect-theory parameters are applied. Three complementary experimental approaches are considered, each defined by a specific set of directional perturbations of the parameters (α, β). In general, directional changes are represented by vectors (11):

$$(\Delta\alpha, \Delta\beta) = (s_\alpha, s_\beta), \tag{11}$$

where (s_α, s_β) denotes the direction of change applied to the gain- and loss-sensitivity parameters, respectively. The first set D_1 represents coherent and asymmetric attitudes toward gains and losses, corresponding to increasingly rational behavior, increasingly emotional behavior, gain-oriented asymmetry, and loss-oriented asymmetry. It is defined as (12):

$$D_1 = \{(+1, +1), (-1, -1), (+1, -1), (-1, +1)\}, \tag{12}$$

The second set D_2 models unequal responsiveness of α and β, allowing one parameter to vary more slowly than the other. It is determined as follows (13):

$$D_2 = \{(+0.5, +1), (-0.5, -1), (+1, +0.5), (-1, -0.5)\}, \tag{13}$$

The third set D_3 isolates single-parameter effects by modifying only one sensitivity parameter at a time. It is defined as (14):

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$$D_3 = \{(+1,0),(-1,0),(0,+1),(0,-1)\}. \tag{14}$$

For a selected direction (s_α, s_β), parameters are modified incrementally according to (15):

$$\alpha = \alpha_0 + s_\alpha \cdot t, \qquad \beta = \beta_0 + s_\beta \cdot t, \tag{15}$$

where t denotes the perturbation magnitude expressed in direction sets. The maximum deviation is constrained by (16)

$$|\alpha - \alpha_0| \leq 0.5, \qquad |\beta - \beta_0| \leq 0.5, \tag{16}$$

ensuring that simulated behavioural changes remain within realistic bounds.

The loss-aversion parameter λ is updated consistently with changes in α according to

$$\lambda = \begin{cases} \lambda_0 \cdot \big(1 - 0.3(\alpha - 0.8)\big) & \text{if } s_\alpha \neq 0, \\ \lambda_0 \cdot \big(1 - 0.3(\beta - 0.8)\big) & \text{otherwise} \end{cases} \tag{17}$$

This functional form operationalizes a controlled dependency between sensitivity parameters and loss aversion, enabling systematic analysis of behavioural perturbations while preserving interpretable parameter relationships. However, it should be noted, that this specification is a modelling assumption introduced for experimental tractability; alternative formulations of this dependency may lead to quantitatively different results, although the qualitative patterns of robustness are expected to remain comparable.

3.2 Input data

The simulation experiments are based on synthetically generated multi-criteria decision problems. For each experiment, a decision matrix $\mathbf{X} = [x_{ij}]$ of size 5×5 is generated, where i denotes decision alternatives and j denotes evaluation criteria. Each matrix element represents the performance of alternative i with respect to criterion j and is sampled from a uniform distribution as (18):

$$x_{ij} \sim \mathcal{U}(0, 100) \tag{18}$$

For each criterion j, a neutral reference point N_j is defined, representing a reference level at which neither gains nor losses are perceived. Neutral points are independently sampled from the same bounded range as the decision matrix values described as (19):

$$N_j \sim \mathcal{U}(\min\, x_i, \max\, x_i), \quad j = 1, \ldots, 5. \tag{19}$$

This assumption ensures that neutral reference points lie within the feasible performance space of the analyzed decision problem. Criteria types are defined to reflect both profit-type and cost-type evaluations. The set of criteria types is specified by a vector $\mathbf{ct} = (ct_1, \ldots, ct_5)$, where (20):

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$$ct_j = \begin{cases} \text{profit}, & \text{if } j \text{ is odd}, \\ \text{cost}, & \text{if } j \text{ is even}. \end{cases} \tag{20}$$

This alternating structure ensures a balanced representation of gain-oriented and loss-oriented criteria within each simulated decision problem. The equal weighting scheme was applied to model the importance of the criteria weights. All input data components are generated independently for each iteration of the simulation experiment, allowing for a diverse and unbiased exploration of decision-making scenarios.

3.3 Evaluation flow

The evaluation follows a simulation-based procedure repeated independently for each iteration. At the start, a decision matrix, criteria types, and neutral reference points are generated according to the input specification, and a decision-maker is sampled by drawing RIDM parameters α_0, β_0, and λ_0.

