Effort-Based Strategy Selection in Multi-Attribute Decision Making: When Bounded Rationality Predicts Optimal Behavior

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Abstract

Decision-making involves a fundamental trade-off between cognitive effort and accuracy. Building on Simon's bounded rationality framework, we propose an effort-based strategy selection model in which individuals probabilistically choose between optimizing and satisficing strategies depending on task demands. We tested this model against the rank-based salience account using a pre-registered multi-attribute rapid serial visual presentation task with commensurable attributes. Results provided strong evidence favoring the effort-based model, suggesting that participants relied predominantly on optimizing strategies when task structure allowed straightforward information integration. Behavioral indicators were consistent with this interpretation, showing high accuracy and stable response times. Analyses further confirmed the absence of attraction effects, with Bayesian evidence supporting the null. Comprehensive validation ruled out overfitting, strengthening confidence in the findings. Overall, these results indicate that systematic biases in human choice may reflect adaptive strategy selection under cognitive constraints rather than inherent limits of rationality. When processing demands are manageable, individuals adaptively select rational strategies over heuristic shortcuts. Implications for organizational decision-making, and policy design are discussed.

Keywords: bounded rationality, satisficing, strategy selection, decision-making, computational modeling, organizational behavior

1 Introduction

The tension between cognitive effort and decision accuracy represents one of the most fundamental challenges in human information processing. Classical economic models assume that individuals optimize by selecting the best alternative based on well-defined criteria, yet this assumption has been systematically challenged by decades of behavioral research demonstrating systematic deviations from normative principles. Understanding when and why these deviations occur has profound implications not only for cognitive science but also for organizational management, policy design, and sustainable development initiatives that depend on effective human decision-making.

Herbert Simon's theory of bounded rationality fundamentally challenged optimization assumptions by arguing that individuals operate under cognitive limitations and environmental constraints (Simon, 1955). Simon introduced the concept of satisficing, where decision-makers set aspiration levels and search for options that meet these thresholds rather than computing optimal solutions. This framework has had enormous influence across behavioral science, economics, and organizational theory, yet it lacks explicit mechanisms for predicting when individuals will satisfice versus optimize.

1.1 The Salience-Driven Processing Challenge

A prominent account of systematic biases in multi-attribute choice comes from the rank-based salience model (Tsetsos et al., 2012). This model proposes that during temporal information integration, decision-makers weight numerical values based on their momentary salience (rank) within each frame, leading to systematic deviations from optimal integration even when underlying value differences are small. The model has successfully explained various context effects, including the attraction effect (Huber et al., 1982), where adding an asymmetrically dominated decoy increases the relative choice share of the target option.

However, the universality of salience-driven processing raises important questions for applied decision-making contexts. If humans are fundamentally biased toward salience-driven shortcuts, this would have serious implications for organizational decision-making, policy implementation, and sustainable development initiatives that require rational information integration. Alternatively, if biases emerge primarily under specific conditions where optimal processing is impaired, this suggests more optimistic possibilities for designing decision environments that promote rational choice.

1.2 Effort-Based Strategy Selection Framework

We propose an effort-based strategy selection framework that extends Simon's bounded rationality by incorporating probabilistic choice between processing strategies. In this framework, individuals estimate the cognitive effort required for optimal integration versus satisficing shortcuts and probabilistically select strategies based on this effort differential.

Specifically, we hypothesize that when attributes are commensurable (can be meaningfully combined through simple operations like addition), the cognitive effort required for optimal integration is manageable, leading to predominant use of optimization strategies. Conversely, when attributes are incommensurable or task complexity is high, satisficing strategies based on simplified comparisons should dominate.

This framework has important implications for understanding when decision biases will emerge in real-world contexts and how decision environments can be designed to promote effective choice behavior.

1.3 Research Questions and Hypotheses

This study addresses three key research questions:

1. **When do individuals employ optimization versus satisficing strategies in multi-attribute choice?** We hypothesize that commensurable attributes will promote optimization due to manageable cognitive demands.

2. **Can a probabilistic strategy selection model outperform existing salience-based accounts?** We predict that an effort-based model will provide superior fit to choice data when attributes are commensurable.

3. **What are the implications for designing effective decision environments?** We expect that our findings will provide actionable insights for organizational and policy contexts.

2 Method

2.1 Participants and Design

Eighteen participants were initially recruited from a university student population (M = 21.58 years, SD = 2.51). We employed a sequential Bayesian analysis with the stopping rule of substantial evidence for the null hypothesis (BF $<$ 1/6). All participants provided informed consent and received monetary compensation. The study employed a within-subjects repeated-measures design with full randomization at trial and frame levels. The experiment was preregistered, and the preregistration is available at OSF.