The RIDM method is applied to obtain reference scores and a baseline ranking, which serves as a benchmark for assessing stability under parameter perturbations. For each decision-maker profile, α and β are incrementally modified in the prescribed direction up to a maximum deviation of $\Delta_{\max} = 0.5$, updating λ accordingly, and RIDM is reapplied. A change that alters the relative ordering of the two alternatives defining a ranking position is recorded as a successful ranking shift.

Within each iteration, all directions and experimental approaches are applied across behavioural profiles. A total of 20,000 iterations are performed to enable statistical analysis of ranking stability and sensitivity to risk-related preference changes.

4 Results

This section presents the results of the simulation experiments conducted for the considered approaches to modelling decision-makers' behavior. As a first step, the distributions of the simulated parameters are analyzed to illustrate the characteristics of the generated decision-maker profiles and to verify the correctness of the simulation setup.

Figure 1 shows the joint distributions of the prospect-theory parameters α, β, and λ for 1,000 randomly selected iterations from the full set of simulation experiments. The relationships are presented in three parameter pairs, allowing direct comparison of their mutual dependencies. The parameters α and β exhibit similar distributions, with α ranging from 0.6 to 1.0 and β from 0.5 to approximately 1.1.

The (α, λ) and (β, λ) pairs show a wide spread, with λ values ranging from about 1.3 to 3.2. The (α, λ) distribution is relatively uniform, while (β, λ) is more concentrated, especially for β between 0.65 and 0.95, indicating that sensitivities

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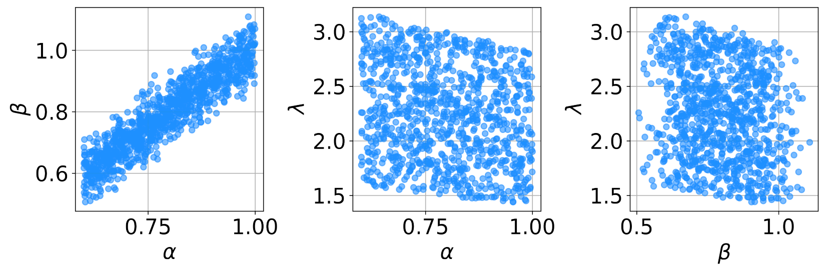

Fig. 1. Distribution of generated α, β, and λ parameters representing simulated decision-makers' attitudes toward risk across 1,000 selected iterations.

to gains and losses are balanced but loss aversion varies substantially. The simulated parameters cover a broad spectrum of risk attitudes, from risk-tolerant to strongly risk-averse.

Figure 2 shows the distribution of neutral reference points. Although sampled uniformly, their bounds vary across iterations and criteria based on observed performance values, producing higher density near the center of the scale and ensuring all reference points remain feasible within the generated decision problems.

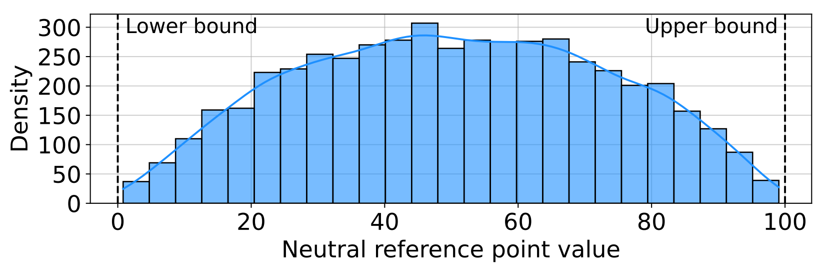

Fig. 2. Histogram of generated neutral reference points based on a uniform distribution across 1,000 selected iterations.

4.1 Different profiles of decision-makers

Figure 3 presents the percentage shares of successful and unsuccessful simulation runs for the four considered decision-maker profiles: (a) rational, (b) emotional, (c) gain-oriented, and (d) loss-aversion-oriented, based on 20,000 iterations. The results indicate substantial differences in ranking sensitivity across behavioural types. In particular, the gain-oriented attitude allows the highest percentage share of successful ranking shifts, reaching 37.1% of all runs. In contrast, the

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rational decision-maker profile exhibits the lowest share of successful outcomes at 14.9%, which is 2.8% lower than in the case of the emotional decision-maker. This observation suggests that asymmetric sensitivity to gains substantially increases the likelihood of inducing local ranking disturbances, whereas symmetric and theory-consistent attitudes lead to more stable rankings.

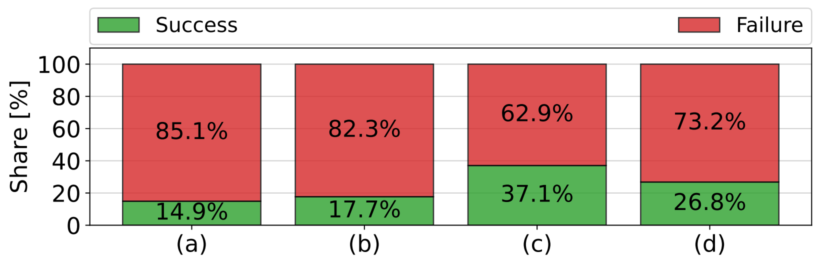

Fig. 3. Percentage share distributions of performed experiments with 20,000 iterations comparing successful and failed runs regarding obtaining shifts in ranking positions for four considered decision-maker behaviors: (a) rational, (b) emotional, (c) gain-oriented, and (d) loss-aversion-oriented.

In all scenarios, α and β were modified with equal magnitudes ($t = 1$) and bounded as described in Section 3. After each change, the loss-aversion parameter λ was recalculated according to Eq. 17 to maintain consistency between sensitivities to gains and losses and overall loss aversion. This ensures that differences in ranking stability reflect the assumed decision-maker profiles rather than unequal parameter scaling.

Table 1. Comparison of mean difference (Δ) required to notice ranking shifts between particular positions according to modeled decision-makers' behavior: (a) rational, (b) emotional, (c) gain-oriented, and (d) loss-aversion-oriented.

Rank	(a)			(b)			(c)			(d)		
shift	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$
$1 \leftrightarrow 2$	0.22	0.22	-0.14	-0.23	-0.23	0.16	0.18	-0.18	-0.12	-0.17	0.75	0.11
$2 \leftrightarrow 3$	0.22	0.22	-0.14	-0.22	-0.22	0.15	0.17	-0.17	-0.11	-0.15	0.15	0.10
$3 \leftrightarrow 4$	0.22	0.22	-0.14	-0.22	-0.22	0.15	0.16	-0.16	-0.11	-0.15	0.15	0.10
$4 \leftrightarrow 5$	0.23	0.23	-0.15	-0.23	-0.23	0.15	0.18	-0.18	-0.12	-0.16	0.16	0.11

Table 1 summarizes the average parameter changes needed to induce a one-position shift between adjacent alternatives, reported by decision-maker profile and rank pair. For rational and emotional profiles, $\Delta\alpha$ and $\Delta\beta$ are comparable across ranks, while λ changes in opposite directions. Gain- and loss-aversion-oriented profiles require smaller changes in one parameter relative to the other,

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indicating that asymmetric attitudes reduce resistance to local ranking disturbances.

Across all profiles, the changes of examined parameters are relatively consistent across different rank positions, indicating that local ranking stability is primarily driven by behavioural characteristics rather than by the absolute position in the ranking.

4.2 Unequal rates of parameter changes

Results of the second experimental approach, which focuses on unequal responsiveness of the parameters α and β, are presented below. In this approach, the parameters are modified with different rates of change, modeling scenarios in which decision-makers adjust their sensitivity to gains and losses at different speeds. Figure 4 indicates that the success rates of inducing ranking shifts are more homogeneous than in the first experimental approach. The share of successful runs varies from 12.9% for scenarios with slower decreases in *alpha* to 21.4% for scenarios with slower decreases in β, resulting in a narrower range of outcomes compared to the directional attitude experiment. Unequal changes in α and β represent decision-makers who adapt asymmetrically to changes in gains and losses, reflecting differences in behavioural responsiveness rather than purely directional preferences.

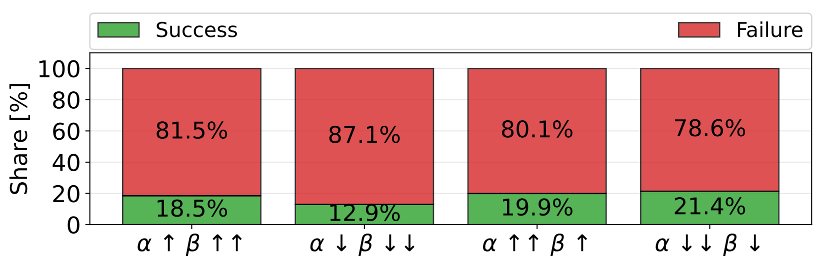

Fig. 4. Percentage share distributions of successful and unsuccessful simulation runs across 20,000 iterations for the second experimental approach, comparing scenarios with unequal rates of change in the parameters α and β.