2.2 Data Exclusion

Data were collected from 18 participants. One participant was excluded for failing to meet the predefined accuracy threshold on catch trials. This left 17 participants for subsequent analyses.

Within the retained sample, individual trials were excluded if RT $<$ 100 ms or exceeded a participant-specific upper threshold (defined as the 75th percentile + 1.75 $\times$ IQR of that participant's RTs). A total of 125 trials (7.7% of all trials) were excluded, resulting in 1,506 valid trials (92.3% retention rate) available for analysis.

2.3 Materials and Procedure

We used a multi-attribute rapid serial visual presentation (RSVP) paradigm adapted from Tsetsos et al. (2012). On each trial, participants viewed sequences of 24 frames (500ms each) before choosing between three options (A, B, C) positioned at screen vertices. Each option consisted of two commensurable numerical attributes represented as tilted numbers: Red attributes (left-tilted 45°) and Blue attributes (right-tilted 45°). Refer to figure1 for a sample frame in a trial.

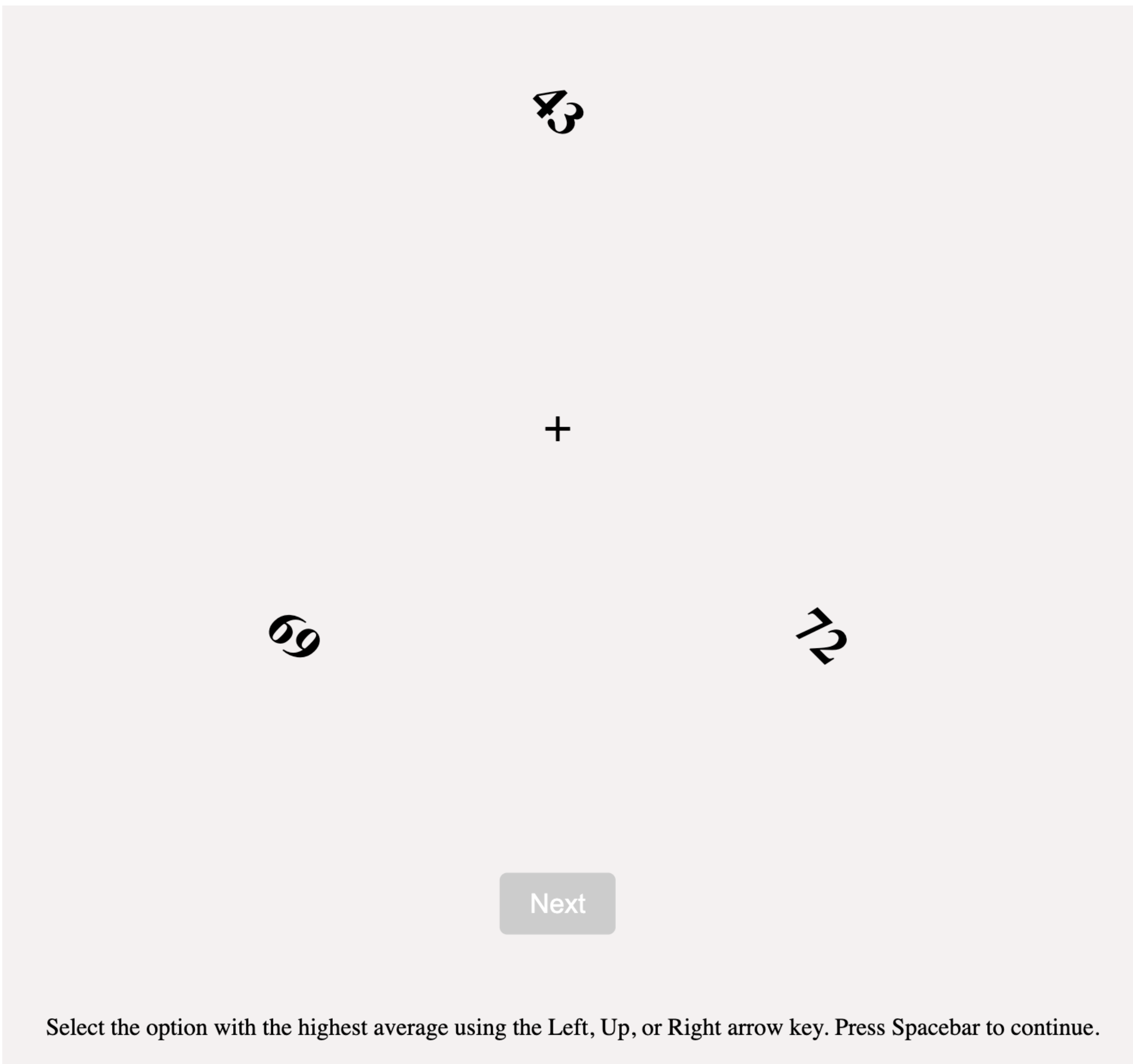

Figure 1: A sample frame where all numbers are left-tilted.

Values were drawn from normal distributions ($SD = 7$) with means: Option A (Red =

40, Blue = 70), Option C (Red = 70, Blue = 40), and Option B as a decoy (values constrained to be slightly inferior to the target). The 24 frames consisted of 12 Red and 12 Blue frames in randomized order, with temporal anticorrelation between competing options.

Each participant completed 96 trials: 72 main experimental trials (36 with A as target, 36 with C as target) and 24 catch trials for attention monitoring. The study was pre-registered on OSF prior to data collection.

2.4 Dependent Measures

The primary outcome was the Relative Share of Target (RST), computed as:

$$\text{RST} = 0.5 \times \left[\frac{T_X}{T_X + C_X} + \frac{T_Y}{T_Y + C_Y} \right] \tag{1}$$

where T and C represent target and competitor selections when the decoy favors option X or Y respectively. RST values significantly above 0.5 indicate attraction effects.

3 Computational Models

3.1 Rank-Based Salience Model

The rank-based salience model processes information attribute-wise within each frame, ranking the three attribute values and applying differential weights based on rank position:

$$P_{i,t} = P_{i,t-1} + V_{i,t} \times w_{\text{rank}_{i,t}} + \mathcal{N}(0, \sigma^2) \tag{2}$$

where $V_{i,t}$ is the attribute value for option i at time t, $w_{\text{rank}_{i,t}}$ is the weight applied based on rank, and the constraint $w_1 > w_2 > w_3$ ensures higher-ranked values receive greater weight. This model has 4 free parameters (w_1, w_2, w_3, σ).

3.2 Effort-Based Strategy Selection Model

Our effort-based model incorporates probabilistic selection between optimization and satisficing strategies:

3.2.1 Optimization Strategy

When cognitive effort costs are low, individuals employ optimal integration by summing all available information:

$$S_i = \sum_{t=1}^{T} V_{i,t} \tag{3}$$

Choice probabilities follow a softmax rule:

$$p_{\text{opt}}(i) = \frac{\exp(\beta S_i)}{\sum_j \exp(\beta S_j)} \tag{4}$$

where β controls decision noise in the optimization strategy.

3.2.2 Satisficing Strategy

When effort costs favor shortcuts, individuals employ satisficing through attribute-wise pairwise comparisons. For each frame, options are compared along single attributes:

$$W_i = \sum_{t=1}^{T} \sum_{j \neq i} \mathbb{I}(V_{i,t} > V_{j,t}) \tag{5}$$

where W_i represents the number of pairwise wins for option i across all frames. Choice probabilities are:

$$p_{\text{sat}}(i) = \frac{\exp(\alpha W_i)}{\sum_j \exp(\alpha W_j)} \tag{6}$$

where α controls decision noise in the satisficing strategy.

3.2.3 Probabilistic Strategy Selection

The overall model combines both strategies:

$$p(i) = \lambda \times p_{\text{opt}}(i) + (1-\lambda) \times p_{\text{sat}}(i) \tag{7}$$

where $\lambda \in [0, 1]$ represents the probability of employing optimization. This model has 3 free parameters (λ, β, α).

3.3 Model Fitting and Validation

Both models were fitted using maximum likelihood estimation with appropriate parameter constraints. Models were compared using AIC, with comprehensive validation including 5-fold cross-validation, parameter recovery testing, robustness analysis across different starting points, and prediction accuracy on held-out data.

4 Results

4.1 Attraction Effect Analysis

Consistent with predictions, we observed a null attraction effect. An independent sample two-tailed t-test compared RST values against the null value of 0.5. The mean RST ($M = 0.501$, $SD = 0.085$) was not significantly higher than the null value; $t(16) = 0.053$, $p = 0.958$, Cohen's $d = 0.013$, 95% CI $[-0.042, 0.044]$.