Furthermore, Table 2 reports the mean magnitudes of parameter changes required to induce ranking shifts between adjacent positions. The results show comparable changes required for increasing and decreasing trends for both parameters. For scenarios in which α changes more slowly than β, decreasing trends require 0.01-0.03 higher parameter changes than increasing trends. Conversely, when β changes more slowly than α, increasing trends require changes larger by 0.01-0.02 than decreasing trends. It suggests that delayed adjustment of sensitivity to losses or gains may either weaken or strengthen ranking instability, depending on which element of behavior is less responsive.

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Table 2. Comparison of mean difference (Δ) required to notice ranking shifts between particular positions according to modeled decision-makers' behavior with unequal rates of changes in α and β.

Rank	$\alpha\uparrow\beta\uparrow\uparrow$			$\alpha\downarrow\beta\downarrow\downarrow$			$\alpha\uparrow\uparrow\beta\uparrow$			$\alpha\downarrow\downarrow\beta\downarrow$		
shift	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$
$1\leftrightarrow 2$	0.11	0.22	-0.07	-0.13	-0.25	0.09	0.22	0.11	-0.14	-0.22	-0.11	0.15
$2\leftrightarrow 3$	0.11	0.22	-0.07	-0.12	-0.25	0.09	0.21	0.11	-0.14	-0.21	-0.10	0.14
$3\leftrightarrow 4$	0.11	0.21	-0.06	-0.12	-0.24	0.08	0.21	0.11	-0.14	-0.20	-0.10	0.14
$4\leftrightarrow 5$	0.11	0.22	-0.07	-0.13	-0.25	0.09	0.22	0.11	-0.14	-0.20	-0.10	0.13

4.3 Modifications of a single parameter

The third experimental approach focuses on scenarios in which only one parameter, either α or β, is modified, while the other is held constant. This setup models decision-makers whose sensitivity to either gains or losses changes independently, without a simultaneous adjustment of the complementary component. As in the previous experiments, the loss-aversion parameter λ is recalculated after each modification, reflecting the assumed interdependence between sensitivity to gains and overall loss aversion in decision-makers' behavior.

The observed success rates are more diverse than in the second experimental approach and closer to those obtained for distinct decision-maker profiles in the first approach. The percentage of successful ranking shifts ranges from 18.8% for decreases in β to 28.7% for decreases in α, as illustrated in Figure 5. Furthermore, the scenario involving the increase of β exhibits a slightly smaller success rate, compared to the increase of α. This indicates that isolated changes in gain sensitivity can influence ranking stability slightly stronger than isolated changes in loss sensitivity.

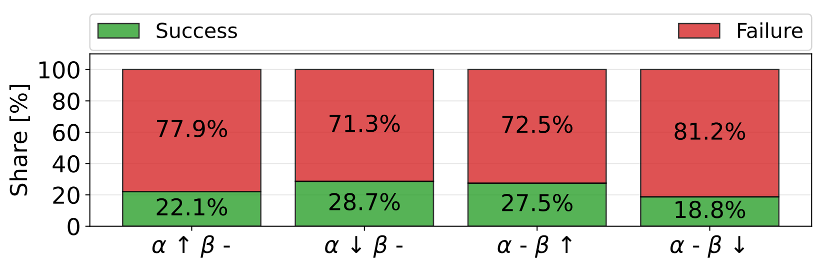

Fig. 5. Percentage share distributions of performed experiments with 20,000 iterations comparing successful and failed runs regarding obtaining shifts in ranking positions with changes introduced in only a single parameter (α or β).

The mean magnitudes of parameter changes required to induce ranking shifts for this experimental approach are reported in Table 3. The smallest required

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change is observed for decreasing values of α, with an average magnitude of approximately -0.18 relative to the baseline. The remaining scenarios exhibit comparable absolute changes, ranging from 0.19 to 0.2, with slightly higher changes for decreasing β. Also, increases in β are associated with slightly larger mean changes in the λ parameter compared to other cases, indicating that stronger adjustments in loss aversion are needed when decreasing sensitivity to losses in order to induce a ranking shift. This suggests a higher behavioural resistance to ranking changes driven solely by decreasing loss sensitivity than by increasing it.