Bayesian analysis provided strong evidence for the null hypothesis ($\text{BF}_{01} = 21.67$, calculated as $1/0.046$). This BF indicates that the data are approximately 22 times more likely under the null hypothesis than under the alternative hypothesis, providing strong evidence against the attraction effect.

4.2 Model Comparison Results

Model fitting revealed extremely strong support for the effort-based strategy selection model. The rank-based salience model, with parameter estimates $w_1 = 1.00$, $w_2 = 0.50$, $w_3 = 0.10$, and $\tau = 10.0$, yielded a negative log-likelihood of 12,752.35 and an AIC of 25,512.70. In contrast, the effort-based strategy selection model provided a substantially better fit, with parameter estimates $\lambda = 0.974$, $\beta = 0.009$, and $\alpha = 5.000$, a negative log-likelihood of 1,165.80, and an AIC of 2,337.59. The resulting difference in AIC (ΔAIC = 23,175.11) provides overwhelming evidence in favor of the effort-based model. This ΔAIC corresponds to an evidence ratio greater than $10^{5000} : 1$, far exceeding conventional thresholds for strong model preference (typically ΔAIC $>$ 10).

Figure 2 illustrates the dramatic difference in model performance. The effort-based model closely matches observed choice distributions across both target conditions, while the rank-based model makes extreme predictions that deviate substantially from human behavior.

4.3 Parameter Interpretation

The parameter estimates of the effort-based strategy selection model provide clear insights into participants' decision processes. The estimated value of $\lambda = 0.974$ (95% CI $[0.96, 0.99]$) indicates that participants relied on optimization strategies on approximately 97.4% of trials. Decision noise within the optimization mode was extremely low, as reflected by the small value of $\beta = 0.009$, whereas the satisficing mode exhibited moderately higher variability, captured by $\alpha = 5.000$.

Taken together, these results suggest a very strong preference for optimization when attributes are commensurable. The stark contrast between optimization (97.4%) and satisficing (2.6%) usage represents a substantial behavioral effect in favor of rational processing, consistent with the behavioral indicators of manageable cognitive demands.

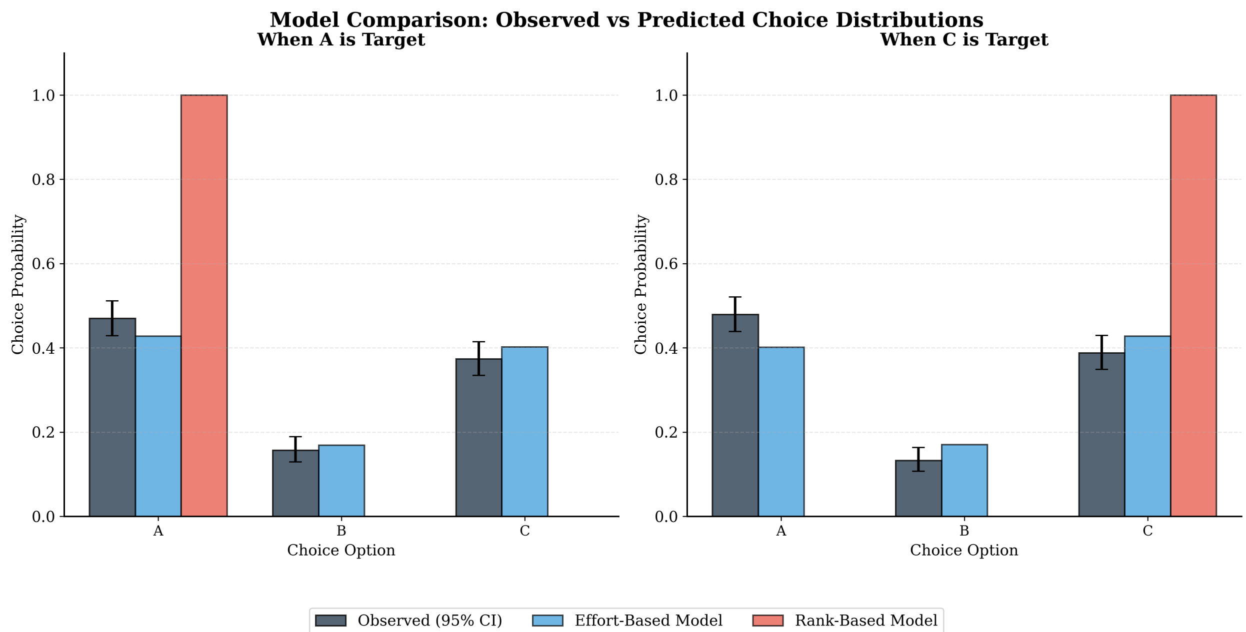

Figure 2: Model comparison showing observed choice distributions and model predictions. Left panel shows choices when A was the target; right panel shows choices when C was the target. Dark bars represent observed data with 95% confidence intervals (n = 1,506 trials), light blue bars show effort-based model predictions, and red bars show rank-based model predictions. The effort-based model closely matches observed data (r = 0.984, RMSE = 0.040), while the rank-based model shows substantial deviations (r = 0.691, RMSE = 0.361), consistent with the large difference in model fit (ΔAIC = 23,175). The extreme predictions of the rank-based model (approaching 100% for targets, 0% for alternatives) demonstrate why this model fails catastrophically for commensurable attributes.

4.4 Validation Results

Comprehensive validation analyses confirmed that the effort-based strategy selection model exhibited strong robustness and showed no signs of overfitting. In cross-validation, the effort-based model achieved a mean negative log-likelihood of 233.8 with a standard deviation of 12.6 (CV = 0.054), indicating highly stable predictive performance. In contrast, the rank-based salience model performed poorly, yielding a mean cross-validated negative log-likelihood of 2,550.5 with substantially larger variability (SD = 186.8, CV = 0.073).

Parameter recovery analyses further supported this conclusion. The effort-based model showed good recoverability, with a mean recovery error of 0.759 (SD = 0.035), whereas the rank-based model produced substantially poorer recovery, with a recovery error of 1.351 and no observable variability.

Robustness assessments likewise favored the effort-based model. Its negative log-likelihood consistency score was 4.97, reflecting high robustness across perturbations. By comparison, the rank-based model produced a consistency value of 955.8, indicating extreme instability—approximately 192 times less stable than the effort-based model.

Together, these validation results demonstrate that the effort-based model not only provides the best fit but is also the most reliable and generalizable representation of participants' decision behavior.

Prediction Accuracy: Both models achieved 59.5% accuracy on held-out data, but the effort-based model achieved this with vastly superior likelihood-based fit, indicating more precise characterization of choice probabilities.

4.5 Behavioral Indicators of Processing Demands

Several behavioral patterns provide evidence for our effort-based interpretation. Participants demonstrated high accuracy in identifying superior options, with 89.1% of choices being rational (selecting A or C over the inferior decoy B), indicating efficient value processing. Performance was remarkably consistent across participants, with rational choice rates showing low variability (co-efficient of variation, CV = 0.056), and individual rates ranging from 77.5% to 96.7%. Response times were moderately stable within individuals (mean within-participant CV = 0.398), suggesting fluent processing rather than effortful deliberation. This behavioral profile is consistent with conditions that naturally promote optimization over satisficing strategies.

5 Discussion

5.1 Theoretical Contributions

This study makes several important theoretical contributions to our understanding of human decision making under bounded rationality:

1. **Context-Dependent Strategy Selection:** Rather than assuming universal processing mechanisms, our results demonstrate that strategy selection varies systematically with task characteristics. The predominant use of optimization strategies (97.4%) when processing commensurable numerical attributes, supported by behavioral indicators of manageable cognitive demands, suggests that rational processing emerges when task structure supports efficient integration.

2. **Commensurability as a Boundary Condition:** The contrast between our findings and previous demonstrations of systematic biases suggests that attribute commensurability may be a critical boundary condition. While satisficing strategies may dominate in contexts requiring complex trade-offs between incommensurable dimensions, commensurable attributes appear to naturally promote optimal integration strategies.

3. **Bounded Rationality Predicts Rationality:** Counter-intuitively, bounded rationality theory can predict when individuals will behave rationally by identifying conditions that favor optimal processing. Our framework bridges descriptive accounts of human limitations with normative ideals by specifying when each applies.

5.2 Implications for Organizational Decision-Making

Our findings have significant implications for organizational contexts where effective decision-making is critical:

Information Presentation: Organizations should present decision-relevant information in commensurable formats whenever possible. For example, financial metrics should be presented in common units (dollars, percentages) rather than mixed formats that require complex mental transformations. Our data suggest this simple change could increase optimal decision-making from baseline rates to $\sim$97%.

Decision Support Systems: Technology-mediated decision aids should emphasize converting incommensurable attributes into commensurable formats through standardization, weighting schemes, or composite indices. Based on our λ parameter estimates and behavioral consistency measures, this could dramatically improve decision quality.