Table 3. Comparison of mean difference (Δ) required to notice ranking shifts between particular positions according to modeled decision-makers' behavior with changes introduced in only a single parameter (α or β).

Rank	$\alpha \uparrow \beta$ —			$\alpha \downarrow \beta$ —			α — $\beta \uparrow$			α — $\beta \downarrow$		
shift	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$	$\Delta\alpha$	$\Delta\beta$	$\Delta\lambda$
$1 \leftrightarrow 2$	0.21	—	-0.14	-0.19	—	0.13	—	0.21	-0.14	—	-0.24	0.16
$2 \leftrightarrow 3$	0.20	—	-0.13	-0.18	—	0.12	—	0.20	-0.13	—	-0.22	0.16
$3 \leftrightarrow 4$	0.20	—	-0.13	-0.18	—	0.12	—	0.19	-0.13	—	-0.22	0.15
$4 \leftrightarrow 5$	0.21	—	-0.14	-0.18	—	0.12	—	0.20	-0.13	—	-0.23	0.16

4.4 Discussion

The findings have important managerial implications for the design of management information systems and decision-making under risk. By incorporating a behavioral component through prospect-theory parameters (α, β, λ), the proposed approach enables a more realistic representation of managerial decision processes. It allows for assessing the stability of recommendations under changes in risk perception and identifying behavioral thresholds at which preferred alternatives change, improving transparency and supporting more informed decisions.

From a strategic perspective, the approach enables behavioral robustness analysis by simulating different decision-maker profiles and evaluating their impact on the stability of choices. This is particularly relevant for investment decisions, resource allocation, and strategic planning, where sensitivity to managerial preferences may affect outcomes [1, 12]. The results also highlight the importance of accounting for cognitive diversity, supporting the integration of individualized decision profiles into decision support and business intelligence systems.

At the same time, the high sensitivity of results to behavioral parameters underscores the need for appropriate governance mechanisms. In particular, this justifies the need to introduce mechanisms that limit excessive subjectivity in decisions, such as collegial procedures, the aggregation of assessments from multiple decision-makers, or the formalization of assumptions regarding risk perception within decision-making processes [4]. From an organizational management perspective, the proposed approach supports the development of more advanced,

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hybrid decision support systems that integrate multi-criteria analytical methods with a behavioral approach. Consequently, the research findings contribute to the development of management practices based on a deeper reflection on the role of risk perception in decision-making processes, strengthening the organization's ability to make accurate and stable decisions under conditions of uncertainty.

5 Conclusion

This study analyzed the stability of RIDM-based rankings under systematic modifications of decision-makers' risk preferences modeled by using prospect-theory parameters. Large-scale simulations examined directional attitudes toward gains and losses, unequal parameter responsiveness, and isolated single-parameter changes. Ranking stability strongly depended on both the direction and structure of behavioural modifications: gain-oriented and asymmetric attitudes induced shifts more easily than rational or emotionally consistent behaviors, and changes in gain sensitivity had a stronger impact than comparable changes in loss sensitivity. Managerial decisions under risk proved highly sensitive to decision-makers' behavioural characteristics, particularly asymmetric sensitivity to gains and losses, with profit-oriented profiles showing greater instability than more balanced ones. The findings highlight the importance of accounting for behaviour in decision processes and using prospect-theory-based tools as reflective support, while noting that results are conditioned by the assumed functional dependency between sensitivity parameters and loss aversion, which may affect quantitative outcomes.

Despite its contributions, the study has several limitations. The experiments were conducted on fixed-size, synthetic decision problems and relied on simulated behavioural profiles, which may affect the generalizability of the results to real-world settings. The fixed number of alternatives and criteria further limits applicability to larger or structurally different problems. Neutral reference points were generated using uniform distributions within decision-space bounds, which may not fully reflect actual preference structures. Moreover, the loss-aversion parameter λ was updated using a predefined functional relationship, whereas real behavioural interactions between gains, losses, and loss aversion may be more complex. Consequently, the results should be interpreted as indicative rather than definitive.

Future research should address these limitations by extending the analysis to decision problems with varying sizes and structures, exploring other distributions and elicitation methods for neutral reference points, and investigating more flexible or data-driven relationships between prospect-theory parameters. Incorporating empirical data from surveys or controlled experiments with decision-makers would be particularly valuable for validating the behavioural assumptions and strengthening the practical relevance of the findings.

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