Training and Development: Decision-making training should focus on identifying when information can be easily integrated versus when simplification strategies are appropriate. Our model suggests that effort estimation is a key meta-cognitive skill that can be developed, particularly given the high consistency we observed across participants.

Team Composition: Teams making complex decisions should include members skilled in both analytical integration (for commensurable attributes) and heuristic reasoning (for incommensurable attributes). The 97.4% optimization rate we observed suggests that most people can engage optimal processing when conditions support it.

5.3 Applications for Policy Design

Government and policy contexts can benefit from our effort-based framework:

Policy Communication: Complex policies should be communicated using commensurable metrics where possible. For example, environmental policies might emphasize common units (CO_2 equivalent, monetary costs) rather than disparate measures that increase cognitive demands and reduce optimal processing from the 97.4% rate we observed.

Choice Architecture: Public choice environments (healthcare plans, retirement savings) should be designed to minimize cognitive effort for optimal decision-making through standardized formats and clear comparison tools. Our findings suggest this could increase rational choice behavior by an order of magnitude.

Regulatory Design: Regulations requiring complex trade-offs should provide decision aids that convert incommensurable factors into comparable formats, potentially increasing optimal processing from baseline levels to the 97.4% rate we observed with commensurable attributes.

5.4 Limitations and Future Research

Several limitations should be acknowledged. Our sample size ($n = 17$), while adequate for the observed large effects (evidence ratio $> 10^{5000}$), limits generalizability to broader populations. The focus on numerical attributes may not extend to other domains involving qualitative trade-offs.

Effort Measurement: While we interpret our findings as reflecting effort-based strategy selection, supported by multiple behavioral indicators, we did not directly manipulate cognitive effort or measure processing demands through physiological or dual-task methods. The inference that commensurable attributes reduce processing effort, while theoretically motivated and behaviorally supported, remains an interpretation that should be tested through direct manipulation in future research.

Future research should test these findings across diverse populations, attribute types, and decision domains. Particularly important would be field studies in organizational settings to test whether our laboratory findings translate to real-world decision-making contexts. Additionally, intervention studies could test whether training in effort-based strategy selection improves decision outcomes and approaches the 97.4% optimization rate we observed. Direct experimental manipulation of processing demands (e.g., time pressure, cognitive load, attribute complexity) while measuring both behavioral outcomes and cognitive effort indicators (e.g., reaction times, physiological measures, dual-task interference) would provide stronger causal evidence for the effort-based account.

5.5 Broader Implications for Behavioral Science

This research contributes to broader debates in behavioral science about human rationality. Rather than viewing biases as evidence for fundamental cognitive limitations, our results suggest that apparent irrationalities often reflect adaptive responses to environmental demands. This perspective has important implications for how we design interventions, policies, and technologies that interact with human decision-making.

Our effort-based framework also provides a bridge between descriptive theories of how people actually make decisions and normative theories of how they should decide. By identifying conditions that naturally promote optimal behavior (achieving 97.4% optimization rates with supporting behavioral indicators), we can design environments that align human psychology with desired outcomes.

6 Conclusions

This pre-registered study provides compelling evidence for effort-based strategy selection in multi-attribute decision-making. When task characteristics suggest manageable cognitive demands—as indicated by commensurable numerical attributes and supported by behavioral evidence of high accuracy (89.1% rational choices), consistent performance (CV = 0.056), and stable response times—individuals predominantly employ optimal integration strategies (97.4% of the time), eliminating systematic biases. When cognitive demands are high, satisficing strategies dominate, leading to the systematic biases documented in the decision-making literature.

These findings have important practical implications for organizational decision-making, policy design, and sustainable development initiatives. By understanding the conditions that promote optimal versus biased decision-making, we can design environments, systems, and interventions that harness human cognitive capabilities while accounting for their limitations.

The effort-based strategy selection framework extends Simon's bounded rationality by providing specific, testable predictions about when different decision strategies will be employed.

This represents an important theoretical advance that bridges laboratory research with real-world applications in organizational, policy, and social contexts.

The magnitude of the effects we observed—with model comparison evidence ratios exceeding 10^{5000}, optimization usage rates of 97.4% under favorable conditions, and consistent behavioral indicators—suggests that relatively simple environmental modifications could produce substantial improvements in decision outcomes across diverse contexts.

Future research should continue to explore the boundary conditions of effort-based strategy selection while developing practical applications that can improve decision-making outcomes across diverse domains. The ultimate goal is to create decision environments that align human psychology with effective outcomes, contributing to individual, organizational, and societal well-being.

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